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"AGGREGATE SHOCKS VS REALLOCATION SHOCKS: AN APPRAISAL OF THE APPLIED LITERATURE"

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Aggregate Shocks vs Reallocation Shocks: an Appraisal of the Applied Literature

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Abstract

This paper critically appraises the different approaches that have characterized the literature on the macroeconomic effects of job reallocations from Lilien's seminal work to recent developments rooted in structural general equilibrium models, nonlinear econometric techniques and the concepts of job creation and destruction. Despite a flourishing of empirical analysis no unifying theoretical framework has obtained consensus in the scientific debate. We face a corpus of research which is heterogeneous in variables' selection and experimental design. This widespread heterogeneity makes the evaluation of results a daunting task. Reliability of outcomes becomes almost impossible to assess when, even within models of the same generation, the lack of a rigorous theoretical background hinders well defined experimental design and makes comparisons difficult. The strong pace at which the empirical literature on the macroeconomic effects of job reallocations has been growing in recent years suggests that a general assessment of the state of the art is valuable and maybe indispensable. As a guiding principle for our excursion we track down the methodological development of the proposed solutions to the crucial problem of observational equivalence. We do not linger on specific econometric methods nor on strictly theoretical issues not relevant to our main purpose. We draw the conclusion that the asymmetric and non-directional nature of allocative shocks, which holds the key to the solution of the problem, is better captured by multivariate, non-linear, dynamic econometric models and numerical simulation techniques. Davis and Haltiwanger's perspective on job creation and destruction seems to us of paramount importance for future research because of its potential to encompass a wealth of micro-level data sets within a rigorous analytical framework.

Keywords: Sectoral shifts, methodology, measurement, assessment
JEL Classification Numbers: $E30$, $C10$, $J21$

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1 Introduction

Lilien's sectoral shifts hypothesis (SSH hereafter) is a powerful and compelling idea which has been exercising a strong influence on business cycle analysis for over twenty years. Up to the early 1980s most models of unemployment cycles regarded aggregate shocks as the only driving force.

Lilien (1982b) formalized the SSH[1], focusing on the macroeconomic effects of reallocation shocks. Davis (1987), stressing the difference in scope and method between "reallocation models" and "aggregate models", recommends a two-group classification. Models where an aggregate shock is the main triggering force should be grouped under the label of "normal business-cycle hypothesis" (henceforth NBCH). Using this taxonomy Keynesian and new-classical models can be bunched together to the extent that they rely on aggregate impulses. Instead the SSH label would accommodate those models where fluctuations are set off by allocative shocks affecting the composition of demand.

Lilien's insight has generated a large response. It has enjoyed mixed fortunes, meeting stern criticism as well as strong support. The relevance of inter-sectoral (and intra-sectoral) labour reallocations as a source of aggregate unemployment fluctuations is the object of an ongoing controversy. Such debate persists because of the empirical difficulty in separating "reallocation unemployment" from unemployment generated by aggregate shocks. Whether the SSH would contribute a useful breakthrough or not, it is a matter which will be settled only when this incumbent problem of observational equivalence is solved.

In this paper we appraise critically the different methodologies that have characterized the sectoral shifts empirical literature from the date of publication of Lilien's seminal work to present. We have observed a flourishing of empirical studies, however no unifying analytical framework has obtained a widespread consensus. We face a body of research which is heterogeneous in variables' selection, modeling strategies and results. Given the fast growth of empirical literature on sectoral shifts over the last two decades, a general assessment of the current state of the art seems useful and necessary. As a guiding principle for our excursion we try to track the methodological development of the proposed solutions to the aforementioned problem of observational equivalence. We do not linger on specific econometric methods nor on strictly theoretical issues not relevant to our main purpose. We draw the conclusion that the asymmetric and non-directional

[1]Sectoral Shifts Hypothesis was the apt and original tag chosen by Lilien to identify his views. Given subsequent developments, which also focused on intra sectoral movements and the processes of job creation and destruction, it would be more correctly comprehensive to label the whole approach as Labor Reallocation Hypothesis (LRH). However as our perspective is on the developments of applied methods as they sprung out of Lilien's seminal paper, we keep the SSH label.

nature of allocative shocks holds the key to the solution of the problem and is better captured by multivariate non-linear dynamic econometric models or numerical simulations techniques.

We wish to clarify from the outset a difficulty besieging this field which has influenced our work. The notion of an aggregate shock is vague and devoid of a clear meaning in a general equilibrium context (c.f. Black (1995) often refers to this issue). Our view is that, at this stage, aggregate shocks can only be defined vis-a-vis allocative shocks. The latter are properly defined disturbances to the current allocation of resources with associated specific behavioural asymmetries which can bring about temporary spikes in unemployment, while aggregate impulses must have a specific directional sign for the activity of all sectors/firms. This view, though not an operational definition yet, suggests specific empirical features on which to base a meaningful identification. Davis (1987), in a similar perspective, suggests the best operational definition of aggregate shocks: aggregate shocks should be seen as the cross-sectional average of marginal product disturbances. Throughout this article we consider Davis's definition as the most accurate approximation to the concept of aggregate shock. Thus, in our survey, research efforts aimed at proving or disproving the aggregate or reallocation approach are indirectly seen as a quest for the existence and proper definition of aggregate shocks.

Our work is organized as follows: in section 2 we present a summary of the SSH as well as a description of the estimation approach which characterized the seminal contributions. This section ends by reviewing the observational equivalence controversy surrounding the empirical implementations of the hypothesis and by classifying alternative modeling procedures aimed at its solution. Section 3 deals with time series analysis. The effectiveness of the unemployment-vacancy relationship as a discriminating tool is surveyed in section 3.1. Sections 3.2, 3.3 and 3.4 respectively discuss the so-called "purging" methodology, two testable implications of the SSH[2] and stock market measures of sectoral shocks.

All the procedures presented in sections 3.2, 3.3 and 3.4 are characterized by extensive use of generated regressors: in section 3.5 we provide a brief discussion of efficiency and inference issues concerning the use of generated regressors in sectoral shifts analysis. Section 3.6 describes an upgrade in modeling sectoral shocks via vector auto-regressions (VAR) free of dispersion measures. In section 3.6.1 we look at the linear VAR approach developed by Campbell and Kuttner (1996). In section 4 and its subsections the job creation and job destruction approach, initiated by Davis and Haltiwanger(1990, 1992), is discussed. We emphasize the potential power of this contribution as a 'discriminating' testing tool. Section 5 is entirely devoted to models which rely on micro-level data. Another increasingly popular way to explore the SSH is via

[2]The so-called "Past-Patterns-of-Labor-Reallocation" and "Stage-of-Business-Cycle" effects.

numerical simulation techniques based on well specified equilibrium models: this approach is the subject of section 6. Section 7 provides a summary of the paper and presents some possible directions for future research.

A word of warning: throughout this article we identify papers/books by the initials of the authors (followed by the last two digits of the paper's issue date where necessary). Analogously when the author or authors have set a standard of analysis through a series of works, we would address the whole set of papers/books only by the authors' initials.

2 Lilien's Sectoral Shifts Hypothesis

The SSH represents a prototype structure for a class of models dealing with the aggregate effects of allocative shocks. It was first formalized by Lilien in two path-breaking articles (1982*a*, 1982*b*). Lilien's dispersion hypothesis claims that intersectoral shifts in demand composition operate as the driving force of unemployment fluctuations. The basic insight is that idiosyncratic shocks bring about flows of job reallocation from declining sectors to expanding ones. Such a process of labour reallocation can be slow and may entail prolonged unemployment spells. It follows that the higher the dispersion of employment demand throughout the economy the higher aggregate unemployment will be.

The starting point of our discussion is Lilien's (1982b) turnover model which explicitly refers to the search model in Lucas and Prescott (1974) for a theoretical underpinning. Lilien makes no attempt to frame his insight within a fully blown theoretical structure and develops a rather simple turnover model as the basis for empirical analysis. Pivotal to Lilien's flow model is a stochastic net hiring equation

$$y_{it} = Y_t + \varepsilon_{it} \tag{1}$$

where the typical firm's net hiring y_{it} is decomposed in an aggregate hiring rate Y_t common to all firms and a firm specific component ε_{it}. The properties of the stochastic process $\{\varepsilon_i\}_t$ characterize the SSH. The random variable ε_{it} is distributed

$$\varepsilon_{it} \sim (0, \sigma_{it}^2) \tag{2}$$

with the time-period subscript t attached to σ_i^2 indicating the time dependence of the variance. Since ε_{it} has a changing variance over time, the model can entail a non constant natural rate of unemployment (NRU). Cyclical fluctuations of aggregate unemployment are not necessarily deviations from a stable natural rate due to aggregate (i.e. non sector specific) disturbances. The time changing variance, σ_{it}^2, can justify fluctuations in aggregate employment as fluctuations of the NRU itself. By imposing restrictions on the firm's hiring-layoff behavior and appealing to the law of large numbers Lilien derives an aggregate layoff function

$$L_t = g\left(Y_t, \sigma_t\right) \tag{3}$$

where σ_t denotes a measure of overall hiring dispersion and is positively related to layoffs. Higher hiring dispersion leads to a larger aggregate volume of layoffs. Inserting this equation within a simple flow model allows Lilien to derive a dynamic reduced form equation for the unemployment rate which can be generalized as

$$u_t = F\left\{A(L)u_t, B(L)\sigma_t, C(L)z_t\right\} \tag{4}$$

where $A(L)$, $B(L)$ and $C(L)$ are polynomials in the lag operator L, u_t and σ_t are measures of unemployment rate and of inter-sectoral dispersion of demand conditions and z_t is a vector of aggregate control variables. Equation (4) suggests that, after controlling for serial correlation and aggregate factors, unemployment could still be sensitive to sectoral shifts.

To empirically implement this insight, Lilien proxies the variance of reallocation shocks by a weighted standard deviation of cross-sectoral employment growth rates using an eleven-sectors decomposition of the US economy

$$s_t = \left[\sum_{i=1}^{K} w_{it}.\left(\Delta \ln x_{it} - \Delta \ln x_t\right)^2\right]^{\frac{1}{2}} \tag{5}$$

where x_{it} is employment in sector i at time t, x_t is aggregate employment at time t, K is the number of sectors and w_{it} are weights defined as the relative size of each sector, that is $\left(\frac{x_{it}}{x_t}\right)$. Using US annual data from 1948 to 1980, Lilien estimates a linearized version of equation (4) including the dispersion proxy s_t:

$$u_t = \alpha_0 + \alpha_1 s_t + \sum_{\forall j} \alpha_j z_{t-j} + e_t \tag{6}$$

Lilien's results bear out that s_t is significantly and positively correlated with unemployment over the considered sample period. The empirical evidence seems to suggest that much of US unemployment in the 1970's, contrary to that of the early 1960's, can be explained by sectoral shifts. Demand management policies were then ill suited for that specific unemployment spate; instead speeding up the process of labor reallocation would have had a stronger impact on unemployment.

The SSH triggered a quick response from the economic profession. It was almost immediately recognized that a problem of observational equivalence was embedded in Lilien's approach [see

Lilien (1982a), Abraham and Katz(1987, 1986), Weiss (1986)]. This problem arises because Lilien's dispersion proxy is likely to reflect aggregate disturbances if cyclical responsiveness varies across sectors. Thus the positive u-s (unemployment-sectoral dispersion) correlation could be capturing the effects of aggregate shocks instead of labor market turbulence. Observationally equivalent predictions can then be generated by two alternative business cycle theories. In the attempt to overcome this identification problem, researchers have proposed procedures which can be distinguished depending on whether they exploit properties of aggregate data or micro-level data. In the following sections we examine both micro-data and aggregate-data methods. Following the historical development sectoral shifts analysis, we set off by discussing time series and aggregate data modeling.

3 Time Series Models of Sectoral Shifts

The 'Time Series' literature on the analysis of sectoral shifts can be roughly categorized in five groups:

1. methods exploring correlation between observed dispersion and vacancy rate;
2. methods aimed at developing a 'purging' methodology, i.e. decomposition of dispersion proxies into sectoral and aggregate components;
3. methods using dispersion indexes defined in terms of stock prices (or accounting data[3]);
4. methods where sectoral shocks are modeled directly using VAR systems, free of dispersion measures;
5. methods based on multivariate volatility models.

We discuss each method in turn, starting from the ones relating vacancies and unemployment.

3.1 Sectoral Shifts and the Beveridge Curve

Discriminating methods related to the unemployment-vacancy ($U-V$) relationship, the so-called Beveridge curve, dominated the early debate. Interest in these procedures faded when Hosios (1994) clearly exposed their potential limits.

Abraham and Katz(1987, 1986) first suggested the possibility of separating the effects of sectoral shifts from those of aggregate shocks by looking at the correlation between vacancies,

[3] Accounting data are essentially micro information. However they have been used in conjunction with aggregate data and within frameworks typical of the aggregate-data approach.

V, and Lilien's dispersion index, s. If the observed dispersion has been brought about by reallocation shocks, then there must be a positive relation between V and s. On the other hand, a negative correlation between V and s suggests that aggregate shocks have generated the apparent labor market dispersion. In other words, if aggregate shocks were the relevant triggering force we should have movements along the Beveridge curve (negative "U-V" comovements), while if sectoral shifts were the real source of a recession we should observe an outward shift of the curve (positive "U-V" comovements). AK estimate a vacancy equation using the help-wanted advertising index (HWAI) as a measure of vacancies. The linear vacancy equation they estimate is

$$V_t = \pi_0 + \pi_1 s_t + \sum_{j=1}^{T} \pi_{2j} z_{t-j} + e_t \tag{7}$$

where z is a vector of aggregate components, s_t is the standard dispersion proxy as in (5), and $\{e_t\}$ is a white noise process. If π_1 were positive the sectoral shifts hypothesis would be corroborated while if it were negative it would have to be rejected. Since the estimated $\hat{\pi}_1$ is a negative number significantly different from zero, AK argue that empirical evidence does not bear out the SSH. AK's evidence has been subsequently supported by Blanchard and Diamond (1989) in a different perspective.

Critics of the sectoral shifts approach have interpreted these results as definitive rebuttals of the hypothesis and the $V - s$ experiment as a procedure fully capable of discriminating between the two sources of fluctuations (Johnson and Layard (1986)).

The view that only aggregate shocks are responsible for negative "U-V" comovements has been challenged by Hosios (1994). His paper develops an equilibrium matching model where reallocation shocks can induce a negative short term "U-V" relationship. Hosios models allocative disturbances both as changes in the separation rate and changes in relative price dispersion among firms. The implied "U-V" comovements will depend upon the type of sectoral shock experienced. A change in the separation rate will bring about the usual positive "U-V" comovement, but a temporary relative price shock will induce "U" and "V" to move in opposite directions. The driving force in the model is an externality: the negative impact of temporarily laid off workers on job openings. It is more profitable for a firm to hire unattached workers than temporary layoffs since the latter have better alternatives and demand relatively higher wages. A "price-variance" shock will increase the number of searching workers; as the number of temporary layoffs increases, firms find it more difficult to spot unattached workers in the searching pool and are thus less prone to create new job openings. Since the number of searching workers is rising with fewer jobs available, the probability of finding a job decreases and therefore unemployment is increasing while vacancies are falling.

Hosios' analysis implies that U and V data sets, in isolation, are unable to determine whether aggregate shocks or sectoral shifts are the main triggering forces of aggregate unemployment fluctuations.

In an earlier paper Davis (1987) notices that the HWAI, the vacancy proxy in AK, is a stock value. Instead the appropriate variable for the experiment should be some vacancy rate whose behavior over the cycle differs from that of the vacancy stock. Since the pro-cyclicity of the HWAI should be expected, as it largely reflects the search for temporary workers over the cycle, Davis concludes that the results of AK do not provide strong evidence against the SSH.

In related work Palley (1992) argues that a negative "U-V" correlation is consistent with the SSH if it is costly to hire new workers. If hiring and firing costs are asymmetric, in particular hiring costs are higher than firing costs, sectoral shocks can generate movements along the Beveridge curve. Palley decomposes a dispersion index in an aggregate (s_a) and a sectoral (s_s) component and finds that U and s_s are positively correlated, whereas V and s_s are negatively correlated. However, his empirical findings bear out that unemployment fluctuations are mostly generated by aggregate shocks while reallocation shocks explain a significant but steady amount of unemployment. These results should be taken with caution. Palley's model is not a general equilibrium model but rather an example based on Weiss (1986). His handling of the dispersion proxy also suffers from problems which we will discuss below.

Hosios' results seem to set the tone of the discussion in this domain. As long as U and V data are taken in isolation, regardless of the empirical setting, they will not provide the necessary information to sort out the SSH dilemma.

3.2 Purging

Purging Lilien's proxy of aggregate effects has been often suggested as an effective way to handle the observational equivalence problem. This practice amounts to filtering out aggregate effects either directly from the dispersion measures (Mills, Pelloni, and Zervoyanni(1995, 1996)) or indirectly from the employment growth rates used to construct the indices Abraham and Katz (1987)Neelin (1987)Samson (1990). Because of its simplicity, this analytical tool, despite its shortcomings, has been commonly applied in sectoral shifts analysis.

As we have seen, Lilien aimed at estimating a linear version of (4)

$$u_t = \alpha_0 + \sum_{j=0}^{p} \alpha_j s_{t-j} + \sum_{j=0}^{q} \alpha_{2j} z_{t-j} + e_t \tag{8}$$

Because of the observational equivalence problem, a statistically significant $\widehat{\alpha}_1 > 0$ would not necessarily corroborate the SSH. The purging methodology recommends the decomposition of s_t into an idiosyncratic component and a component measuring the response to aggregate shocks. In general, to obtain residuals 'purged' of aggregate influences, s_t is regressed on a vector of aggregate variables $\widetilde{z}_t$

$$s_t = \beta_0 + \sum_{j=0}^{q} \beta_j \widetilde{z}_{t-j} + v_t \tag{9}$$

There is wide variation across papers in the choice of variables included in $\widetilde{z}_t$. Some authors Abraham and Katz (1987)Neelin (1987)Samson (1990) use monetary aggregates while others (Mills, Pelloni, and Zervoyanni (1995, 1996)) resort to a larger array of real and monetary aggregates.

The estimated residual $\widehat{v}_t$ from equation (9) provides the 'purged' component of s_t. The generated residual, supposedly driven only by reallocation shocks, is then used in an unemployment equation

$$u_t = \gamma_0 + \gamma_1 \widehat{v}_t + \sum_{j=0}^{T} \gamma_{2j} z_{t-j} + \xi_t \tag{10}$$

As the choice of variables in z_t and $\widetilde{z}_t$ is at the discretion of the researcher, the problem of under/over-purging arises. Some authors, concerned with the potential omission of relevant aggregate components, would further smooth the estimated residual $\widehat{v}_t$ before including it in the final unemployment equation. Abraham and Katz (1987) epitomizes this point of view. The first step of this "careful purging" is analogous to the previous procedure. For the employment growth rate of each sector they estimate equations of the form:

$$\Delta \ln x_{it} = \beta_{i0} + \sum_{j=1}^{T} \beta_{ij} \tilde{z}_{t-j} + v_{it} \tag{11}$$

where $\Delta \ln x_{it}$ is employment growth rate in sector i at time t and the vector $\tilde{z}_t$ consists only of a measure of unanticipated money growth. The sectoral residuals $\widehat{v}_{it}$ are then used to compute the weighted average residual for each period over the N sectors of the economy :

$$\bar{v}_t = \sum_{i=1}^{N} \left(\frac{x_{it}}{x_t}\right) \widehat{v}_{it} \tag{12}$$

In a standard purging procedure the generated variable $\bar{v}_t$ would be used as a measure of dispersion Samson (1990). If, as in Abraham and Katz (1987), Neelin (1987) and Samson (1990), the elements of vector z_{t-j} are just measures of unexpected and/or expected money, such a dispersion proxy would be cleaned up of monetary effects while still containing other real aggregate impulses. Some researchers (e.g. Samson 1990), though acknowledging this flaw, maintain that no actual purging procedure can distinguish properly between aggregate and sector specific components. They argue that simple purging procedures such as (9) or (12), though possibly leading to under-purged indices, are preferable to stronger ad hoc filtering methods because they do not mis-identify sectoral and aggregate shocks. Abraham and Katz are instead concerned by potential under-purging and introduce an extra cleansing step. They add the generated $\bar{v}_t$ as a regressor in a new set of sectoral employment equations:

$$\Delta \ln x_{it} = \gamma_{i0} + \sum_{j=1}^{T} \gamma_{ij} z_{t-j} + \lambda_i \bar{v}_t + \varepsilon_{it} \tag{13}$$

where the disturbances ε_{it} are assumed to follow an $AR(1)$ process:

$$\begin{aligned} \varepsilon_{it} &= \rho_i \varepsilon_{it-1} + e_{it} \\ e_{it} &\sim iid\left(0, \sigma_e^2\right) \end{aligned} \tag{14}$$

Finally, using the results from this step, Abraham and Katz construct their purged measure of dispersion S_t^{AK} as:

$$S_t^{AK} = \sum_{i=1}^{N} \left(\frac{x_{it}}{x_t}\right) \left(\frac{\widehat{v}_{it}}{\sigma_e^2}\right) \tag{15}$$

The extra purging is aimed at removing the component of the residuals $\widehat{v}_{it}$ which moves together with the average residuals. This method, however, does not provide a clear identification of the nature of the shocks. No explicit discussion is provided to back up this methodology and it is hard to see how the additional purging step can separate aggregate and reallocation shocks. It rather seems that a researcher, when using this or a similar approach, would face a high risk of over-smoothing (thus over-purging) the dispersion proxy. This methodology is likely to remove those sectoral shocks which have similar effects on the economy as a whole. For example, if the correlation between the sector specific disturbances e_{it} is different from zero, then a conspicuous part of the sectoral noise could be captured by the artificial regressor $\bar{v}_t$, since the correlation among sectoral shocks would look like an economy-wide oscillation.

Some of the ambiguities in the methodology of Abraham and Katz (1987) can be attributed to the lack of detailed and clear definitions of sectoral and aggregate shocks, a problem common to many other works in this field. If an aggregate shock is meant to have an homogeneous impact on the whole economy, then it becomes extremely difficult to distinguish it from highly correlated sectoral shocks.

Furthermore Abraham and Katz treat σ_e^2 (the variance of the purged sectoral innovation) as a constant. This assumption is at odds with the very hypothesis of sectoral shocks: a time-varying variance is one of the crucial building blocks of the SSH.

The potential drawback of ad hoc over-purging or under-purging is not peculiar to the method of Abraham and Katz but is common to the whole purging literature. The purging strategy, despite its popularity and practicality, is exposed to the criticism of ad-hoc "fine tuning". Empirical results will vary widely according to the choices made by the researcher in terms of filtering steps and variables included in the vector z_t. It is not surprising that the mild purging technique of Samson (1990) and the "careful purging" approach of Neelin (1987) provide contrasting results for the Canadian labor market. The use of different purging procedures looks decisive. For instance, Samson uses a measure which is not totally free of aggregate impulses and that is much more variable in absolute terms because it is not divided by any variability measure. As shown by Pesaran and Evans (1984), the non-scaling of an index by a variance measure could enhance its relative statistical significance. Since Abraham and Katz's and Neelin's measures are based on a set of assumptions which drastically reduce sectoral volatility, it is reasonable to ask whether their dispersion measures would be significant had they not been normalized by a time constant variance. It is unclear if the difference between under and over-purged indices is due to their different treatment of aggregate impulses or simply to the larger variability of the under-purged indices. In general, articles with purged indexes tend to reject the sectoral shifts hypothesis. Two exceptions are Mills, Pelloni, and Zervoyanni (1995) and Byun and Hwang (2006). MPZ95 apply an updated time series methodology, modeling money supply explicitly and expanding the sector decomposition with respect to Lilien's original contributions. Analyzing US quarterly data over the period 1960-1991 they find a positive and statistically significant relationship between a measure of the unemployment rate and both purged and un-purged dispersion proxies. Mills, Pelloni, and Zervoyanni's subsequent applications (1996, 1997) to UK data also provide support to the SSH. BH06 also challenges AK's criticism of the SSH. BH06 argues that dispersion would sufficiently capture sectoral shifts only when an allocative shock has a symmetric location-scale distribution. If the sectoral shock's distribution is asymmetric, the shape of the distribution could significantly affect estimation results even in the presence of identical dispersion levels. BH extends Lilien's symmetric mean preserving spread flow model by allowing for asymmetric distributions with a mean-variance preserving and mean-variance-skewness preserving transformations. The outcome clearly shows that the skewness and kurtosis could be important factors in capturing the variations in aggregate unemployment. A numerical experiment measures the quantitative magnitude of the explanatory powers of skewness and kurtosis. Results indicate that the skewness measure substantially improves the accuracy of the approximations while the kurtosis coefficient only has a minimal effect. Hence, the measure of skewness should be brought into both Lilien's and AK's reduced forms. Once a skewness measure is introduced into both models, the empirical results suggest that the dispersion measure and the skewness measure have a positive and a negative effect on the unemployment rate respectively, thus bearing out the SSH. The missing skewness effect may have led AK to a spurious rejection of Lilien's view. It follows that "the natural rate of unemployment fluctuates more closely with the actual unemployment rate compared to the AK's result of relatively flat natural rate". This paper could provide an explanation of Lilien's and AK' s conflicting results in terms of embedded crucial asymmetries. We can see how, once skewness is introduced, even the AK's approach cannot reject the SSH. However, because the econometric approach is based on the first generattion of estimating equations, we cannot rule out possible mis-specification errors and spurious regressions. The outcomes can explain the difference between AK and Lilien, yet they cannot robustly support the SSH.

3.3 Two Implications of the Sectoral Shifts Hypothesis

Before progressing further it is useful to discuss two testable implications of the SSH which can be easily incorporated in linear dynamic models with a dispersion proxy.

Davis (1987) originally set forth two sources of testable restrictions implicit in the SSH, which we will refer to as: (1) the "Past-Patterns-of-Labor-Reallocation" ("PPLR") effect on current employment; (2) the "Stage-of-Business-Cycle-Effect" ("SBCE") in the relationship between unemployment and the dispersion proxy.

PPLR are an important source of information because of workers' attachment to specific sectors. Such attachment results from short-term barriers to labor mobility due to sector-specific human capital investment, lump-sum sector-switching costs (time costs of searching for a job and a better match) and other short-run barriers (e.g. sectoral/wage differentials reflecting non competitive forces). These obstacles make the contemporaneous response of aggregate unemployment to inter-sectoral reallocations depend on past patterns of labor reallocation. Any sectoral shock which intensifies an already existing mismatch of skills, location and information, would reinforce past patterns of labor reallocation and substantially increase unemployment. A reallocation shock reversing recent past patterns of job reallocations would be accompanied by a moderate increase, or possibly a decrease, in unemployment. The rationale being that workers who have recently switched industries would find it easier to return to the original sectors because of sector specific human capital, personal contacts and information.

These implications of the SSH are testable and Davis (1987) suggests "horizon covariances" as measures of the current direction of inter-sectoral reallocations relative to past directions:

$$s^H_{t,j} = \sum_{i=1}^{K} w_{it} \left(\Delta_1 \ln x_{it} - \Delta_1 \ln x_t\right) . \left(\Delta_j \ln x_{i,t-1} - \Delta_j \ln x_{t-1}\right) \quad \text{with } j = 1, 2, .., J \qquad (16)$$

where the symbols have the same meaning as in (5). The $s^H_{t,j}$ are weighted cross-sectoral covariance between the one-period inter-sectoral movements recorded at time t and the j-period inter-sectoral movements recorded at time $(t-1)$. If the measured values of $s^H_{t,j}$ are relatively high, then the time t direction of sectoral reallocations reinforces past labor reallocation patterns. Instead, smaller values of the $s^H_{t,j}$ signal the reversing of past patterns. Clearly the SSH predicts that the values of $s^H_{t,j}$ should enter a Lilien-type unemployment equation with a positive sign.

Davis (1987) finds that horizon covariances display the predicted positive sign and are statistically significant both with quarterly and annual US data over the period 1953-1986. Moreover the estimates based on annual data suggest that a large amount of unemployment fluctuations are accounted for by long-horizon covariances.

In Mills, Pelloni, and Zervoyanni (1995) the inclusion of various $s^H_{t,j}$ as additional regressors in an unemployment equation yields positive coefficients which are not significantly different from zero. These differences in results could be due to data (different sample periods and frequencies) and/or developments in econometric methodology. However Mills, Pelloni, and Zervoyanni (1996) find additional evidence of effects of PPLR in UK quarterly data over the period 1976-1991.

SBCE, the other auxiliary implication of sectoral shifts, is linked to the observation that inter-sectoral reallocations imply foregone production. If the opportunity cost of unemployment is pro-cyclical, rational agents have an incentive to shorten unemployment spells during expansions and lengthen them during recessions. Thus, for a given amount of labor reallocation, there will be less measured unemployment during expansions and more during recessions.

As Davis (1987) stresses (p.368), the substitution mechanism involved in the SBCE is distinct from that of the reallocation time hypothesis ("RTH"). Both hypotheses arise from the variation over time in the value of foregone production connected with labor mobility and unemployment. However they operate on different margins. The SBCE margin concerns the duration of an unemployment spell once the amount of job-reallocation is given. The margin for the RTH involves the actual amount of job-switching.

Davis (1987) and Mills, Pelloni, and Zervoyanni (1995, 1996) perform tests of the SBCE by introducing recession interaction variables and their lags into unemployment equations. While Davis rejects the "SBCE", both the above Mills, Pelloni, and Zervoyanni's papers confirm the presence of significant SBCE on the relationship between the magnitude of labor mobility and unemployment. The differences may be due to methods of econometric analysis and/or use of different interaction variables and/or the alternative approaches to the dispersion proxy purging.

3.4 Stock Market Based Measures of Sectoral Shocks

The vulnerability of the employment dispersion index to Abraham and Katz's critique has prompted various attempts at building alternative measures of inter-sectoral dispersion. Loungani, Rush, and Tave (1991), Loungani, Oyer, and Rush (1993), Brainard and Cutler (1993) build indices based on stock market data. Their intuition[4] is that the behavior of an industry stock price could be an accurate predictor of that industry's future fortunes. Investment in physical and human capital is expected to increase (decrease) if a sector is experiencing rising (declining) stock prices. That being the case, in subsequent periods capital and labor should be reallocated from the contracting sectors to the expanding ones. Thus dispersion indices defined in terms of sectoral stock markets data (instead of sectoral labor market data) could capture more accurately sector specific information.

Loungani, Rush, and Tave (1991), the pioneering work in this field, claim that "the main advantage of a stock market dispersion measure over Lilien's employment-based measure is that sectoral stock prices largely react to disturbances that are perceived to be permanent, which need not be true of sectoral employment changes..." . As sectoral stock prices correspond to the discounted sum of present and expected future sector profits, the larger the divergence in industries' fortunes, the larger will be the dispersion in sectoral stock prices. Large reshuffles of resources across the economy and higher unemployment should then be associated with greater dispersion in stock prices. An increase in the dispersion of stock prices would act as a leading indicator of unemployment. Loungani, Rush, and Tave (1991) construct their stock market dispersion measure using yearly average indices of various industries' stock prices, published by Standard and Poor. Given the necessity of an homogeneous sample, the industrial decomposition is limited to 45 different sectors. They deflate each index using the GNP price deflator and then calculate the index:

$$S_t = \left[\left(\sum_{i=1}^{n} \left(g_{it} - g_t \right)^2 / n \right) \right]^{\frac{1}{2}} \tag{17}$$

and its weighted form:

$$SW_t = \left[\left(\sum_{i=1}^{n} w_{it} \left(g_{it} - g_t \right)^2 \right) \right]^{\frac{1}{2}} \tag{18}$$

[4]Following an original argument by Black (1987).

where g_{it} is the growth rate of stock prices for industry i at time t, g_t the average growth rate of stock prices at time t , n the number of sectors in the sample period, and the weight w_{it} is, as usual, sector i's employment share.

Loungani, Rush, and Tave (1991) introduce contemporaneous and lagged values of either S or SW in unemployment reduced form equations using U.S. annual data for the period 1931- 1987. In general the lagged dispersion variables have the positive predicted sign and are statistically significant.

To control further for aggregate impulses, Loungani, Rush, and Tave implement a 'purging' exercise. They construct an index (S^{LRT}) reflecting movements in stock market dispersion accounted for by aggregate demand shocks. The S^{LRT} proxy is just the series of predicted values of stock prices growth generated by regressing each industry's growth rate on the present value and leads of output growth rate. Once contemporaneous and lagged values of the S^{LRT} index are substituted in the unemployment equations for either S or SW, they always appear to be insignificantly different from zero and often perversely signed. Therefore Loungani, Rush, and Tave conclude that the significance of their S and SW proxies cannot be assigned to aggregate impulses. Since results are robust to alternative specifications and to the choice of sample period, Loungani, Rush, and Tave claim that their measures closely reflect inter-sectoral dispersion which thus significantly affects unemployment.

Brainard and Cutler (1993) present an interesting extension of Loungani, Rush, and Tave's work. Brainard and Cutler construct a time series of the variance of sectoral stock market excess returns, which they term cross-section volatility (CSV). Under the capital asset pricing model (CAPM) excess returns capture the arrival of sector-specific information about the sector's future profitability. It follows that, at least in principle, excess returns could be exploited as a tool to separate aggregate and reallocation shocks. The introduction of the CAPM represents a substantial move since it provides a theoretical basis for separating aggregate movements in stock prices from idiosyncratic movements while there is no corresponding theory for movements in employment growth rates. Furthermore, the efficient markets hypothesis suggests that the arrival of information about the future profitability of a firm is captured in a single and immediate movement in its stock price, thus ensuring a tight temporal correspondence between the arrival of a shock and the response of stock market dispersion.

Brainard and Cutler's measure should be an improvement relatively to Loungani, Rush, and Tave. In fact the sectoral stock price growth, g_{it}, can be decomposed into two components, with one being sector specific and the other related to the average stock price growth rate:

$$g_{it} = \beta_{i0} + \beta_{i1} g_t + \epsilon_t \tag{19}$$

therefore, unless $\beta_{i1} = 1$, $(g_{it} - g_t)$ will depend on g_t and Abraham and Katz's critique will stand, meaning that indexes based on stock prices capture aggregate disturbances. Brainard and Cutler define excess returns as the sector specific component from a regression of sectoral returns on the average market return:

$$R_{it} = \widehat{\beta}_{0i} + \widehat{\beta}_{1i} R_{mt} + \widehat{\varepsilon}_t \tag{20}$$

where R_{it} is industry i's total return at time t and R_{mt} is the return on the market portfolio at time t (computed by using Standard and Poor's Composite Index). Excess returns are then defined as:

$$\eta_{it} = \widehat{\beta}_{0i} + \widehat{\varepsilon}_t \tag{21}$$

where $\widehat{\beta}_i$ and $\widehat{\varepsilon}_t$ are the estimated values of β_{0i} and ε_t. The cross-section volatility (CSV) is defined as the weighted variance of one-quarter excess returns :

$$CSV_t = \sum_{i=1}^{N_t} w_{it} \left(\eta_{it} - \bar{\eta}_t\right)^2 \tag{22}$$

where $\bar{\eta}_t$ is the average excess return and w_{it} is the employment share of sector i. Since the unemployment equation is an unresolved issue, Brainard and Cutler estimate several specifications using US quarterly data from 1948:1 to 1991:2. They find that the cross-section volatilities present the right signs and are statistically significant in every specification, especially at longer lags. The inclusion of variables such as money growth and the relative oil price improves the fit of the equations considerably but does not alter the conclusions about cross-section volatility. In order to carry out comparisons across the different specifications, Brainard and Cutler report the associated impulse response functions (IRF) for unemployment. For all specifications the IRF profile is similar: the impulse response of unemployment to cross-section volatility rises for two or three years and then declines. After three years the impact on unemployment of a one-standard deviation shock to CSV is about 0.3%. Brainard and Cutler conclude that "..although cross-section volatility has a significant effect on unemployment, the magnitude of the response to cross-section volatility shocks is not large, suggesting that a very large shock would be needed to account for the increases in unemployment that are characteristic of recessions..[however]...there have been periods in which the reallocation shocks captured by cross-section volatility have generated substantial increases in unemployment; for example, they accounted for 60% of the

4.0 percentage points increase in aggregate unemployment between 1973 and 1975; similarly, in the late 1960s reallocation unemployment rose 0.7 percentage points despite a strong macroeconomy..". In summary, despite such episodes, the overall effect of reallocation shocks on total unemployment seems to have been mild.

Fortin and Araar (1997) apply the CSV measure to Canadian data and obtain results which are qualitatively similar to those of Brainard and Cutler for the US: sectoral shifts have been an important source of unemployment fluctuations during specific episodes but in general their relevance for Canadian unemployment is minor. Caporale, Doroodian, and Abeyratne (1996) employ the CSV index alongside an ARCH measure of inflation uncertainty, the growth rate of high powered money, the inflation rate and the three-month treasury bill rate. Brainard and Cutler's results receive further corroboration from Caporale, Doroodian, and Abeyratne. The CSV variable Granger-causes unemployment but explains only a small portion of unemployment changes, which are mainly accounted for by aggregate shocks.

In carrying out their exercise Brainard and Cutler control for potential weaknesses of the CSV measure. First, CSV may be reflecting changes in firms' leverage ratios more than divergence in industrial fortunes. Risk considerations could induce a higher stock price volatility in response to increases in the debt-equity ratio. Because of this potentially damaging factor, Brainard and Cutler construct a leverage-adjusted series (a CSV series adjusted by weighting returns with annual debt-equity ratios) and compare it with the unadjusted CSV series. They conclude that the two series do not differ substantially.

Another concern is that excess returns could capture variations in the expected value of physical capital that are unrelated or inversely related to the expected value of human capital. Thus it would be possible for a firm to have contemporaneously positive excess returns and zero or negative excess employment. To ensure that employment is related to excess returns, BC93 pool each industry's time series and derive sectoral excess employment changes as measured by the residuals of sectoral employment growth rates regressions on the growth rate of total employment. The generated residuals are summed over different time horizons ranging from one quarter to five years and finally regressed on the one-quarter excess return. The estimated coefficients indicate that excess returns significantly predict employment growth, although the effect is small: an industry with a 10% excess return is predicted to have additional employment growth of roughly 0.8% after two years. Notice that no incremental effect is registered after four years although the initial effect persists.

However the above procedures do not provide conclusive evidence on the reliability of CSV as an appropriate proxy for human capital reallocation. Recent episodes in the stock markets cast doubts on the predictive power of excess returns over sectoral employment rates. It has happened that, as firms announced cuts in employees' payrolls, their share price experienced sudden upward jumps, as if such announcements were indication of higher future profits. We do not wish to probe further the rationale underlying this kind of stock market response, but we wish to stress how it can be misleading for sectoral shifts analysis. In fact such episodes provide examples in which the logical sequence advocated by BC is entirely subverted. The upward price jump in such episodes emerges in response to the announcement of future lay-offs, thus perverting the supposed relation between excess returns and employment growth. Moreover, the chronological sequence would still imply a positive correlation between CSV and unemployment, since the announced lay-offs are going to take place only in the future and therefore stock market turbulence will grow before a series of lay-offs. Therefore the timing can be deceiving and lead researchers to wrong conclusions.

A further criticism directed to both Loungani, Rush, and Tave (1991) and Brainard and Cutler (1993) is that they do not provide a compelling argument supporting the view that their stock prices dispersion indices are immune from aggregate influences. We have already seen how the Loungani, Rush, and Tave measure can be affected by aggregate factors. In practice Brainard and Cutler's CSV could also be affected by the uneven impact of aggregate forces. There is no sufficient evidence that all sectors would respond similarly to aggregate shocks and the reliability of all these measures (S,SW,CSV) is based either on untested theoretical assumptions or on purging exercises. In the latter case they are subject to the standard 'ad-hockery' criticism.

For the sake of completeness we report some results concerning stock market measures and the Beveridge Curve. As a benchmark specification, Brainard and Cutler (1993) regress the logarithm of the vacancy rate against the contemporaneous unemployment rate, contemporaneous and lagged values of CSV and a measure of employment dispersion. Under alternative specifications, they find that the U-V relationship shifts out in response to positive changes in CSV. However Zagorsky (1994), using Loungani, Rush, and Tave (1991)'s measure, finds a negative relationship between vacancies and the dispersion proxy, corroborating aggregate views of business cycles.

As we have seen above, Hosios (1994) has clearly exposed the limits of the evidence related to the Beveridge Curve. Nonetheless, it is worthwhile to stress how exercises based on similar measures lead to contradictory results.

3.5 Generated Regressors in the Analysis of the Sectoral Shifts Hypothesis

All the procedures described above make extensive use of generated regressors in measuring sectoral shocks. The inclusion of generated regressors in linear models has often been the object of dispute. In the following discussion we use results from Pagan (1984) and Oxley and McAleer (1993). Consider reduced form equations of the type used by Lilien (1982a) and Abraham and Katz (1987), such as (6). The first question is: how does the inclusion of a Lilien-type proxy for sectoral shocks affect estimation? Lilien's proxy is a weighted average of sectoral employment changes: for inference to be valid in this case it is needed that sectoral employment changes used in the proxy be "unexpected". This is equivalent to a weak exogeneity assumption. Following Pagan (1984) we conclude that inference based on Lilien's employment reduced form can be considered reliable, granted that the sectoral dispersion index captures unexpected components in sectoral movements.

However, unlike Lilien, Abraham and Katz (1987) use generated regressors in the construction of the dispersion variables they include in reduced form (6). The 2-step procedure used by Abraham and Katz to build their dispersion index starts from a "short" employment growth equation of the following kind:

$$y_i = \gamma x_i + u_i \tag{23}$$

where y_i denotes the growth rate of sectoral employment and all the other regressors are grouped in vector x_i. The second step is based on a "long" employment growth rate equation

$$y_i = \delta \left[\sum_{i=1}^{N} \; w_i \hat{u}_i \right] + \gamma \; x_i + \varepsilon_i \tag{24}$$

As usual the w_i's are the sectoral weights, $w_i = \frac{xit}{Xt} \quad for \; i = 1, 2, ..., N$. Abraham and Katz estimate $\hat{u}_i$ in order to account for common sectoral components in the "long" equation (24). In turn, equation (24) delivers $\hat{\varepsilon}_i$ which is finally used to build the dispersion measure that should isolate the idiosyncratic component of employment's dynamics in each sector. Abraham and Katz assume that $\hat{u}_i$ can be split into two orthogonal components:

$$\hat{u}_i = (C + v_i) \quad where \; E[C, v_i] = 0 \tag{25}$$

with C a common (to all sectors) stochastic trend and v_i a sector specific shock. The constructed variable $\sum_{i=1}^{N} \; w_i \hat{u}_i$ can be rewritten as

$$\sum_{i=1}^{N} \; w_i \left[C + v_i \right] = C \sum_{i=1}^{N} w_i + \sum_{i=1}^{N} \; w_i v_i = C + \sum_{i=1}^{N} \; w_i v_i \tag{26}$$

Therefore equation (24) becomes

$$y_i = \delta \left[C + \sum_{i=1}^{N} \ w_i v_i \right] + \gamma x_i + \varepsilon_i \tag{27}$$

The constructed regressor ($\sum_{i=1}^{N} \ w_i \hat{u}_i$) captures a weighted average of idiosyncratic sectoral components, as well as a shared stochastic trend. This can lead to an inconsistent estimate of the residual $\hat{\varepsilon}_i$ and a systematic error in the measurement of the sectoral dispersion index, which can severely harm inference within reduced forms such as (6).

Abraham and Katz's conclusion that the dispersion indices are not significant in reduced form (6) might depend on a statistical bias towards the non-rejection of the null hypothesis: we notice that equation (6) also includes lagged unemployment, which does not appear in any of the two steps used by Abraham and Katz to construct their dispersion index. As Pagan (1984) points out, if these extra regressors appear amongst the variables used to construct the generated regressors, then the two-step estimator is perfectly efficient. This is not the case for Abraham and Katz's dispersion index, so we expect rather large standard errors in their reduced form employment equation. This makes inference more uncertain and represents an additional bias against the significance of the estimated coefficients.

Samson (1990) overtly recognizes that her dispersion index is characterized by a downward bias in the measurement of sectoral shocks. Again, a "bad measurement" critique applies.

Finally, we consider the procedure adopted by Brainard and Cutler (1993). The generated regressors used in the unemployment equations they estimate raise the same efficiency issues encountered in the work of Abraham and Katz. The presence of extra-variables in the unemployment equations, variables which are not considered in the construction of the sectoral shocks' proxy, can induce efficiency losses when using a simple 2-step OLS estimation method.

Problems of efficiency and inference associated with generated regressors have been largely ignored in the literature, notwithstanding their harmful effects.[5]

3.6 VAR Models of Job Reallocation

The inclusion of dispersion indices within reduced form equations is increasingly regarded as a dead-end strategy. As a consequence researchers have resorted to alternative econometric methodologies. These new methodologies make an extensive use of vector auto-regressions (VAR) of either time series or micro data sets.

[5] An exception are Mills, Pelloni, and Zervoyanni (1995) who acknowledge the potential efficiency losses induced by generated regressors and jointly estimate the unemployment and money growth equations. Perhaps surprisingly, they find that standard errors are only slightly larger and coefficient estimates modestly different with respect to those obtained using OLS in a two-step procedure.

The seminal paper in this area is Long and Plosser (1987) which aims at empiricallly testing the multi-sectoral real business cycle (RBC) model of Long and Plosser (1983)[6].

Long and Plosser (1987) set up a thirteen-dimensional VAR of monthly data of sectoral outputs and apply factor analysis on the innovations to determine whether co-movements in sectoral outputs are the result of a common aggregate shock or a set of independent sectoral disturbances. Since the model, as conceived, assigns all the co-movements to one or two unobservable common factors (viewed as aggregate disturbances), the entailed experiment has to be seen as an upper bound of the explanatory power of aggregate shocks. Even within this context, the common factor(s) can explain only 47% of the variance of the aggregate innovation.[7]

Long and Plosser conclude that the explanatory power of a common aggregate disturbance is significant but rather small. The methodological approach of this paper has become popular in the sectoral shifts literature and has been updated in line with recent developments of time series analysis[8].

3.6.1 The Approach of Campbell and Kuttner

Strictly within the sectoral shifts literature a pioneering contribution is made by Campbell and Kuttner (1996), who propose a structural VAR (SVAR) approach to identify aggregate and sector-specific impulses. Their methodological claim is that a SVAR approach can explicitly spell out any identifying assumptions while allowing to evaluate the sensitivity of results to alternative restrictions[9].

As a starting basic structure Campbell and Kuttner use a bivariate VAR of the natural logarithms of manufacturing employment share and aggregate employment [10]. Both variables are included in the model in terms of first differences, since both of them are found to be I(1).[11]

[6] Long and Plosser (1983) proposes a stochastic general equilibrium model with multi-sector technologies, showing that random productivity shocks independent across sectors can capture co-movements in sectoral activities over business cycles.

[7] This outcome is reflected in the relatively small off-diagonal elements of the correlation matrix of the innovations.

[8] In this paper we restrict our interest to VAR models of job reallocations. In the wake of Long and Plosser (1987) there is another important strand of literature dealing with sectoral output models using dynamic factor models, c.f. Acconcia and Simonelli (2008), Foerster, Sarte, and Watson (2008) and references thereafter.

[9] Early, important applications and discussions of SVAR models in macroecononmics are Blanchard and Quah (1989), Lippi and Reichlin (1993) and references thereafter.

[10] The manufacturing share variable can be seen as a two-sector (manufacturing and non-manufacturing) decomposition of the whole economy. This decomposition is due to the observation that shifts between manufacturing and non-manufacturing employment account for most of the cyclical variation in employment growth dispersion.

[11] The manufacturing share variable is modelled as a unit root I(1) process, although it is bounded between zero and one. The time series behavior of such a variable looks random, but its variance cannot diverge beyond a certain limit represented by the full variation spectrum of size one being a normalized measure. The inclusion of this variable as an I(1) process might have unpredictable effects on the inference which is subsequently drawn.

Campbell and Kuttner (1996) first define the vector $y_t = (\Delta x_t, \Delta w_t)$ where x_t represents the natural logarithm of total employment and w_t stands for the natural logarithm of the manufacturing sector employment share; then they write down a VAR representation of this vector

$$\mathbf{y}_t = \mathbf{A}(L)\mathbf{y}_t + \epsilon_t \tag{28}$$

where A(L) is a matrix of lag polynomials of order p and $\epsilon_t = u_t + v_t$ is a vector of white noise shocks consisting of two components: orthogonal aggregate shocks, u_t, and reallocation shocks, v_t. Thus $A_{hk}(L)$ is a lag polynomial summarizing the effect over time of the h^{th} variable on the k^{th} variable and $A(0)$ would be the sub-matrix of the contemporaneous effects whose elements along the main diagonal are zeros

$$A(0) = \begin{pmatrix} 0 & a^0_{xw} \\ a^0_{wx} & 0 \end{pmatrix} \tag{29}$$

The model's dimension implies a two-sector (manufacturing and non-manufacturing) decomposition of the whole economy, which is justified by the observation that shifts between manufacturing and non-manufacturing employment account for most of the cyclical variation in employment growth dispersion.

Campbell and Kuttner have to impose identifying restrictions to recover the structural disturbances, since in the estimated standard form of (28) the elements of the VAR innovation vector would be mixtures of the structural disturbances.

As a first identifying scheme Campbell and Kuttner set $a^0_{xw} = 0$ so that the orthogonalized estimated innovations would correspond to the structural shocks. Once this restriction is introduced, the $A(0)$ sub-matrix becomes lower triangular, that is

$$A(0) = \begin{pmatrix} 0 & 0 \\ a^0_{wx} & 0 \end{pmatrix} \tag{30}$$

and aggregate employment is ordered ahead of manufacturing in a Wold causal chain. This assumption, corresponding to a Choleski decomposition of the standard VAR covariance matrix, bans contemporaneous effects of reallocation shocks on total employment. Under this restriction Campbell and Kuttner find that reallocation shocks account for a large amount (59%) of the variation in manufacturing employment, but can explain only a small fraction (approximately 6%) of aggregate employment fluctuations. Furthermore, the contemporaneous and long run sectoral responses to aggregate shocks are both positive and statistically significant, whereas the

On the other hand it does not look reasonable to explain the variability of employment growth rate through movements in the levels of manufacturing share and the unit root tests seem unequivocally indicate that the share process is integrated. This modelling issue remains unsolved.

long run aggregate employment elasticity with respect to sectoral impulses is not significantly different from zero.

This triangularization solves the identification problem and provides a lower bound of the explanatory power of sectoral reallocation shocks. It does not, however, have an overwhelming theoretical justification. It is a statistical artifact which enables the authors to restrict the range of inferences. The second identification scheme of Campbell and Kuttner is instead non-recursive and grounded on long-run neutrality assumptions imposed on the total impact matrix (see Blanchard and Quah 1989, King and Watson 1997). The long-run multipliers are defined as[12]

$$\gamma_{xw} = \left[a_{xw}^{0} + A_{xw}(1)\right] \;/\; \left[1 - A_{xw}(1)\right] \tag{31}$$

$$\gamma_{wx} = \left[a_{wx}^{0} + A_{wx}(1)\right] \;/\; \left[1 - A_{wx}(1)\right] \tag{32}$$

Campbell and Kuttner assume that aggregate shocks have no long-run effect on the manufacturing employment share, thus $\gamma_{wx} = 0$. This assumption is consistent with the claim that aggregate shocks can bring about only transitory changes in the profitability of capital across sectors with no lasting effects on capital distribution. Under this restriction the results of the innovation analysis change dramatically. The estimates of a_{xw}^{0} and γ_{xw} are large and significant and bear out the short and long-run relevance of reallocation shocks. A 1% positive shock to the manufacturing share raises total employment by 0.5% within a month, and a permanent 1% shock raises total employment by almost 0.8% in the long-run. Reallocation shocks can account for over half of the variance of total employment (51%), and for nearly all of the variance in manufacturing.[13]

A third, non-recursive identification method relies on changes in the price of crude petroleum. Following Loungani (1986) it is assumed that oil prices affect total employment only to the extent that they generate inter-sectoral reallocations. This insight is embodied into the model by augmenting the original bivariate VAR with the univariate auto-regression of the percentage change of crude oil price (c.f. p.330 Hamilton 1994). The results for the estimated multipliers are similar to those obtained under the long-run restrictions. The variance decomposition associates 43% of aggregate employment variability to reallocation shocks and 10% to oil shocks: a total 53% of the variance is therefore explained by non-aggregate shocks.

[12] Although equations (31-32) can provide valid approximations of the long-run multipliers for a single structural equation, their meaning is misleading in a SVAR because the two multipliers fail to take account of unobservable spill-overs between equations.

[13] An instrumental variables procedure (see King and Watson 1992) has been used to estimate system (28) under either identification restriction (the short-run restriction $a_{xw}^{0} = 0$ and the long-run restriction $\gamma_{wx} = 0$).

To check robustness of their results Campbell and Kuttner apply a finer sectoral disaggregation and estimate a seven-dimensional VAR. The five extra variables are the employment shares of the construction, insurance/real estate, transportation, wholesale/retail trade and government sectors. This finer disaggregation reinforces the importance of reallocation shocks: sectoral shocks account for 27% and 82% of the aggregate variance under the first and second set of restrictions, respectively[14], which amounts to an increase of 21 and 31 percentage points relative to the bivariate model.

It is apparent that when Campbell and Kuttner allow for intra-sectoral movements, the relative importance of reallocation shocks for aggregate employment fluctuations increases.[15]

There is no doubt that Campbell and Kuttner's paper represents a methodological breakthrough and an advance in the analysis of the aggregate effects of sectoral shocks. Loungani (1986) was the first to acknowledge that Campbell and Kuttner's findings corroborate the view that aggregate fluctuations should be studied in conjunction with intra/inter-sectoral reallocations. They also bolster the empirical relevance of the SSH (and RTH) vis-a-vis the NBCH. Nevertheless, Campbell and Kuttner's paper cannot settle the causality issue of whether the triggering force is sector specific (SSH) or aggregate (RTH); it can only claim that (un)employment fluctuations and permanent changes in employment sectoral shares are statistically interdependent phenomena.

A further issue is that Campbell and Kuttner's SVAR suffers limits and shortcomings typical of long-run identifying restrictions: Faust and Leeper (1997) argue that long-run neutrality restrictions are not normally sufficient to draw reliable inferences because of aggregation problems across variables and across time. One of the points made by Faust and Leeper is that long-run zero restrictions must be tied to a restriction on finite-horizon dynamics. If this extra constraint is not explicitly introduced we may have different reduced forms fitting the sample equally well and yet extrapolating to the infinite future in very different ways. In other words we may obtain different reduced form long-run matrices, $A_{w_i x}$. This requirement is not met in Campbell and Kuttner (1996) since no restrictions are explicitly imposed on finite-horizon dynamics.

Campbell and Kuttner do not meet at least one of the other two requirements suggested by Faust and Leeper. In the paper there are no explicit assumptions to support the view that at least one of the two "identified" shocks must be viewed as the aggregation of a larger number of underlying shocks and therefore Campbell and Kuttner's model fails to satisfy Faust and

[14]This model is not estimated under the third constraint (the oil price restriction).

[15]Campbell and Kuttner also find that intra-sectoral movements can explain more aggregate variability than inter-sectoral ones.

Leeper's shock aggregation property. There are no a-priori reasons to prefer Campbell and Kuttner's specification to any potential alternative.

Campbell and Kuttner's results could also be muddled by time aggregation problems. It is possible that there are feedbacks among the variables at frequencies higher than that of the observed data; in this case the orthogonality assumption is not met. However, Campbell and Kuttner's use of quarterly data may be sufficient to reduce the susceptibility of their model to this criticism.

There is a further serious drawback harming Campbell and Kuttner's experiment. They characterize reallocation disturbances as having a directional (positive/negative) nature as aggregate shocks do[16]. This sort of "directional behavior" is not consistent with the underlying economic hypothesis: allocative shocks should generate a reallocation process which is followed by an oscillation in aggregate unemployment, be the shifts to a sector positive or negative. The sign-dependence of reallocation shocks in Campbell and Kuttner - positive shocks involving higher employment and vice versa - does not capture the "size" but the "direction" of shocks.[17] This account of allocative disturbances misrepresents the impact channel of labor market turbulence. It is the magnitude of current reallocations brought about by the idiosyncratic shock which determines the aggregate response and not the shock's direction. In fact the direction of a reallocation shock, in the perspective of its aggregate effects, is not a properly definable concept. Of course, a shock's direction has a clear meaning if we look at its impact on a specific sector. The idea that the shock's direction is irrelevant (at the aggregate level) while size matters suggests that the SSH could be naturally tested within a non-linear framework.

3.6.2 Multivariate Volatility Models

The linearity restrictions of Campbell and Kuttner (1996) are the starting point of Pelloni and Polasek(1999, 2003) who develop a multivariate GARCH in mean (VAR-GARCH-M) to examine whether volatile growth in sectoral employment shares has an impact on aggregate employment[18].

Pelloni and Polasek (1999) formulate the SSH in terms of sectoral time series models containing volatility effects. The authors claim that current time series techniques open up the

[16]Campbell and Kuttner mention this peculiar feature of their model but do not add any further comments about its suitability. Treating sectoral shocks in the directional way typical of aggregate shocks makes their work akin to Blanchard and Quah (1989). In its essence their exercise is more one of separating supply and demand shocks than one aimed at the identification of the effects of sectoral reallocations.

[17]It is interesting to note that Campbell and Kuttner, though the variables of interest are all I(1), do not investigate the possibility that the process of labor reallocation and aggregate employment are cointegrated. Whatever the reason, this is a common trait of this literature. Only Pelloni and Polasek (2003) introduce the possibility of a cointegration model which is however discarded in favor of a VAR-GARCH-M representation.

[18]For an comprehensive and penetrating discussion of ARCH models in Macroeconomics c.f. Hamilton (2008).

possibility of framing the SSH in a richer dynamic dimension without appealing to ad-hoc dispersion measures. They point out that Lilien's net hiring function (1) can be generalized through an explicit heteroschedasticity assumption on ϵ_{it}, the sector specific hiring shock:

$$\varepsilon_{i,t} = u_{i,t}(h_t^i)^{1/2} \tag{33}$$

$$h_{it} = \alpha + \sum_{j=1}^{q} \theta_j^i \varepsilon_{i,t-j}^2 \tag{34}$$

with $u_{i,t} \backsim iidN(0,1)$ and $h_{it} \equiv Var\,(\varepsilon_{i,t}|I_{t-1})$. Equation (33) is the (ARCH) generating process of the sector specific component in equation (1).

In principle, the ARCH/GARCH representations of the shocks can be seen as reasonably akin to Lilien's original claim of heteroscesdasticity. In operational terms this idea is implemented via a multivariate GARCH in mean (VAR-GARCH-M) model of the growth rates of aggregate employment and of sectoral employment shares. If we denote the sectoral shares' vector as y_t, Pelloni and Polasek's VAR representation is

$$\mathbf{y}_t = \mathbf{A}(L)\mathbf{y}_t + \mathbf{B}(L)\mathbf{h}_t + \epsilon_t \tag{35}$$

where B(L) is a lag polynomial, $\mathbf{h}_t$ a vector of conditional variances and ϵ_t a vector of mutually and serially uncorrelated random errors.

According to this specification the conditional means are functions of the contemporaneous and lagged values of the conditional variances. The estimated conditional variances are interpreted as measures of actual reallocations and the $\mathbf{B}(L)\mathbf{h}_t$ component represents how the measured volatility (i.e. the effective reallocations) feeds back on the means (aggregate employment and sectoral employment growths).

An additional feature of this approach is the suggestion that shocks could display a time-changing (conditional) variance: larger past shocks imply larger current volatility. This error-clustering effect is consistent with the maintained economic hypothesis of sectoral shifts. The SSH can reasonably encompass an arrival process of information, reflecting changes in sector-specific fundamentals, reaching a sector in clusters. In this case, allocative shocks may present a profile of persistent volatility changes whereby a large shock tends to be followed by another large shock. Such persistence effect can also be enhanced by the dynamic market response to incoming news.

Pelloni and Polasek (1999) apply a five-dimensional model to US quarterly series between 1975 and 1990.[19] They find that both aggregate and sectoral volatilities matter, though the

[19] The Bayesian estimation procedure is based on the Gibbs-Metropolis algorithm, which can provide an exact small sample solution. Testing for model selection using Bayes factor the authors find the VAR-GARCH-in-mean model to be preferable than simple VAR and VAR-GARCH specifications.

latter seems to have more "weight". A variance decomposition analysis, carried out by imposing a Choleski factorization, finds that, with a year-ahead forecast horizon, sectoral innovations account for 65% of the aggregate employment variance, whereas aggregate innovations cannot explain more than 28% of the sectoral variances, regardless of the forecast horizon. This is a surprising result since the triangularization orders aggregate employment ahead of sectoral shocks so as not to allow contemporaneous effects of reallocation shocks over total employment growth[20]. Reallocation shocks, though embedded in an unfavorable specification, have a large and significant role in explaining aggregate employment behavior. In comparison with Campbell and Kuttner (1996) these results provide stronger evidence in favor of reallocation shocks. The GARCH structure seems to capture important features of the system's dynamics, reinforcing the role of sectoral disturbances.

Pelloni and Polasek (2003) and Panagiotidis, Pelloni, and Polasek (2003) further corroborate the evidence in favor of sectoral shifts by looking at other countries besides the US.[21]

The work of Pelloni and Polasek(1999, 2003) extends Campbell and Kuttner (1996) by explicitly allowing the dispersion of sectoral shocks to affect conditional means. More importantly, this result is achieved without resorting to generated regressors and constructed dispersion indices. Leaving aside issues concerning Bayesianism in general (the appropriateness of the chosen prior, the robustness of Bayes factor testing, etc. ...), the Bayesian methodology is useful for robust estimation of large models over a small sample. However, the results hint at a possible over-parameterization of the model. Given their small sample (quarterly data for 15 years), Pelloni and Polasek end up having slightly more than one observation for each parameter. As pointed out by Harvey, Ruiz, and Shephard (1994), although the multivariate GARCH model could be estimated efficiently by maximum likelihood, the normally required number of parameters can be so large that it is necessary to impose restrictions. Pelloni and Polasek do not mention this problem and all the restrictions they try to impose are statistically rejected in favor of the unconstrained model. The idea of imposing a non-linear structure on a VAR which can capture inter-sectoral reallocations and feed them back into the means is attractive, but the non-linear form which is finally superimposed must be compatible with the data.[22]

Panagiotidis and Pelloni (2007), while testing linearity for the Canadian and US labor mar-

[20]This triangularization is analogous to the first set of restrictions of Campbell and Kuttner (1996) and provides a lower bound estimate of the contribution of sectoral shocks to the explanation of total employment variance.

[21]In particular, Panagiotidis, Pelloni, and Polasek (2003) develop a generalized impulse response function (GIRF) within a VAR-GARCH-in-mean model.

[22]The detection of an underlying GARCH structure in low frequency data as those used by Pelloni and Polasek is not impossible but somehow unlikely. Undetected outliers may lead researchers to reject the null of no GARCH effects when instead an alternative non-linear representation may be be more appropriate.

kets, find that the null hypothesis of a linear specification for the US, as in Campbell and Kuttner (1996), is statistically rejected. However they cannot unambiguously accept or reject the presence of GARCH effects, thus leaving the issue of the legitimacy of a GARCH representation for sectoral shocks open to discussion.

3.6.3 A Regime Switching Model of Sectoral Shifts

Storer (1996) conducts a shock decomposition exercise by means of Markov-switching regression (MSR) model capturing regime shifts induced by natural resource shocks. Storer uses labour market data of two Canadian provinces which responded in opposite directions to the oil price shocks of the 1970's and 1980's. The province of Alberta is a net producer of natural resources and the production of petroleum and natural gas is paramount for its economy. In contrast, Ontario is a manufacturing province and a net user. Thus oil price shocks should affect these two provinces in opposite directions: the oil price rises of 1973 and 1979 should favor Alberta while the 1986 downfall should bring about a reverse of fortunes. Storer labels sectoral shocks affecting both provinces in a similar ways as aggregate shocks. From the equilibrium solutions of a fairly standard search model, Storer defines the recruitment intensity equations for each province:

$$\log \theta_{A,t} = \alpha_1 + \alpha_2 \mu_t + \alpha_3 (1 - \eta_t) + \epsilon_{A,t} \tag{36}$$

$$\log \theta_{O,t} = \alpha_4 + \alpha_5 \mu_t + \alpha_6 \eta_t + \epsilon_{O,t} \tag{37}$$

Recruitment intensity,θ, is the ratio between vacancies and searching workers $(\frac{V_t}{U_t})$ while the terms μ and η would describe aggregate and regional states. The state variable μ_t is equal to 0 when the aggregate state is bad at t and equal to 1 when the aggregate state is good at t. The variable η_t represents the regional states: $\eta_t = 0$ if Alberta is favored at t or $\eta_t = 1$ if Ontario is favored at t.The regimes are thus described as the outcome of a four-state discrete time unobserved Markov chain, $\{\Omega_t\}$,defined by the joint occurrence of the aggregate and regional states:

$$\Omega_t = \begin{cases} 1 & \text{if } \mu_t = 0 \quad \text{and } \eta_t = 0 \\ 2 & \text{if } \mu_t = 0 \quad \text{and } \eta_t = 1 \\ 3 & \text{if } \mu_t = 1 \quad \text{and } \eta_t = 0 \\ 4 & \text{if } \mu_t = 1 \quad \text{and } \eta_t = 1 \end{cases} \tag{38}$$

The one-step 4×4 transition probability matrix (Markov matrix) of process $\{\Omega_t\}$is given by $\mathbf{P} = [p_{ij}]$, $i, j = 1, 2, 3, 4$,where the $p'_{ij}s$ are the one-step transition probabilities: $p_{ij} = P_{i,j}^{t-1,t} = \Pr(\Omega_t = j \mid \Omega_{t-1} = i) = \Pr(\mu_t = k, \eta_t = \lambda \mid \mu_t = k, \eta_t = \lambda)$. As μ_t and η_t are independent random variables, each element of the Markov matrix is given by the product of the conditional probabilities relative to the aggregate and regional states. For instance, $p_{11} =$

$\Pr[(\mu_t = 0, \eta_t = 0 \mid \mu_t = 0, \eta_t = 0)] = p_b p_A$ and $p_{12} = \Pr[(\mu_t = 0, \eta_t = 1 \mid \mu_t = 0, \eta_t = 0)] = p_b(1- p_A)$.

The identification of aggregate and sectoral shocks is guaranteed by non-negative restrictions: At each t, the aggregate state is the same in each region (α_2 and $\alpha_5 \geq 0$) while regional imbalances would favor only one region (α_3 and $\alpha_6 \geq 0$). Thus if the economy is in state $\Omega_t = 3$ we have:

$$\log \theta_{A,t} = \alpha_1 + \alpha_2 + \alpha_3 + \epsilon_{A,t} \tag{39}$$

$$\log \theta_{O,t} = \alpha_4 + \alpha_5 + \epsilon_{O,t} \tag{40}$$

The above MSR model is applied to quarterly data for market tightness in Alberta and Ontario during the period 1966-1998. Storer, using levels of logarithms, obtains maximum likelihood estimates and inferences via Hamilton's non-linear algorithm (Hamilton 1989) for a discrete-valued unobserved state vector. Estimation results suggest that aggregate shocks are of paramount importance for Alberta, while in Ontario the two types of shocks have had the same size effects. Shocks persistence is pervasive. Not only aggregate shocks but also sectoral shocks have lasting effects and bad aggregate state is the least persistent state. Further estimates carried out using first differences corroborate the previous outcomes

Storer's approach is rich of stimulating and penetrating methodological insights. It is surprising that it has not been taken up and carried further by other authors. First he uses an almost natural experiment for asymmetric labour responses to an idiosyncratic shock. Modeling this phenomenon and its intrinsic volatility and non-linearity by a MSR model seems to be a promising strategy. MSR is evidently a powerful modeling tool for labor market states following different processes over different subsamples in response to aggregate and sectoral shocks. If MSR has not been further developed in this context, neither have models with no-sharp thresholds (e.g. smooth transition autoregressive, STAR, models). Neither Markov switching ARCH (SWARCH) or Markov switching stochastic volatility (MSSV) models[23] of job reallocations have been developed. Generalizing the VAR-(G)ARCH-M model of Pelloni and Polasek(1999, 2003) or a multivariate stochastic volatility to include the Storer's MS provides an intriguing perspective.

4 Job Creation and Job Destruction Models

The literature on job creation and destruction has altogether provided an alternative outlook to explore the intrinsic asymmetries and nonlinearities of allocative shocks. As vital information

[23] For SWARCH and MSSV models c.f. Hamilton and Susmel (1994) and So, Lam, and Li (1998), respectively.

may be lost by looking at employment dispersion (or proxies of it) across highly aggregated sectors of the economy, it may pay large dividends to explore finer sectoral subdivisions or intra-sectoral movements. In an attempt to bring together theory and measurement Davis and Haltiwanger(1992, 1999) and Davis, Haltiwanger, and Schuh (1996) develop a novel framework to analyze gross job flows across U.S. manufacturing establishments using the Longitudinal Research Database (LRD) at the Center for Economic Studies of the U.S. Census Bureau[24]. The LRD is a panel data set gathering employment data at annual and quarterly frequencies for each plant in the panel.

4.1 Measuring Job Flows

Davis and Haltiwanger(1990, 1992) and Davis, Haltiwanger, and Schuh (1996) propose the notion of job creation (denoted as "POS") and job destruction (denoted as "NEG") as the theoretical underpinnings for the organization, measurement and analysis of the information extracted from the LRD. Following Davis, Haltiwanger, and Schuh (1996), POS (NEG) at time t can be defined as employment gains (losses) summed over all plants that expand (contract) or start up (shut down) between periods $t-1$ and t:

$$POS_t = \sum_{e \in S^+} X_{est} - X_{est-1} = \sum_{e \in S^+} \Delta X_{est} \quad \text{with} \quad S^+ \subseteq S \tag{41}$$

$$NEG_t = \sum_{e \in S^-} |X_{est} - X_{est-1}| = \sum_{e \in S^-} |\Delta X_{est}| \quad \text{with} \quad S^- \subseteq S \tag{42}$$

where the symbol X denotes a job, i.e. an employment position filled by a worker, and the subscripts e, s and t indicate establishment/plant, sector and time period, respectively. If S is the reference sector (e.g. U.S. manufacturing) then S^+ is the subset of plants in S that are expanding or starting up, while S^- is the subset of the contracting or closing up plants.

The definitions of employment change (NET), such as net job creation, gross job reallocation (SUM) and excess job reallocation (EXC) easily follow from definitions (41) and (42)

$$NET_t = POS_t - NEG_t \tag{43}$$

$$SUM_t = POS_t + NEG_t \tag{44}$$

$$EXC_t = SUM_t - |NET_t| \tag{45}$$

All the above definitions refer to job reallocations as opposed to worker reallocations. A link between job and worker reallocations clearly exists and can be formalized by defining gross worker

[24]c.f. Schuh and Triest (1998) for an interesting discussion of models of job creation and destruction.

reallocation at time t as the number of people who change place of employment or employment status between $t-1$ and t. The amount of worker reallocation induced by job reallocation can at most equal SUM but cannot be smaller than the largest value between POS and NEG: these definitions provide both an upper (SUM) and a lower (the larger between POS and NEG) bound on the amount of worker reallocations.[25]

Davis, Haltiwanger, and Schuh (1996) detect four major stylized facts characterizing job flow data:

1. gross flow rates are large at all times;
2. the asymmetric cyclicality between POS and NEG brings about a counter-cyclical SUM, since during recessions NEG increases sharply, while POS decreases relatively little or even increases;
3. most job reallocation is persistent or permanent;
4. job flows are concentrated in a relatively small number of establishments.

These empirical traits, together with other features detected in due course (for a discussion see Schuh and Triest 1998), have provided a basis for imposing specific restrictions on the empirical analysis of the effects of job reallocations and a substantial literature has followed their original contribution. Clear cut outcomes in this literature are that, within manufacturing, there exists a negative correlation between job reallocation and employment growth and that JD varies more than JC over the cycle. For instance Baldwin, Dunne, and Haltiwanger (1998) find that,both in Canada and US, the rate of JC and JD is very high (1 in 10 manufacturing jobs are created and destroyed every year) and that JD is more volatile than DC over the period 1972-1993. Over their sample[26], Canadian JD and JC standard deviations are 2.6 and 2.1 respectively while the US JD standard deviation is 2.8 vis-a-vis a JC standard deviation of 1.9. However Foote (1998), using manufacturing and non-manufacturing data collected by the Michigan State Unemployment Insurance System over the period 1978-88, argues that this result may be specific to manufacturing or other declining sectors. Foote, following Caballero, Engel, and Haltiwanger (1997), develops a (S,s) model to derive a testable form linking the relative standard deviations of JC and JD in an industry to the relative means of the job flows of that specific industry. He finds that for sectors which are growing, instead of contracting like manufacturing, JC is relatively more volatile than JD.

[25] Of course all these definitions can be expressed in terms of rates instead of levels, (c.f. Davis, Haltiwanger, and Schuh 1996).

[26] Data from Annual Census of Manufacturing of Statistics Canada and the LRD at the U.S. Census Bureau.

In a later paper, Davis and Haltiwanger (1999) extend and complement the LRD series with data drawn from the Bureau of Labor Statistics (BLS): the sample consists of quarterly time series data for the manufacturing sector covering the period 1947:1 to 1993:3. They estimate SVAR models by imposing restrictions which take advantage of the diverse POS and NEG dynamics brought about by aggregate and reallocation shocks.

Letting $y_t = (POS_t, NEG_t)'$, Davis and Haltiwanger (1999) suggest a bivariate VAR(p) of the form $y_t = A(L)y_t + \epsilon_t$. Here $A(L)$ denotes a p-order matrix lag polynomial which can have a linear moving average, MA(∞), representation

$$\begin{pmatrix} POS_t \\ NEG_t \end{pmatrix} = \begin{pmatrix} 1 & b_{ps} \\ b_{na} & 1 \end{pmatrix} \begin{pmatrix} \epsilon_{a,t} \\ \epsilon_{s,t} \end{pmatrix} + \begin{pmatrix} B_{pa}(L) & B_{ps}(L) \\ B_{na}(L) & B_{ns}(L) \end{pmatrix} \begin{pmatrix} \epsilon_{a,t} \\ \epsilon_{s,t} \end{pmatrix} \tag{46}$$

where $B_{hk}(L)'s$ are lag polynomials and $\epsilon_t = (\epsilon_{at}, \epsilon_{st})'$ is a vector of structural orthogonal disturbances. The estimated unrestricted VAR would yield an $MA(\infty)$, $y_t = D(L)\eta_t$ ($D(L)$ being an infinite-order matrix lag polynomial of estimated coefficients), whose vector of innovations, η_t does not necessarily coincide with the vector of structural shocks, ϵ_t, as each of its elements would be a combination of the elements of ϵ_t. To identify the impact of the shocks Davis and Haltiwanger impose restrictions capturing the directional and symmetric effects of aggregate shocks vis-a-vis the asymmetric and non-directional nature of reallocation shocks. An aggregate shock would cause POS and NEG to move in opposite directions (a negative aggregate shock would simultaneously reduce POS and increase NEG) while a reallocation shock would induce POS and NEG to move in the same direction (a reallocation shock would increase both POS and NEG and thus increase SUM).

The coefficients of the sub-matrix $B(0)$ which captures the contemporaneous responses of NEG to aggregate shocks and of POS to allocative shocks are restricted to be negative and positive respectively, $b^0_{na} < 0, b^0_{ps} > 0$. These two restrictions together with $cov(\epsilon_{at},\ \epsilon_{st}) = 0$ introduce a set of "weak" restrictions which, though not capable of exactly identifying the structural parameters, can restrict their range of permissible values and generate qualitative identifying information with strong economic significance.

To narrow further the structural parameters range and generate more precise inference, Davis and Haltiwanger impose tighter inequality conditions. These restrictions follow from recent theories of POS and NEG dynamics in response to aggregate and allocative innovations and can be summarized as follows:

1. $\mathbf{b^0_{na} \leq -1}$. This restriction states that an aggregate shock would bring about a NEG response at least as large as a POS response. Theoretically this claim can be based on the reallocation timing hypothesis (RTH) of Davis (1987) and/or on search and matching

models (SMM) (see Mortensen and Pissarides 1999). An aggregate negative shock, under the RTH, would lead to reallocation bunching during a recession while, in the SMM, it would generate an asymmetric response in NEG and POS dynamics (NEG rises more rapidly than POS because of the sluggishness brought about by the matching process).

2. $|\mathbf{b_{ps}}| \leq \mathbf{1}$. This assumption asserts that the contemporaneous response of POS to a reallocation shock is smaller in magnitude than the contemporaneous NEG response. From a theoretical point of view this restriction has a twofold justification. First, the inherent asymmetry between the matching and separation processes induced by the instantaneousness of job separations and the time-consuming nature of matching Pissarides (1985)Mortensen and Pissarides (1994). Second, the potential presence of an "option value effect" which could boost the waiting time of employers and employees in response to sunk costs associated with the creation of new vacancies and job matching Davis and Haltiwanger (1992).

3. $\sum_{\mathbf{l=1}}^{\mathbf{m}} \mathbf{B_{ps}}(\mathbf{l}) > \mathbf{0} \;\; \forall \mathbf{m},\ \mathbf{s.t.}\ \mathbf{2} \leq \mathbf{m} \leq \mathbf{M} < \infty$. The third and last restriction states that reallocation shocks would ultimately raise job creation.

Davis and Haltiwanger (1999) also impose restrictions on the total impact matrix in the fashion of Blanchard and Quah (1989) and King and Watson (1992).

The mechanics of job creation represent the focus of Caballero, Engel, and Haltiwanger (1997), who provide a micro-foundation for aggregate employment dynamics based on adjustment costs and a combination of aggregate (common-across-plants) and idiosyncratic (plant-level) shocks. Changes in the variance (and higher moments) of the plant-level shocks are interpreted as reallocation shocks. Using quarterly, plant-level data for the U.S. manufacturing sector between 1972 and 1980 from the LRD, Caballero, Engel, and Haltiwanger find that about 90% of the fluctuations in microeconomic adjustment accounting for changes in average employment growth are driven by aggregate, rather than reallocation, shocks. Aggregate shocks are assumed to be the cross-sectional average of plant level shocks.

4.2 Job Flows over the Long-Run and over the Business Cycle

We have already stressed the overwhelming importance of Davis and Haltiwanger (1999) who bring to the fore in a clear manner the asymmetric, non-linear nature of allocative shocks and exploit this feature alongside other theoretical predictions so as to provide a coherent empirical framework. Though it does not solve the fundamental problem, it provides, alongside useful quantitative information, a methodological example on which to build. Which restrictions should be brought to bear in order to achieve an exact identification is still a matter to be settled, but the approach of DH is extremely valuable and promising.

A by-product of the JC and JD framework is the new research agenda which aims to shed light on some puzzling stylized facts of both long-term trends and business cycle fluctuations.

The first set of contributions focuses on a secular decline in business-level volatility (Faberman 2006, Davis, Haltiwanger, Jarmin, and Miranda 2006, Davis, Haltiwanger, Jarmin, and Miranda 2007) using new data sources (the Business Employment Dynamics - BED - from the BLS and the Longitudinal Business Database - LBD - from the Census Bureau, which cover the whole private sector of the U.S. economy.

Faberman (2006), using data from BED, shows a decline in job reallocation rates across establishments. Previous work on JC and JD had detected a specific stylized fact: cyclical fluctuations in the labor market tend to be connected to large, irregular movements in gross job destruction and only small changes in gross job creation. The evident implication of this observation is that job reallocation is countercyclical, and that business cycle dynamics are tied up to large movements in job destruction. However Faberman, using the new BED data set and extending it back several years (by merging it with the data set by Davis and Haltiwanger 1999), challenges this evidence. The slow labor market recoveries associated to the 1990-92 and the 2001-03 downturns are only apparently similar, whereas the behavior of their underlying gross job flows is quite different. The 1990-92 period exhibits a relatively slow decline in job destruction; on the other hand a large and persistent decline in job creation, alongside a spike in job destruction, marks the 2001-03 phase. The latter therefore clearly violates conventional wisdom about the dynamics of job creation. Faberman's empirical evidence, spanning the postwar period from 1947, involves both manufacturing and non-manufacturing establishments and indicates that the large 2001-3 drop in job creation happens in both sectors and is unique over the sample period. The episodic patterns are part of a historical decline in both magnitude and volatility of job reallocation. A decline which is characterized by an increase in the relative volatility of job creation (vis-a-vis job destruction).

Davis, Haltiwanger, Jarmin, and Miranda (2006), using data from the LBD and COMPUSTAT for the period 1976 onwards, find a large secular decline in the cross-sectional dispersion of business growth rates and in the time-series volatility of growth rates at firm level. Measuring the time-t growth rate of firm/establishment i as[27]

$$\gamma_{it} = \frac{x_{it} - x_{it-1}}{(x_{it} + x_{it-1})/2} \tag{47}$$

[27]This measure is standard in work on labour flows, c.f. Tornqvist, Vartia and Vartia (1985) and the appendix in Davis, Haltiwanger, and Schuh (1996).

they compute a cross sectional and size-weighted standard deviation for each t as a measure of dispersion. The chosen volatility measure is a moving ten-year window of the standard deviation of the firm/establishment growth rates. The authors also develop a similar but modified version which is capable of taking short lived firms into account, including entries and exits which would be otherwise ignored by the ten-year window.

DHJM06 confirm the rise in volatility among publicly traded firms emerged in other studies and also show that its impact is overwhelmed by declining volatility among privately held firms, a pattern which holds in every major industry group. The plot of DHJM's employment-weighted modified volatility measure against annual averages of monthly unemployment flows suggest that secular declines in the intensity of firm volatility have contributed to large declines in unemployment flows and frictional unemployment over the sample period. If firm volatility is interpreted as a proxy for the intensity of allocative shocks, a lower intensity of firm volatility (allocative shocks) would thus result in less job loss, smaller unemployment inflows and outflows rates , and less frictional unemployment. Davis, Faberman, Haltiwanger, Jarmin, and Miranda (2008) further bear out these results. Working along similar lines,they find compelling evidence that the intensity of idiosyncratic labour demand shocks has a large and positive effect on the incidence of unemployment.

In a related contribution, Groshen and Potter (2003) discuss the 'jobless recovery' of 2002-2003. The authors divide recessional adjustment into two components: cyclical and structural adjustments, where cyclical shocks are temporary and structural shocks are permanent. They examine the importance of temporary layoffs by tracking this measure over the past six recessions. They find that during the recoveries of 1991-1992 and 2002-2003 structural shocks were prevalent, while temporary layoffs increased little in 1991-1992 and barely rebounded in 2002-2003. The authors also track the direction of job flows in seventy major US industries, those identified by two digits in the Standard Industrial Classification system, during and after the 1981-1982 downturn and the 2001 downturn. By comparison, the 2001 downturn was characterized by structural gains or losses, where structural gain means that employment increased both during recession and recovery, and structural loss means jobs were lost both in recession and recovery. Based on this evidence and the findings for temporary layoffs, the authors suggest that the recessions of the early 1990s and early 2000s were more strongly structural than past recessions, and probably attributable to allocative shocks. This finding is challenged by Rissman (2003) and Aaronson, Rissman, and Sullivan (2004). The first paper analyzes the annualized quarterly employment growth net of aggregate employment growth by industry from 1954:Q1 to

2003:Q2. The sectoral classification is based on NAICS with the exclusion of mining. By controlling for the idiosyncratic responses to the 'common' component in employment fluctuations through time dummies the author argues that sectoral reallocation shocks were not unusually large, by historical standards, during the most recent recessions. An important assumption in Rissman (2003) is that the 'cyclical' component of employment growth is industry-specific: the author argues that this assumption is reasonable because aggregate cyclical fluctuations impact each industry differently. However, by interpreting all sector-specific time-effects as aggregate fluctuations, this procedure runs the risk to partly underestimate sectoral shocks' relevance. In a follow-up paper, Aaronson, Rissman, and Sullivan (2004) argue that the fall in the proportion of the unemployed on temporary layoffs during the 2001 recession is not large enough to explain a major portion of the decline in post-recession employment growth. On the flip-side these authors also claim that the increase in the share of unemployed labor force because of permanent layoffs was not high, by historical standards, during that period.

4.3 Using Real Exchange Rates to Identify Sectoral Reallocation

The recurring problem of distinguishing pure reallocation shocks from aggregate ones has been the object of some attention in the JC and JD literature. As a way to circumvent the fundamental identification problem some researchers have proposed to use real exchange rate fluctuations as a proxy of demand shocks which force a labor reallocation across sectors with different exposure to international competition. A significant contribution to the debate on job flows and sectoral shifts is due to Gourinchas (1998). Adopting a classification based on export shares and import penetration ratio, the author exploits real exchange rate variation to identify the effects of sectoral shifts on gross and net job reallocations within the US manufacturing industry[28].

Industries are grouped into two categories: the first one includes industries open to international competition (tradable sector), while the second one consists of industries which do not export nor compete with foreign firms in the domestic market (non-tradable sector). Under the initial assumption that real exchange variation can be considered exogenous for individual firms in the short and medium term, the author uses such variation to identify changes in the relative demand of goods in different sectors[29]. Confirming previous findings by Davis and Haltiwanger (2001), the paper documents that job creation and job destruction both grow in response to a reallocation shock (that is, an appreciation of the real exchange rate). This positive comovement

[28] Job flows are measured, like in Davis and Haltiwanger (1990), using sectoral data on job creation and destruction for both 2-digit and 4-digit industries by the Census's LRD.

[29] In order to control for possible endogeneity of exchange rate shocks, the author also provides estimates in which real exchange rate is instrumented.

contrasts with the opposite reactions of job creation and destruction to aggregate shocks[30]. The author also finds that:

- job destruction experiences larger swings than job creation;
- exposure to international competition seems to increase turbulence in employment growth;
- all manufacturing groups experience long term negative growth in net employment, confirming the declining importance of manufacturing employment in the US economy;
- manufacturing industry can be neither defined as tradable nor non-tradable (roughly same share);
- creation and destruction are more volatile in tradable industries.

The most interesting result is clearly the fact that, following an exchange rate shock, job creation and destruction move in the same direction: this is interpreted as evidence of pure reallocative shocks, which are often assumed to induce a simultaneous increase in job creation and destruction. However, Gourinchas (1998) stresses that the simultaneous move occurs within the tradable sector, unlike the intersectoral channels sometimes emphasized in the literature.

Many of the findings of Gourinchas are confirmed by Klein, Schuh, and Triest, who document the significant effect real exchange rates have on job creation and job destruction in U.S. manufacturing industries between 1973 and 1993[31]. This paper also finds that responsiveness of job flows to real exchange movements varies with the industry's openness to international trade. Like in Gourinchas (1998), the authors find that appreciations induce significant job flows, whereas depreciations have only limited effects.

Haltiwanger, Kugler, Kugler, Micco, and Pages (2004) use harmonized measures on job creation and destruction for various countries in Latin America to investigate the impact of trade openness on net employment and gross job reallocation. They find that reductions in tariffs and exchange rate appreciations increase the pace of job reallocation within sectors; however the effects are not very large given the magnitude of the changes undergone by the countries during the period under examination.

For a comprehensive survey of the literature regarding the relationship between international trade and job flows, interested readers can refer to Klein, Schuh, and Triest (2002).

[30] These results are at odds with evidence presented by Davis, Haltiwanger, and Schuh (1996) who remark on the striking absence of a systematic relationship between the magnitude of gross job flows and exposure to international trade.

[31] Interestingly, Klein, Schuh, and Triest find that job creation has a much weaker response to international trade shocks.

5 Other Research Based on Micro-Data

Evidence on sectoral shifts based on micro (individual-level) data was first provided five years after the original contribution of Lilien (1982a). Micro-data offer a wealth of information on individual job market behavior and inter-industry mobility, both of which are the very essence of the SSH.

The seminal contributions in this area are those of Murphy and Topel (1989), Loungani, Rogerson, and Sonn (1989) and Loungani and Rogerson (1989).[32] These papers provide contrasting empirical results. Murphy and Topel (1989) strongly reject the SSH while Loungani, Rogerson, and Sonn (1989) and Loungani and Rogerson (1989) find support for it. Such contradictory conclusions arise because of differences in the definition of industry switching and the structure of the chosen data (panels vs cross-sections). Murphy and Topel use an eighteen-year time series (1968-1985) of cross-sections of individual data on prime-age males drawn from the Annual Demographic File (the March Survey) of the Current Population Survey (CPS). Each March Survey file contains individual information on current labor force status, industry and occupation; it also gathers retrospective information on industry and occupation of longest job held during the previous calendar year and on unemployment during the last calendar year. The CPS does not follow individuals over time, therefore the collected individual information applies to a fifteen-month period at most.

On the other hand, both Loungani, Rogerson, and Sonn (1989) and Loungani and Rogerson (1989) use data from the Michigan Panel Study on Income Dynamics (PSID) for the periods 1974-1985 and 1974-1984 respectively. The PSID interviews individuals in the Spring of each year and collects information on their current employment status, occupation and industry and weeks of unemployment experienced during the last calendar year.

Although the CPS may present advantages in terms of size, it cannot provide a work history of the interviewees as the PSID does. With respect to the task at hand the data set chosen by Loungani, Rogerson, and Sonn (1989) and Loungani and Rogerson (1989) seems more suitable for the analysis of labor reallocations.

All three papers split their samples between 'switchers' (individuals changing sectors), and 'stayers' (those who remain in the same industry). Their definitions of industry switching are substantially different. Murphy and Topel do not include unfinished unemployment spells among sector switches, whereas Loungani, Rogerson, and Sonn and Loungani and Rogerson denote as

[32] Also Davis and Haltiwanger (1992, 1999) belong to the micro-data category, although they have been separately discussed in a previous section.

'switchers' those individuals who do not return to their original industry within two years of the switch. Given their definition of sector mobility Murphy and Topel find that 'switchers' account on average for 24% of total unemployment. Moreover this share is virtually constant over the period 1970-1985, while total inter-sectoral mobility is strongly pro-cyclical and tends to be higher when unemployment is comparatively low. Therefore Murphy and Topel conclude that unemployment fluctuations are explained by 'stayers', who account for the bulk of total unemployment.

Loungani, Rogerson, and Sonn and Loungani and Rogerson argue that Murphy and Topel's findings rely heavily on their definition of inter-sectoral mobility. When Loungani and Rogerson adopt Murphy and Topel's definition of industry switching to analyze their PSID sample, they draw (at least qualitatively) conclusions similar to those of Murphy and Topel's. However, when they use their own definition of 'switchers' on the same sample, the results change dramatically. Under Loungani and Rogerson's definition, switchers account for approximately 25% of total unemployment during expansions and nearly 40% during recessions. The results obtained under different definitions of mobility are clearly in conflict.

Starr-McCluer (1993) discusses the methodological issues underlying these contradictory outcomes. Murphy and Topel ignore that: (i) censored spells often end with a sectoral switch; (ii) censored spells increase in relative importance during recessions. If inter-sectoral job changes include only complete switches, like in Murphy and Topel (1989), then a pro-cyclical bias is introduced because transition spells last longer during recessions and are more likely to be censored. This means that the contribution of 'switchers' to total unemployment is underestimated during recessions.

On the other hand, a counter-cyclical bias characterizes Loungani and Rogerson's methodology. Though censored spells are a small share of their sample, they account for a large fraction of unemployment. For these reasons Starr-McCluer chooses to use "competing risks" transition analysis to address the censored spells problem. This approach is appropriate for duration models in which spells can end into a set of possible different states. Thus it should be able to differentiate between transition into similar and different jobs (c.f. Lancaster 1979). Applying her methodology to a sample from the PSID, she obtains results suggesting a negative duration dependence of transiting from unemployment to a job in the original sector (from a 0.24 probability at the beginning of the spell to a 0.11 probability after 9 months), whereas the hazard to work in a different sector increases with spell duration (from a 0.02 to a 0.09 probability after 9 months). As a consequence, while the spell unfolds, the probability of it ending in respecialization (i.e. transition to a different sector) rises. It is very important to notice that this hazard becomes roughly constant after 9 months (partly due to the very small number of spells still in progress beyond such time) and that "...fairly long spells have a 50-50 chance of ending with a return to similar work...". Starr-McCluer argues that, after controlling for individual characteristics, workers who become unemployed during recessions are more likely to respecialize. A one-tenth of a percentage point decrease in national unemployment has an extremely strong effect on workers from the manufacturing and construction sectors: the hazard of exiting into similar jobs would rise by 5.5%, whereas the hazard of exiting into different jobs would rise by 24.1%. Starr-McCluer notices that "...while spells beginning in recession were unusually likely to end in respecialization, transitions into new industries or occupations accelerated with recovery, not when recession was ongoing. This probably contributes to the contradictory results of Murphy and Topel and Loungani and Rogerson...". Overall, the results of Starr-McCluer support the sectoral shifts hypothesis. She finds that the share of unemployment associated with respecializations rises from 28% in expansions to 34.5% in recessions.

Also Thomas (1996) takes a skeptical stand on Murphy and Topel's findings: he observes that 'switchers', despite constituting a small fraction of the unemployed, can still play a substantive role if they form a sufficiently large proportion of the long-run unemployed. Thomas (1996) uses the 1986 wave of the 'Labour Market Activity Survey' for Canada and provides evidence that 'switchers' have indeed longer spells of unemployment. He also uses "competing-risks" duration models that can distinguish among sectoral re-employment outcomes.

A very interesting contribution in this area comes from Shin (1997), who brings together the micro-data approach and the dispersion index literature. In order to compute sectoral dispersion measures, he uses U.S. accounting data from the Compustat database on publicly traded companies. Sectoral shocks are approximated by the dispersion of sectoral returns to physical capital under the assumption of complementarity between capital and labor. Alongside this dispersion index across industries ('ACROSS'), he also computes a dispersion index within industries ('WITHIN') using the 20 manufacturing industries defined by 2-digit standard industrial classification (SIC) codes. Following the job creation and job destruction literature Davis and Haltiwanger (1992) the WITHIN measure is adopted as a proxy for intra-sectoral shocks. The ACROSS index is purged of aggregate effects using the filtering methodology proposed by Abraham and Katz (1986). Shin runs several regressions of the aggregate unemployment rate on both indices and other variables controlling for aggregate monetary and real shocks. He finds that, although the magnitude of intra-sectoral shocks is larger than that of inter-sectoral shocks, the latter is the only variable which can explain the dynamics of aggregate unemployment. Shin argues that the assumption of complementarity between physical and human capital is robust because sectoral returns to physical capital can indeed help predict sectoral employment growth rates; nonetheless the validity of this assumption for all sectors and for all periods is questionable. Furthermore, Shin's procedure to 'purge' the dispersion index is similar to that of Abraham and Katz and the critiques moved to their work can be extended to Shin's. It is also unclear why the measure of intra-sectoral reallocation (WITHIN) is not filtered of aggregate components as its inter-sectoral counterpart (ACROSS).

A special discussion must be devoted to the procedure proposed by Neumann and Topel (1991) to extract a clear time series signal for sectoral shocks via low-frequency filtering of repeated cross-sections. They analyze geographical differences in equilibrium unemployment and consider an 'islands model' featuring independent labor markets characterized by specific industries and labor force. Their reduced form unemployment equation is

$$u_{st} = \alpha_s + \gamma_t + X_{st}\beta + \eta_{st} \tag{48}$$

where u_{st} is a measure of the unemployment rate in labor market s at date t, γ_t a period effect common to all markets (a matrix of time-diagonal dummies) controlling for aggregate fluctuations, and X_s a vector of factors determining local unemployment.

The period effect γ_t captures aggregate fluctuations in unemployment, and the elements of β represent the impact of regressors X_{st} on unemployment, net of aggregate fluctuations. Neumann and Topel construct three key variables to be included in X_{st}:

1. an estimate of the covariance structure of local labor demands ("RISK"), based on the empirical covariances of industry employment innovations in each market.
2. an index of local sensitivity to industry specific oscillations ("SHOCK"). This variable accounts for the geographic non-neutrality induced by aggregate disturbances that have a larger impact in markets specialized on the affected industry;
3. finally (and most importantly), a market-specific index of structural change in the sectoral distribution of employment.

Neumann and Topel acknowledge that the effect of sectoral employment growth dispersion on aggregate unemployment could be due to the well-known non-neutrality of business cycles across sectors. They control for the disparate impact of aggregate shocks generated by differences in industry composition through the local variable SHOCK.

To construct a measure of sectoral shocks they separate permanent changes in the sectoral composition of demand (associated with workers reallocation) from transitory changes in composition which are related to local cycles and other random events. Within a labor market s let

$e_t = (e_1\ e_2\ ....\ e_{n-1}\ e_n)$ be the vector of employment shares across n industrial sectors at time t and let the direction of permanent change in industry composition be defined as the vector

$$\Delta e_t^* = \sum_{j=1}^{J} \delta_j e_{t+j} - \sum_{j=1}^{J} \delta_j e_{t-j} \tag{49}$$

$$\text{where} \quad \sum_{j=1}^{J} \delta_j = 1$$

Δe_t^* is the difference between moving averages of past and future vectors of employment shares at date t and it approximates the permanent shifts in sectoral employment. Neumann and Topel use 1948-1981 quarterly data for Spain and set $J = 16$ (a 8 year span) when computing Δe_t^*. The actual difference between current and past employment shares is defined as

$$\Delta e_t = e_t - \sum_{j=1}^{J} \delta_j e_{t-j} \tag{50}$$

Assuming that Δe_t consists of a permanent and a transitory component, and that the permanent component is the only factor reflecting reallocation of resources across sectors, Neumann and Topel identify the permanent component as the period-specific least-squares projection of the current change (50) onto the vector that measures the direction of permanent change (49). The permanent component is therefore approximated by the OLS estimator

$$\Delta e_t^P = \left(\Delta e_t^{*\prime} \Delta e_t^*\right)^{-1} \left(\Delta e_t^{*\prime} \Delta e_t\right)\ \Delta e_t^* \tag{51}$$

A natural measure of permanent shocks is the Euclidean length of Δe_t^P

$$PERM_t = \parallel \Delta e_t^P \parallel \tag{52}$$

If Δe_t is orthogonal to Δe_t^*, then $PERM = 0$ and the current shock is a purely transitory one. Transitory shocks are the complement to one of permanent shocks and can be residually defined as

$$TRANS_t = \parallel \Delta e_t - \Delta e_t^P \parallel \tag{53}$$

Neumann and Topel find that permanent shifts in the composition of employment within states lead to transitory increases in unemployment, while transitory departures from the slowly moving industry composition have negligible effects. These results lend some support to the view that permanent sectoral demand shifts are significant determinants of unemployment even though the impact of these shifts is not big relative to typical cyclic fluctuations in unemployment. Allowing for lagged responses does not substantially change their estimates.

This procedure is elegant and effective, but it does require some kind of cross sectional pooling: for this application the pooling criterion is naturally provided by the geographic districts which represented the main focus of Neumann and Topel's analysis. However, such a natural and convenient pooling criterion is not always available.

The effects of changes in the composition of employment is also examined by Beaudry, Green, and Sand (2007). They ask whether changes in sectoral composition of employment, especially shifts in composition between high paying sectors and low paying sectors, have general equilibrium effects on the determination of within sector wages. This question is relevant because general equilibrium effects could be eventually measured as aggregate shocks, even though the original trigger is pure reallocation of productive resources. Beaudry, Green, and Sand argue that a change in industrial composition, through its effect on the bargaining environment, can affect wages in sectors not directly involved in the compositional change. In such sectors, an improved outside option for workers places upward pressure on wages, forcing inefficient firms to exit the market and thereby favoring a reallocation of employment toward more productive firms. The authors look at 10-year and 20-year changes in city-level industry-specific wages using data from the 1970, 1980, 1990 and 2000 US Censuses for 152 cities and find that changes in city-level industrial composition do have effects on wages. Such effects are roughly 3 times greater than what would be predicted by a pure accounting approach. The effect of composition is present over long (20 year) horizons and is present in wages in both tradeable and non-tradeable sectors, suggesting that changes in workers' outside options may have important effects on rationalization of production within an industry. By focusing on longer term differences in wage structure, associated with different industrial composition, this paper shows how reallocation shocks may induce aggregate effects which become apparent only over long periods.

6 The Computational Equilibrium Approach

An increasingly popular way to obtain quantitative approximations of economic relationships is through numerical simulation techniques based on well specified equilibrium models[33]. These simulation methods offer a viable alternative to the direct estimation of reduced form equations and structural systems. Quantitative answers obtained through numerical simulations offer the advantage of being easy to interpret, and usually allow to disentangle the direct and indirect

[33]Numerical simulations of structural equilibrium models have become popular in macroeconomics because of their extensive use in Real Business Cycle ("RBC") analysis (c.f. Kydland and Prescott (1982) and Prescott (1986) as the seminal papers and Cooley (1995) for a set of articles of other leading contributors in this area).

effects of specific perturbations. Furthermore, these techniques considerably reduce the data constraints often encountered in econometric work.

A popular way to implement numerical equilibrium analysis is through the model "calibration" procedure, which uses an equilibrium model, suitably parameterized (calibrated) to match stylized facts of a target economy, in order to provide quantitative answers regarding the functioning of the model itself. In this context equilibrium models become effective measurement tools. They are first tuned to match observed regularities, and then used to measure behavioral and aggregate responses that are often not directly observable from real world data. This procedure can be summarized as a three-step process: constructing a structural model which can appropriately address the questions of interest, assigning specific values to fundamental model parameters (this is the actual calibration process)[34], and using the calibrated model to run experiments and simulate counterfactual scenarios. This final step requires a perturbation of the original equilibrium and amounts to numerical simulations of the model under alternative restrictions. This method provides quasi-experimental measurements of the economic outcomes of interest[35].

At the very outset of the RBC literature, the supply-side specification of sectoral shocks (e.g., sectoral technology shocks) was the object of research by Long and Plosser (1983), who specified a six-sector G.E. model with intermediate input linkages among sectors and *i.i.d.* sectoral productivity shocks. They found that, at this relatively high level of sectoral aggregation, such a model can yield output fluctuations that are both persistent and correlated among sectors. However, attempts to reproduce aggregate volatility at higher levels of disaggregation have not been as successful. The explanation for the limited success of Long-Plosser models is rather straightforward: uncorrelated sector-specific disturbances tend to dissipate through aggregation since, by the Law of Large Numbers, positive and negative supply-side variations in different sectors tend to offset each other.

These issues are explored in more detail by Horvath (2000), who investigates the ability of sectoral shocks to explain movements in aggregate output and reproduce qualitative features of macroeconomic fluctuations. Horvath shows that, within a multi-sector dynamic general equilibrium model, aggregate fluctuations can be induced by independent sectoral technology shocks: this result is achieved through the introduction of forces which limit the annihilating influence of the Law of Large Numbers. His simulations reveal that the time-series properties of the

[34]Parameter values are usually taken from micro-data studies or selected to match some fundamental long term regularities of the economy under investigation.

[35]The third step is not always performed, as in some cases a researcher may just want to verify whether a theoretical model is able to reproduce some data features rather than build counterfactual outcomes.

model's aggregate variables are qualitatively similar to the ones in the data and to results from one-sector business cycle models, even though they don't rely on aggregate shocks. The twist in Horvath's model, with respect to the original idea of Long and Plosser's, is the introduction of an input-use matrix with limited interaction[36], meaning most sectors in the model use almost exclusively similar kinds of intermediate inputs. In this case sectoral shocks to the intermediate input sectors are likely to induce co-movements in the final good sectors and aggregate fluctuations and can help understand the properties and effects of the random productivity shocks used in one-sector real business cycle research. One of the most interesting results in Horvath is that the aggregate Solow residual series estimated from the simulated data in a highly disaggregated model is quite variable and strongly resembles the estimates obtained using US data, suggesting that empirically observed shocks to aggregate multi-factor productivity may be an artifact of aggregation rather than true evidence of aggregate shocks. Given that sectoral (supply-side) shocks are often observable and measurable, this represents a substantial step towards a theory of total factor productivity.

Ramey and Shapiro (1998) show how a two-sector model can produce a rich set of implications for business cycle dynamics by looking at shifts in demand across sectors due to changes in government spending. Their two-sector model with costly reallocation of capital can better replicate the US economy's response to an exogenous military buildup than a one-sector model. Ramey and Shapiro's findings are also relevant for the broader debate concerning the inadequacy of the standard neo-classical model to explain why increases in government spending are found to be accompanied by increases in consumption, real wages and productivity. Rotemberg and Woodford(1992, 1995) and Devereux, Head, and Lapham (1996) have maintained that only models with imperfect competition and increasing returns-to-scale (IRS) are able to rationalize the aggregate effects of government spending. The introduction of multiple sectors is a way to reconcile the neo-classical model with these troubling observations; in particular, Ramey and Shapiro show that imperfect capital mobility among sectors can substitute for imperfect competition as a mechanism for predicting business-cycle dynamics.[37]

A long standing question in the applied macroeconomic literature is how to reconcile sectoral shifts analysis with the observed pattern of pro-cyclical productivity movements and pro-cyclical real wages. The initial contributions in this field (see Davis 1987, Hamilton 1988, Rogerson 1987) have considered the role that sectoral shifts play in generating aggregate fluctuations in the

[36]Such an input use matrix would be characterized by few full rows and many sparse columns.

[37]In related work, Swanson (1999) generalizes the standard one-sector DSGE model to multiple sectors and explores the role of sectoral perturbations (such as changes in the sectoral composition of production) as a channel for the amplification and propagation of economic shocks.

presence of costs associated with shifting inputs across sectors. Such models reduce aggregate productivity to be a weighted average of sectoral productivities, so that sectoral shifts end up having only a second order effect on productivity dynamics and are therefore unable to match the empirical regularity of pro-cyclical productivity. In this context it is possible to show that, after an arbitrary perturbation of the economy from the steady state, we can compute a Solow decomposition which clearly indicates that reallocation effects stemming from the movement of labor across sectors have no first-order impact on aggregate productivity.[38]

Swanson (1999) shows that what is needed for sectoral reallocation to have a first order effect on aggregate productivity, labor productivity and real wages, and to explain the observation of aggregate increasing returns-to-scale is a wedge driving the marginal products of different sectors apart in the steady state. A credible way to introduce this wedge is to postulate the presence of sectoral differences in capital utilization, which result in steady state differences in the marginal productivity of capital.

The work of Swanson is in the spirit of Basu and Fernald(1997b, 2002), who first suggested that using a wedge to differentiate among marginal returns can induce realistic patterns in aggregate productivity and rationalize the puzzling observation of increasing aggregate returns to scale ("IRS") at low levels of disaggregation. For instance, they ascribe observations of aggregate IRS to cyclical movements in the share of production accounted for by durable and non-durable manufacturing. If durables are characterized by higher returns to scale and higher mark-ups than non-durables, then a reallocation from the latter to the former results in an increase in aggregate output relative to inputs, and apparently increasing aggregate returns-to-scale. Basu and Fernald (1997a) argue that a similar line of reasoning can be applied to the observations of pro-cyclical aggregate productivity: reallocations from a low returns-to-scale, low mark-up sector to one with high returns and high mark-ups will be partially measured as increases in the Solow residual. It is possible that a reallocation of labor from low to high mark-up sectors would

[38]This is generally valid for all sectoral models which assume sectoral constant returns to scale ("CRS") production functions $Y_{it} = A_{it} F_i \left(K_{it}, L_{it}\right)$ with perfect competition, free mobility of labor L_{it} and capital stocks K_{it} that are fixed in the short run. If we denote the share of labor's output by α and wage and prices by w and p, then after any perturbation of the economy from the steady state we can compute a Solow decomposition of this kind:

$$\begin{aligned}\widehat{A_t} &= \widehat{Y_t} - \alpha\widehat{L_t} = \sum \frac{p_i Y_i}{Y}\widehat{Y_{it}} - \alpha\widehat{L_t} = \\ &= \sum \frac{p_i Y_i}{Y}\widehat{A_{it}}\end{aligned}$$

which clearly indicates that reallocation effects stemming from the movement of labor across sectors have no first-order impact on aggregate productivity.

deliver first-order increases in aggregate productivity and that sectoral differences in mark-ups[39] are the force driving productivity changes. However, differences in mark-ups are relatively small (in the order of 5 to 10%) and the effects of labor reallocations on aggregate productivity are bound to be correspondingly small.

Swanson (1999) assumes perfect labor mobility between sectors and into and out of the labor force. Labor market frictions, albeit important for sectoral reallocations and unemployment, are not relevant to Swanson's questions and hence are ignored. It is reasonable to expect that the introduction of adjustment costs or search lags to the shifting of labor across sector (as in Phelan and Trejos 2000) would induce drops in the total quantity of labor employed during transitions.[40] The lack of any labor market frictions makes Swanson's model unfit to quantitatively evaluate the impact of sectoral shocks on (un)employment. However, this model represents a definite step forward in the definition of sectoral shifts as multi-dimensional perturbations. It defines sectoral shocks as any reallocation induced by changes in tastes, exogenous government purchases, composition of investment goods, and multiplicative, sector-specific realizations of a random technology shock. In this sense the paper groups under the unique category of sectoral shocks a wide variety of model perturbations which have the common feature of inducing labor and output reallocation across sectors.

The dynamic programming aspects of the multi-sector DSGE model are complex and closed solutions are hard to obtain, so Swanson uses numerical methods to study its properties. He considers four model economies: (*i*) the baseline one-sector model; (*ii*) the basic multi-sector model; (*iii*) a one-sector model with capital utilization; (*iv*) a multi-sector model with capital utilization. In this way it is possible to compare both the hypothesis of variable capital utilization and the sectoral reallocation features of the models. All the macroeconomic parameters are set identically across models and correspond to consensus values[41].

The effect of a pure sectoral shock is best studied in an experiment involving a model of type (*ii*) or (*iv*) in the above classification. Swanson performs such experiment by considering a pure reallocation of demand across the two sectors of a simple economy. The two sectors are assumed

[39]More specifically, denoting sectoral markups as μ_i and letting μ be some measure of economy-wide, average markup, the following decomposition, due to Hall(1988, 1990), can be obtained:

$$\begin{aligned}\widehat{A_t} &= \widehat{Y_t} - \mu\alpha\widehat{L_t} = \\ &= \sum \frac{p_i Y_i}{Y}\widehat{A_{it}} + \alpha \sum (\mu_i - \mu)\widehat{L_{it}}\end{aligned}$$

[40]This effect has been studied also by Davis (1987), Hamilton (1988) and Rogerson (1988).

[41]One of the crucial parameters to define inter-temporal substitution of labor is set to a relatively low level of 1.7 in order to conservatively reduce the responses of the model to economic shocks.

to be identical in everything except for the marginal return to capital in model (*iv*). The demand shift is set to yield a permanent 3% increase in the share of total consumption accounted for by the first good (with a corresponding drop in the second). The 10-year impulse responses to this shock are dramatically larger for the models with unequal capital utilization, and even the qualitative responses are not always identical: output is almost unchanged in model (*ii*) and so are labor input, real wage and investment, whereas output initially drops by 0.7% in model (*iv*) with a coincident 2.5% drop in investment, 0.3% drop in real wage and 0.4% drop in labor input. As for aggregate productivity, the reallocation of production across sectors yields, in model (*iv*), an immediate 0.35% drop which is the driving force of the drop in real wages; in contrast, the same reallocation is negligible in model (*ii*) as we would expect in the light of the neutrality of the labor shifts mentioned before.

Swanson also separately studies the reallocation implications of a sectoral technology shock. The economy in this case is divided into two sectors corresponding to the investment sector, which produces durable goods, and the other sector which produces everything else. The relative sizes of the sectors in steady state are set, respectively, to 32% and 68% of the total (roughly replicating the sizes in the US economy). The hypothetical shock is taken to be a 3% increase in the first sector's technology parameter. We are interested in the responses of model (*ii*) and (*iv*), as before.

Sectoral technology shocks are assumed to be trend stationary $AR(1)$ processes, with a 0.65 autoregressive coefficient (which is roughly in line with estimates for the US). The initial change in output, employment and investment are all positive and twice as large in model (*iv*), with output jumping up by 0.3%, labor input by 0.2% and investment by over 12%. Aggregate productivity is roughly 40% higher in the model with unequal capital utilization. Swanson concludes that these experiments provide solid proof that including sectoral heterogeneity in capital utilization magnifies the responses of equilibrium models to exogenous economic shocks, both in the case of demand side shocks (taste shifts) and in the case of supply side shocks (sectoral technologies). Although sectoral reallocation and capital utilization can each act as a separate amplification and propagation mechanism, the combination of the two yields responses which are larger than the sum of their parts. Furthermore, pro-cyclical real wages and productivity can be obtained even using simple demand side shocks, as long as differences in capital utilization exist among sectors.

An important contribution in this area is made by Phelan and Trejos (2000), who calibrate a variant of Mortensen and Pissarides (1994) model of job creation and destruction. The central proposition of Phelan and Trejos is that an isolated reallocation shock, reflected in a permanent change in the fundamental determinants of demand composition, can bring about aggregate effects.

Phelan and Trejos (2000), as well as Rogerson (1987), employ a multi-sector two-period adaptation of Lucas and Prescott (1974) (with three sectors and three consumption goods produced only through labor). To isolate the effects of technological frictions as opposed to market failures, Phelan and Trejos solve the dynamic programming problem of a benevolent planner, rather than a proper DSGE model. The planner maximizes the expected lifetime utility of a randomly selected agent facing an economy characterized by the some costs of job creation. The solution of the planner's problem is used to run three experiments. The first, what they denote as a 'pure sectoral shock', amounts to imposing a preference shock which changes the relative demands for the goods in the economy. By construction, this demand shift has no long-run aggregate implications but carries effects for the composition of output and employment. The second and third experiments are meant to represent a sectoral shrink comparable to the US military build down of the 1990s, modeled as a fall in the desirability of a sector's output. The accompanying demand shifts are alternatively assumed as evenly distributed across all sectors or benefiting only a small sector of the economy.

Phelan and Trejos calibrate the model's parameters to match U.S. labor market data. The first experiment is the most relevant for the sectoral shifts hypothesis. One sector has to decrease in size at the advantage of the second, while the third sector, and all aggregate variables, are kept unchanged[42]. This is achieved by 'flipping' the preference coefficients between two sectors and starting the time path at the employment levels of what would be the steady state if the preferences parameters had not been 'flipped'. The change in the parameters is set to a value such that a completed transition shall bring a reallocation of 3.5% of the workforce from one sector to the other[43]. What they observe in this experiment is a slow adjustment from one steady state to another. It takes about four years to move halfway from the old to the new steady state, and almost ten years for 80% of the transition to take place. The employment in the 'control' industry hardly moves. Changes in total employment are small and aggregate changes come from the intensive margin (number of hours) rather than the extensive margin (number of jobs). This result is probably due to the presence of internal (sector-specific) and convex costs in job creation, which make it very expensive to set up new jobs in the growing sector and tend to preserve employment levels in the shrinking sector. However, GDP experiences a sizeable

[42]The latter sector operates as a "control", since its response to impulses would allow to separate transitory effects from permanent ones and to learn how sectoral shocks propagate to the rest of the economy.

[43]This number is chosen because it corresponds to the number of agents who lose their jobs in any (steady state) given period.

drop (1.1%) along the transition. This downturn would propagate to the sector unaffected by the sectoral shock. In particular, the combined output of the expanding and shrinking sectors falls initially because the shrinking sector extracts fewer hours per worker (since the good they produce becomes relatively less attractive than leisure), whereas the expanding sector has to divert more efforts to the hiring process (to the detriment of production) because of convex costs of job creation. This response is not small, given the size of the initial impulse. Furthermore, the downturn propagates to sectors unaffected by the shift and lasts a long time.

Such findings are robust to different changes in parameters, initial output composition and sector sizes. The dynamics of the adjustment and aggregate downturn induced by the sectoral shock look remarkably similar to those of the early 1990s U.S. recession, which was long but not deep and spread unevenly across the economy. Phelan and Trejos notice that in those years a big military build-down took place and considerable resources were channeled into other sectors. Also, the effects of sectoral shocks in the presence of labor market frictions can generate a high degree of co-movement across sectors, which is one of the properties of productivity shocks in the real business cycle literature. Phelan and Trejos' main finding is that, due to costs in job creation that are borne separately by each sector, isolated sectoral shocks can have important aggregate implications, even if the size of the 'impulse' is relatively small. They argue that a one-time, permanent change in the sectoral composition of the economy can indeed prompt a non-negligible downturn, which persists and propagates across sectors as in a recession[44].

Unlike Lilien (1982a), Phelan and Trejos do not find that sectoral reallocations account for as much as half of the output volatility observed in U.S. data. However their work, more than any other in the SSH literature, underlines the complementarity of sectoral shifts and RBC theories. They define sectoral shocks as isolated, permanent and unanticipated changes in the long-run composition of output, which are fully deterministic in their nature. This definition is alternative to (although compatible with) the concept of randomly distributed sectoral productivity shocks which are assumed in the earlier literature. They neglect the potential volatility persistence of random shocks' realizations as implied by Lilien (1982a) and explored by Pelloni and Polasek (1999). Incorporating sectoral technology shocks in their model could shed some light on the relative size of demand-side vis-a-vis supply-side shocks.

The discussion so far has highlighted the centrality of real 'costs' of shifting jobs across sectors as a friction translating sectoral disturbances into aggregate effects: a long standing question is

[44]Another interesting finding of Phelan and Trejos (2000) is that shocks which induce sectoral reallocations have "aggregate" properties that resemble those of "productivity shocks" discussed in the real business cycle literature. Sectoral shifts are therefore not a competing theory to real business cycle, but rather a complement theory that maps unknown territory within the productivity shocks' black box.

how large such costs really are. Lee and Wolpin (2006) try to to quantify these costs by looking at the long-term rise in service sector's employment.

The employment share of the service sector has been steadily growing in the U.S. during the second half of the 20th century; at the same time service sector wages have been relatively constant vis-a-vis manufacturing sector wages. Lee and Wolpin use a structural model with two sectors (services and goods) and many occupations within each sector: heterogeneous individuals maximize their lifetime utility by choosing whether to work and, if so, in which sector and occupation. The purpose of their exercise is to evaluate how large are the costs of switching across sectors and/or across occupations. They also study the transitional dynamics of employment shares, with the aim to isolate the main forces that have been leading the long-term rise of services' employment. Switching costs are estimated using a Simulated Method of Moments, meaning that the model is simulated to generate moments that are close to their data counterparts according to a given metric. Estimation results suggest that the cost of switching across sectors are large (between 50% and 75% of the average labor earnings), whereas the costs of switching across occupations within the same sector are much smaller.

Through the implementation of interesting counterfactual experiments Lee and Wolpin find that setting switching costs to zero would result in the almost doubling of aggregate output in equilibrium: this makes for a very large efficiency cost associated to labor frictions. They also assess the importance of alternative factors for the rise of the service sector coming to the conclusion that demand and technology shocks are responsible for the rise of services' employment, rather than demographics and educational changes.

The relevance of technology shocks is also stressed by MacDonald and Andolfatto (2004). They point out that the phenomenon of 'jobless recoveries' (i.e. economic expansions which fail to generate jobs in their early stages) might be due to the costly process of labor reallocation induced by technological change.

They show that, when technological shocks are adopted slowly throughout the economy, there can be expansionary periods in which there is no employment gain: this is due to the diversion of labor input towards search and/or human capital accumulation. Transitional periods can therefore be characterized by jobless recoveries.[45]

The fact that jobless recoveries have not been a regular historical occurrence highlights one

[45] These phenomena are consistent with a model of sectoral shifts as well as a model with no sectoral reallocation (in this second case all the loss in labor supply is due to re-training of the labor force to accumulate human capital). A similar conclusion is reached by Tapp (2007), using a search model with different sectors, who studies the effects of changes in international demand for commodities on aggregate employment in Canada between 2002 and 2006. He finds that the transitional costs of relocating labor across sectors were as large as 3% of GDP and mostly due to the non-transferability of skills across sectors, rather than pure search frictions.

recurring issue in sectoral shifts analysis: labor reallocation shocks tend to produce aggregate effects only under very specific historical and economic circumstances (a point originally made by Lilien 1982a). More work is needed to understand what these circumstances are.

7 Conclusion

In this article we have surveyed and commented on the different generations of empirical models of job reallocations in macroeconomics from 1982 to date.

The first generation of reduced form unemployment equations, embodying an employment dispersion index among the regressors, has proved to be plagued by a severe problem of observational equivalence. Variations in the index could be equally determined by either aggregate impulses or sectoral turbulence. The second generation uses dispersion proxies purged of aggregate influences. Choice of the purging vector can be easily criticized for 'ad-hockery'. In general, the empirical results of first and second generation models are unfavorable to the sectoral shifts hypothesis with the exception of a small group of papers.

The third generation, still based on dispersion indexes, appeared in the early 1990s. The key feature of these models is the use of stock market information. Still, these models are susceptible to criticism as they cannot discriminate between aggregate and idiosyncratic shocks. The widespread use of generated regressors, though in theory may generate problems of statistical inference, might not be troubling in practice. The early debate was also framed in terms of the U-V relationship. Fundamental work by Hosios showed that, at least in this early context, this strategy was a dead end.

Structural Vector Auto-Regressions (SVAR) are the analytical tool of the fourth generation. SVARs can do without generated dispersion indexes. This strategy brings a gain in terms of correct inference, by getting rid of generated regressors, and avoids issues of purging . Nevertheless, it is exposed to the standard criticisms of SVAR modeling and tend to miss the non-directional nature of sectoral shocks. Extensions to multivariate GARCH-M models and Markov-switching regressions seem more promising.

A fundamental step forward has been taken by the next generation of job-creation and job-destruction models which have provided a suitable conceptual framework to analyze rich sources of micro-data. Even more importantly, the development of this concepts has allowed researchers to formulate specific non-linear restrictions within multivariate regression models.

Micro-data have proven to be a valuable source of information about labor reallocation, and have become increasingly popular also outside the JC and JD literature. Most studies using micro-data find evidence of significant inter/intrasectoral job reallocation. Disagreement persists over the relative importance of sectoral shocks in driving aggregate unemployment fluctuations. Such disagreement partly stems from the lack of an accepted, rigorous conceptual framework to differentiate aggregate and sectoral shocks. The lack of an unambiguous theoretical counterpart makes measurement harder. The computational equilibrium approach to the analysis of sectoral shocks can overcome the underlying uncertainty about the nature of reallocative shocks by making explicit assumptions which are directly reflected in simulation results. Reasonably calibrated models of the aggregate economy can be effectively used to account for different sources of aggregate unemployment. This last avenue of research has also the advantage of being able to easily discriminate between alternative theoretical hypothesis regarding the mechanisms through which sectoral shocks operate.

At the end of this long excursion it is possible to state that we are still far from a fully satisfactory empirical practice to assess the macroeconomic effects of job reallocations. However, since the early days of Lilien's seminal work a lot of ground has been conquered. The JC and JD framework, the non-linear multivariate econometric models and the computational equilibrium approach seem to be useful and promising tools to model the intrinsic non-linearities of job reallocations and partly compensate for a still unsettled theoretical frame of reference.

A Legend for Abbreviations

Technical Jargon

- ACROSS = Dispersion Index Across Industries; inter-sectoral reallocation
- BED = Business Employment Dynamics
- BLS = Bureau of Labor Statistics
- CAPM = Capital Asset Pricing Model
- CPS = Current Population Survey
- CRS = Constant Return to Scale
- CSV = Cross-Section Volatility
- DSGE = Dynamic Standard General Equilibrium
- EXC = Excess job reallocation
- G.E. = General Equilibrium
- GIRF = Generalized Impulse Response Function

- HWAI = Help-Wanted-Advertising Index
- IRF = Impulse Response Function
- IRS = Increasing Aggregate Return to Scale
- JC = Job creation
- JD = Job destruction
- LBD = Longitudinal Business Database
- LRD = Longitudinal Research Database
- LRH = Labor Reallocation Hypothesis
- MSR = Markov-Switching Regression
- MSSV = Markov Switching Stochastic Volatility
- NAICS = North American Industry Classification System
- NBCH = Normal Business-Cycle Hypothesis
- NET = Employment change
- NRU = Natural Rate of Unemployment
- OLS = Ordinary Least Squares
- PPLR = Past-Pattern-of-Labor-Reallocation
- PSID = Panel Study on Income Dynamics
- RBC = Real Business Cycle
- RTH = Reallocation Time Hypothesis
- SBCE = Stage-of-Business-Cycle Effect
- SIC = Standard Industrial Classification
- SMM = Search and Matching Model
- SSH = Sectoral Shifts Hypothesis
- STAR = Smooth Transition Autoregressive Model
- SUM = Net job creation, gross job reallocation
- SVAR = Structural VAR
- SWARCH = Switching ARCH
- VAR = Vector Auto-Regression

- VAR-GARCH-M = Multivariate GARCH in Mean
- WITHIN = Dispersion Index Within Industries; Intra-Sectoral Reallocation

Authors

- AK = Abraham, K. G., and L. F. Katz (1986.1986)
- MPZ95 = Mills, T., G. Pelloni, and A. Zervoyanni (1995)
- BH06 = Byun, Y., and H.-S. Hwang (2006)
- DH = Davis, S. J., and J. Haltiwanger (1989,1992,1997,1999)
- DHJM06 = Davis, S. J., J. Haltiwanger, R. Jarmin, and J. Miranda (2006)

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