REAL WAGES AND AGGREGATE DEMAND SHOCKS:
CONTRADICTORY EVIDENCE FROM VARS

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Abstract: This paper revisits two recent studies that estimate the dynamic response of
real wages to aggregate demand shocks. Using identical empirical techniques – structural
VARs with long-run identifying restrictions – and similar post-war data, Gamber and
Joutz (1993) and Spencer (1998) report contradictory findings. After careful examination,
I conclude that the reason for this puzzling result is a lack of robustness of the estimated
wage response functions to model specification, data transformation to induce stationarity,
the choice of proxy for the aggregate real wage, and the choice of variables to include in the
VAR. The implication is that the message from VARs with long-run restrictions regarding
real wage dynamics is not clear, and that further work must be done to understand the role
of relative stickiness of wages and prices in the transmission of aggregate demand shocks.

JEL codes: E0, E1, E3
1. Introduction

In a recent paper, Gamber and Joutz (1993) estimate that real wages respond *positively* to aggregate demand shocks in the short-run. This result is inconsistent with Keynesian “sticky-wage” theories of the business cycle, according to which the transmission of nominal shocks to real activity occurs through countercyclical changes in the real wage and movements along the labor demand curve, but is consistent with sticky-price models (e.g. McCallum 1986) or real-business-cycle “limited participation” models of money (e.g. Christiano, Eichenbaum and Evans 1997). However, in a more recent study, Spencer (1998) directly contradicts these findings – his estimates suggest that the real wage response to such shocks is strongly and robustly *negative*, thus supporting the sticky-wage view.

Surprisingly, the empirical methods used by these studies are almost identical: each is a time-series study that estimates a 3-variable vector autoregression (VAR) including a measure of the real wage, a measure of aggregate real economic activity, and the unemployment rate; each uses aggregate, quarterly, post-war US data; and each identifies the dynamic response of the aggregate real wage to aggregate demand shocks by imposing the plausible restriction that such shocks are neutral (have no effect on real variables) in the long-run. Readers are thus left to wonder both why the findings for real wages differ so dramatically across the studies, and which set of findings best characterizes the actual response of the real wage to aggregate demand shocks.\(^1\)

The aim of this analysis is to determine the extent to which model specification and choice of empirical proxy for the aggregate variables used in the VAR can explain the variation in such key results across these studies, holding the identification strategy and sample period constant. Clearly, this is an important task a) theoretically, in light of the significance of real wage dynamics in distinguishing between alternative theories of

\(^1\) Christiano, Eichenbaum and Evans (1997), using a VAR approach with an alternative set of identification restrictions, find in general a positive dynamic response of real wages to monetary policy shocks.
the transmission mechanism, and b) econometrically, in light of the critique of long-run restrictions by Faust and Leeper (1997). They point out that the use of long-run identifying restrictions in finite samples inherently lacks robustness; in particular, identified impulse response functions can be very sensitive to specification of the statistical model used. At issue, then, is what we can learn about the dynamic behavior of aggregate real wages from VARS that are identified by infinite-horizon restrictions.

My strategy is to vary model specification and empirical proxy along crucial dimensions and to compare the resulting dynamic response functions of real wages, real activity, and unemployment or nominal output, over a common sample period. I find a remarkable degree of robustness for real activity and unemployment/nominal output. However, I am also able to replicate the different results of Gamber and Joutz (1993) and Spencer (1998) for wages, and show that the dynamic response of the real wage is much less robust than as suggested by each of these studies. In particular, the estimated real wage responses are sensitive to lag length in the VAR, data transformation to induce stationarity, and choice of empirical proxies both for the real wage and for the nominal variables used to drive the identification of aggregate demand shocks. The upshot is that a) aggregate demand shocks and dynamic responses can be confidently identified with long-run restrictions, given the robust findings for some variables in the system (so that the Faust/Leeper critique is not necessarily always a practical concern); but that b) we learn little about the transmission mechanism of aggregate demand shocks through labor markets, in particular how real wages respond to such shocks, from long-run restrictions in trivariate VARs. This exercise cannot definitively answer the second question above (how do wages really respond to demand shocks?), but it suggests how to go about getting an answer.

2. Estimating and identifying aggregate demand shocks

Before discussing the results, it is necessary to briefly describe the approach to estimation and identification using long-run restrictions, as pioneered by Blanchard and Quah
(1989) and Shapiro and Watson (1988). Let $z_t$ denote the $n \times 1$ vector of stationary endogenous variables relevant for understanding the dynamic behavior of real wages. Assume that $z_t$ is generated by the structural model

$$z_t = D(L)v_t = (D_0 + D_1 L + D_2 L^2 + \cdots)v_t,$$

(1)

where $v_t$ is an $n \times 1$ vector of white noise shocks with contemporaneous covariance matrix normalized to the identity matrix.\(^2\) The corresponding reduced form is

$$z_t = C(L)\epsilon_t = (I + C_1 L + C_2 L^2 + \cdots)\epsilon_t,$$

(2)

where $\epsilon_t = D_0 v_t$, $E\epsilon_t\epsilon_t' = \Sigma$, and $C(L) = D(L)D_0^{-1}$.\(^3\)

The objective of the empirical work is to obtain estimates of $C(L)$ and $\Sigma$, which are directly estimable from the data record of $z_t$, and then to identify the structural parameters of interest, $D(L)$. Since the mapping from structure to reduced form is not unique, the structural model in (1) must be restricted to achieve this identification.

In this paper, as in Gamber and Joutz (1993, hereafter, GJ) and Spencer (1999), I impose identifying restrictions on the long-run (infinite-horizon) structural multipliers, $D(1) = \sum_{i=0}^{\infty} D_i = \lim_{k \to \infty} \frac{\partial (1 - L)^{-1} z_t}{\partial v_{t-k}}$. From the correspondence between structure and reduced form, it is straightforward to show that the parameters of interest depend on $D(1)$,

$$D(L) = C(L)C(1)^{-1}D(1),$$

(3)

and that

$$D(1)D(1)' = C(1)^{-1}\Sigma C(1).$$

(4)

The identification problem is then solved by imposing a sufficient number of restrictions on $D(1)$ to estimate the unrestricted parameters in $D(1)$ from the estimated “long-run”

\(^2\) Deterministic variables are ignored in this discussion, but are considered in the implementation.

\(^3\) Note that the assumption of stationarity implies that the sequences defined by $D(L)$ and $C(L)$ are square summable.
covariance matrix on the right-hand-side of (4). For example, suppose that economic theory dictates that \( D(1) \) is lower triangular; then \( D(1) \) is just-identified as the Cholesky factor of \( C(1)\Sigma C(1)' \). Once identification of \( D(1) \) is achieved, the full set of structural parameters is identified from (3), given the reduced form estimates of \( C(L) \) and \( C(1) \).

To estimate the response of the real wage to aggregate demand shocks, both GJ and Spencer include three variables in the estimated system (in the vector \( z \)): the growth rate of the real wage, \( \Delta w_t \), the growth rate of productive activity (either output or employment), \( \Delta y_t \), and the unemployment rate, \( u_t \). Presumably, each of these processes is stationary, so that the specification in (1) and (2) is appropriate. Aggregate demand shocks are identified as those shocks that have no permanent (infinite-horizon) effect on the level of the real wage, the level of production, and the unemployment rate; that is, aggregate demand shocks are neutral in the long-run. If the aggregate demand shock is defined to be \( v_{3t} \) (and unemployment is ordered last in the vector \( z \)), then this restriction implies that the first two elements in the final column of \( D(1) \) are zero, or \( \lim_{k \to \infty} \frac{\partial w_t}{\partial v_{3t-k}} = \frac{\partial y_t}{\partial v_{3t-k}} = 0 \).

These two zero restrictions are clearly insufficient to fully identify all the shocks in the system, and therefore the entire set of coefficients in \( D(L) \). However, it is evident from (3) that they are sufficient to identify the dynamic responses of each of the variables in \( z \) to aggregate demand shocks, \( v_3 \), up to a constant (the final element in the third column of \( D(1) \)). Furthermore, Lastrapes (1998, pp. 402-03) and Keating (1998) show that, given the block recursive structure implied by the neutrality restrictions, this constant is uniquely

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4 The covariance matrix on the right-hand-side in (4) is proportional to the spectral density of \( z_t \) at frequency zero (Hamilton, 1994, pp. 188-89).

5 Spencer (1998) derives these restrictions in an illustrative nominal wage contracting model. But this restriction is consistent with most macro models.

6 Recall that \( z_t \) contains wage and output growth, so that the accumulation of the dynamic multipliers measures the effects on levels. Note also that the final element of the final column of \( D(1) \) need not be zero, since long-run neutrality does not imply that \( v_3 \) have no long-run impact on the accumulated unemployment rate. However, if \( u_t \) is indeed stationary, then \( \lim_{k \to \infty} \frac{\partial u_t}{\partial v_{3t-k}} = 0 \), which is consistent with the natural rate hypothesis and demand neutrality in the long-run.
identified as the square root of the corresponding element of Cholesky factor of $C(1)\Sigma C(1)'$. Thus, our restrictions uniquely identify all the parameters of interest, since we care about the responses only to aggregate demand shocks.\textsuperscript{7} It is useful to emphasize that these restrictions do not depend on attempts to identify the other sources of fluctuations of the variables in the system (i.e. shocks $v_1$ and $v_2$). For example, as long as unemployment is ordered last in the system, the relative ordering of the remaining variables will not alter the identification of aggregate demand shocks in any way.

The spirit of this approach is easily maintained if unemployment is replaced in the model with the growth rate of any nominal variable, such as nominal output. If this variable has a unit root, then the long-run neutrality restrictions are implemented exactly as described above; aggregate demand shocks are then interpreted as those shocks that have no long-run effect on real variables (real wage and output), but that can have a permanent effect on the level of nominal output. Again, this is consistent with the natural rate hypothesis and a vertical long-run aggregate supply curve.

Implementing this empirical strategy requires estimating $C(L)$ and $\Sigma$, which are directly obtained from the VAR of $z_t$:

$$z_t = A\delta_t + B_1z_{t-1} + \cdots + B_pz_{t-p} + \epsilon_t,$$

where $\delta$ is a vector containing deterministic and exogenous components (such as a constant and seasonal dummies). The reduced form parameters used in identification are given by

$$C(L) = (I - B_1L - \cdots - B_pL^p)$$

$$C(1) = (I - B_1 - \cdots - B_p).$$

OLS provides efficient estimates of $C(L)$ and $\Sigma$. GJ and Spencer basically follow the same procedure.

\textsuperscript{7} The responses to aggregate demand shocks are given by the final columns in each of the coefficient matrices that comprise $D(L)$; but these are fully determined given the final column in $D(1)$. See also Christiano, Eichenbaum and Evans (1999) for the implications of block recursive models for identification.
3. **Examining the robustness of the dynamic responses**

In this section, I report results from using the empirical techniques discussed above to examine the robustness of the responses of the variables in the VAR system to aggregate demand shocks. I begin by loosely replicating the systems in GJ and Spencer. I then vary the models along various dimensions and compare the response functions to determine sensitivity to model specification and variable choice.

3.1. **Using unemployment**

Figures 1 and 2 report the dynamic response functions from specifications that differ according to the empirical proxies used for measuring real wages, production and unemployment, the data transformations made prior to estimation in order to ensure stationarity, and common lag length in the equations of the VAR. These are the primary differences between the GJ and Spencer studies. The figure shows response functions for the \((\log)\) levels of the real wage and productive activity (i.e. the appropriate elements of \((1 - L)^{-1}D(L)\)), and the unemployment rate (the appropriate elements of \(D(L)\)) to aggregate demand shocks identified according to long-run neutrality. The dashes represent standard error bands computed from Monte Carlo simulations.\(^8\)

The quarterly data are obtained from DRI/Citibase, and correspond closely (if not exactly) to those used in the original studies. For the GJ system, the real wage is proxied by average hourly earnings in manufacturing (Citibase code LEHM) deflated by the (chained) GDP deflator (GDPDFC), production is measured by real GDP (GDP/GDPDFC),\(^9\) and unemployment is the rate of unemployment for men aged 20 and over (LHMUR). In Spencer’s model, the real wage is average hourly earnings in manufacturing *excluding*

\(^8\) The approach I use is the standard one of assuming a diffuse prior and a Gaussian likelihood function. The simulations use approximately 10,000 antithetically accelerated replications, as in Geweke (1988). In a small percentage of the simulations, the simulated roots of the VAR were unstable, causing explosive error bands at long-horizons. I dropped the simulated responses for unstable roots; this has no effect on the simulated short-run bands, but allows the bands to converge as the horizon grows.

\(^9\) In the original, GJ use real GNP and the GNP deflator.
overtime pay (LEMXO) deflated by the producer price index (PW), productive activity
is employment in nonagricultural industries (LHNAG) and unemployment is the total un-
employment rate (LHUR).

Figure 1 reports results for the GJ variables for alternative assumptions regarding
data transformations and lag length. In columns A and B, the data are transformed as in
specification A of GJ (p. 1389): a mean growth shift in real GDP after 1973 is removed,
and both real wage growth and the unemployment rate are linearly detrended prior to
estimation (that is, $\Delta w_t$ and $u_t$ are treated as the residuals from a regression of each of
the observed variables on a constant and linear trend). In columns C and D, the data are
not transformed in any way. Columns A and C assume a common lag length, $p = 4$, while
columns B and D use $p = 8$. The model in column B most closely corresponds to that of
Figure 3 in GJ (p. 1391). In Figure 2, the Spencer system is treated similarly, so that the
results from making the stationarity transformations appear in columns A and B, while
those for no transformations are reported in columns C and D. Column C corresponds to
the base model results reported in Spencer. Each VAR (equation 5) is estimated over a
sample ranging from 1950:I to 1998:II, and includes a constant and seasonal dummies.

Consider first the GJ responses in Figure 1. For both the four and eight lag systems
when the data are transformed (panels A and B), the shapes of the dynamic response
functions are broadly consistent with those reported in GJ (Figure 3, p. 1391): a) the
real wage responds positively to an aggregate demand shock but with a lag, peaks at four

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10 Bils (1985) notes in a panel data study that including overtime pay in the measure of
wages has important effects on the cyclical behavior of real wages.
11 The primary motivation for considering these trends is to ensure stationarity in light
of apparent deterministic nonstationarity in the variables. Handling such nonstationarity
correctly is essential given the use of long-run identifying restrictions. See both Blanchard
and Quah (1989, pp. 660-61) and GJ (p. 1389) for additional discussion.
12 Thus, I am not exactly replicating the two studies. The sample in GJ ends in 1990:4,
while that in Spencer ends two years later; in addition, neither uses seasonal dummies.
Eliminating seasonal dummies has no effect on any of the response functions reported in
the paper.
quarters at about 0.2%, then gradually approaches its original level in the long-run; b) real output rises on impact by about 0.75%, continues to its peak at quarter 3, then gradually declines; and c) unemployment initially declines in response to a positive aggregate demand shock by 0.2 percentage points, continues to fall to a maximum decline of 0.55 percentage points, then rises to its original level. The error bands suggest a significant real wage response only at horizons of three and four quarters. While the quantity variables are precisely estimated according to the standard error bands, the real wage responses are less precise and statistically are not significantly different from zero.

The real wage responses reported in panels A and B are weaker than those reported by GJ in their Figure 3, and are less persistent. The statistical model used for the results reported in column B differs from the original GJ specification only with respect to the data range and the output proxy (GDP vs. GNP). When I re-estimate the model over the sample 50:I to 90:II, as in GJ, the dynamic responses of the real wage (not reported) correspond more closely to their findings in terms of both magnitude and persistence, though some differences remain. This suggests that the original GJ results are sensitive changes in sample size. But the output and unemployment responses once again are almost identical across these sample periods.

In panels C and D, it is clear that the positive real wage response is also not robust with respect to the data transformation. Though the shapes of the response functions of the real wage are similar to those in columns A and B, they are always negative, and significantly so after two years. Yet again, although the magnitudes change, the shapes and inference regarding output and unemployment do not change when the non-transformed data are used, and the responses remain precisely estimated. This latter result is consistent with that of Blanchard and Quah’s bivariate system in output and unemployment.

Figure 2 reports response functions for the set of proxies used by Spencer. In all cases, unemployment falls and employment rises, with dynamic patterns very similar to those for the corresponding variables in Figure 1. The real wage response generally declines
in response to an aggregate demand shock, for both the transformed and non-transformed systems, though there are some exceptions. For example, in the four-lag system, the shapes of the response functions across panels A and C are very similar, but the peak response in the non-transformed system is larger than that of the transformed system.\footnote{As noted, panel C corresponds to Spencer’s baseline model reported in his Figure 1, p. 126; my results are almost identical to his despite the difference in sample range. The reader should be aware that the scale of the real wage response differs across Figures 1 and 2 to allow a better view of the real wage dynamics. This can obscure comparisons of magnitude across the figures. However, the output and unemployment scales are identical across the figures.} More importantly, when we allow eight lags in the estimated VAR and transform the data (panel B), the pervasive negative response is no longer evident; the response is essentially zero and insignificant at all horizons.\footnote{For the models estimated in both figures, Box-Ljung Q-statistics show no sign at all of serial correlation in the residuals for either the four or eight lag systems.}

These figures show that the primary cause of the difference between the real wage response functions in GJ and Spencer (at least over the extended sample) is the choice of whether or not to transform the data. If our prior belief is that the data should not be transformed (detrended and demeaned) prior to estimation, then the evidence supports a negative dynamic response of the real wage to aggregate demand shocks, despite the different wage measures. However, if we have strong priors that the data should be detrended and demeaned by the methods used here, then the real wage response is not robust: there is evidence of a positive response, a negative response and no response. Therefore, since the “correct” approach to data transformation is not obvious, there remains a large degree of uncertainty regarding the dynamic impact of aggregate demand shocks on real wages, and thus on the relative stickiness of aggregate wages and goods prices.

Figures 1 and 2 also suggest that the particular measure of aggregate wage and price affects the shape and magnitude of the real wage response. To check sensitivity along this dimension, in Figures 3, 4, and 5 I consider alternative proxies for the real wage, with real gdp as the scale variable and unemployment of men over 20 as the unemployment variable.
(substituting the alternative scale and unemployment proxies here has no important effect). In Figure 3 the real wage is proxied by hourly earnings including overtime (LEHM, as in GJ) deflated by the producer price index (PW, as in Spencer). Here, as in Figure 1, the detrending procedure has a very important effect on the wage response. Importantly, even when the data are not transformed (panels C and D), there is little evidence of a significant negative response. Note also the large effect on the magnitude of the wage response for the detrended system when the lag length changes, as well as the relatively large standard error bands. In Figure 4, earnings excluding overtime (LEMXO) are deflated by the gdp deflator. In this case, the dynamic response of the real wage is pervasively negative, not significantly depending on the model specification or lag length. Figure 5 considers a totally different real wage proxy – real compensation per hour for nonfarm business (LBCPU7). Here, there is essentially no wage response when the data are detrended, and a negative response when no detrending takes place. The first four figures, when considered together, suggest that excluding overtime wages makes a negative response more likely, especially when the data are detrended (Bils 1986); the role of the price level proxy is less important in determining the directions of the wage response. Overall, the figures confirm the importance of data transformation for the real wage response. They also confirm the robustness of the output and unemployment responses.

As emphasized by Canova (1998) and Rotemberg (1999) among others, the information obtained from the data can differ substantially according to the type of filter used for detrending. Therefore, I also consider detrending the data using the well-known filter proposed by Hodrick and Prescott (1997), as an alternative to the simple detrending methods used above. Perhaps a more sophisticated detrending method will enhance the robust-

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15 Another alternative is the employment cost index. Although this series could help in dealing with the well-known compositional biases associated with the earnings measures (see Abraham and Haltiwanger 1995), it is not available over much of my sample period.

16 As in Spencer (1998), I added lagged oil prices to the VAR as an exogenous variable in all the systems reported above; this addition does not improve the robustness of the real wage response.
ness of the estimated real wage dynamics, given that detrending is the chosen modelling strategy.

In panels A and B of Figure 6, I report the response functions after detrending wage growth, scale variable growth and unemployment using the Hodrick and Prescott filter for the GJ proxies, again for lag lengths four and eight, respectively. In comparison with the corresponding panels in Figure 1, the alternative detrending method leads to a larger impact effect of real wages, but the general shape and inference remain the same for each lag length. In Spencer’s system, the alternative filter does not affect the wage responses for the four-lag system (panel C in Figures 2 and 6); however, with eight lags (panel D), the Hodrick and Prescott filter implies a positive and significant short-run wage response, unlike the zero response in Figure 2. (For the earnings excluding overtime/deflator system as in Figure 4, the alternative filter also tends to induce positive, albeit small and mostly insignificant, real wage responses for both four and eight lags.) Thus, using the Hodrick and Prescott filter generates stronger support for a positive short-run wage response to aggregate demand; but this underscores the lack of robustness across models with and without detrended data.

To briefly indicate the effects of model specification on the importance of aggregate demand shocks relative to other exogenous sources of fluctuations, I report the variation in forecast error explained by aggregate demand shocks for the GJ system (Figure 7) and

\[ \left\{ \sum_{t=1}^{T} (y_t - g_t)^2 + \lambda \sum_{t=1}^{T} [(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2 \right\} , \]

where the arbitrary constant \( \lambda \) determines the penalty for volatility in trend. In Figure 6, \( \lambda = 1600 \), the value suggested by Hodrick and Prescott for quarterly data.

The filter proposed by Rotemberg (1999) is more general than that of Hodrick and Prescott, but yields similar results when \( \lambda \) is large (Rotemberg 1999, p. 13). I repeated this exercise for \( \lambda = 72645 \), the value estimated by Rotemberg for real wages, to mimic his approach. The findings (not reported) were essentially the same as in Figure 6, though the positive response in Panel D was more hump-shaped for the larger \( \lambda \).
the Spencer system (Figure 8).\textsuperscript{19} It is evident that the estimated relative contribution of these shocks is very sensitive to empirical proxy, data transformation and lag length. One clear pattern is that when the variables are not detrended or demeaned, aggregate demand shocks play a larger role in explaining real wages than when the variables are transformed. Their role in explaining output and unemployment is smaller, however, in this case. Again, this latter finding is consistent with Blanchard and Quah (1989).

\subsection*{3.2 Using nominal GDP}

To this point, I have followed GJ and Spencer (as well as the seminal study by Blanchard and Quah 1989) by exploiting the unemployment rate as information to distinguish aggregate demand from real shocks. But as noted above in section 2, a plausible alternative that maintains the spirit of this approach is to replace unemployment with a nominal variable such as the growth rate of nominal GDP. In this case, the model is estimated and the identifying restrictions imposed in the same way as before, but the demand shock has a slightly different interpretation – aggregate demand shocks are those shocks that have no long-run effect on the level of real wages and real output, but can have a long-run effect on the level of nominal GDP. By considering this alternative, we can determine if there is insufficient variation or information in the unemployment data themselves to identify, with any reasonable degree of confidence, the response of real wages to aggregate demand shocks.

To this end, I have reestimated the VAR systems replacing unemployment with the growth rate of nominal GDP. In the remaining figures, panels A and B now report results for systems in which detrended nominal gdp growth replaces detrended unemployment;

\textsuperscript{19} As I note above, long-run neutrality of aggregate demand shocks is insufficient to fully identify the structural coefficients. Thus, additional restrictions would be required to fully decompose the error variance of the real wage, output and unemployment. However, since the shape and scale of the response functions with respect to aggregate demand shocks are just-identified, it is possible to dichotomize this variation into the part caused by demand shocks, and the part caused by all other shocks.
panels C and D once again do not detrend any variables prior to estimation. Since I use real GDP as the scale variable, including nominal GDP is identical to including the GDP deflator as the nominal variable (the log of the deflator is a linear combination of logged real and nominal GDP), which adds the additional advantage of determining the response function of the nominal price level.\textsuperscript{20} The results of these exercises are reported in Figures 9 through 13. The figures differ only according to the real wage proxy used.

Two general patterns are evident in the figures. 1) The responses of real output and the deflator, and thus of nominal output, are very robust across all specifications, and they are consistent with prior expectations about how output and prices should respond to aggregate demand shocks. Price level stickiness is clearly indicated as the deflator responds less on impact than nominal GDP, and only gradually approaches its long-run level. 2) The real wage responses are once again highly dependent on model specification and real wage proxy: there is evidence of positive, negative and negligible wage responses across the figures. For the most part, however, the responses are \textit{not} sensitive to the detrending procedure, unlike most of the systems which use unemployment data. The fragility of the results to data transformation appears to depend primarily on the unemployment rate. Lag length remains important for inference, especially when the producer price index is used to deflate nominal wages. Also note the important differences when nominal GDP is substituted for unemployment; for example, when real compensation is used in the nominal GDP system, there is fairly strong evidence for a \textit{positive} real wage response to demand shocks (Figure 13). Recall that in the unemployment system, real compensation generally falls, or does not respond, given such a shock (Figure 5). In addition, the negative response in Figure 4 does not hold up to the different information provided by nominal GDP (Figure 12). Replacing unemployment with nominal GDP does give a sense of robustness: \textit{if} we are comfortable with a VAR with eight lags, then positive short-run real wage responses

\textsuperscript{20} Spencer takes this approach to examine the separate effects on nominal wage and price (1998, footnote 27).
are generally found, and there is no evidence of a negative response.

4. Conclusion

In this paper, I have shown that the use of long-run restrictions in the context of trivariate VARs, a strategy taken by Gamber and Joutz (1993) and Spencer (1998), does not provide definitive answers regarding the response of aggregate real wages to aggregate demand shocks, despite their claims to the contrary. The contradictory findings of these studies can be explained by differences in: a) data transformation used to achieve stationarity, especially with regards to unemployment; b) the choice of empirical proxy for the economic variables, especially the real wage and the variable used to identify aggregate demand shocks (unemployment or nominal GDP); and c) the lag length used to specify the VAR. Depending on the reader’s priors regarding these modelling choices, he or she can find support in the data for a positive response, a negative response, or no response of real wages to aggregate demand shocks. Without further guidance about the proper statistical specification or the appropriate economic proxies, the message about real wage dynamics from VARs with long-run restrictions is unclear.²¹

Note that my results do not imply that structural VARs with long-run restrictions are inherently unreliable due to the technical problems laid out by Faust and Leeper (1997). Although the sensitivity of the real wage response to alternative statistical specifications seems to be a manifestation of these problems, the responses of output, employment and unemployment are highly robust and plausible. My findings do, though, emphasize the importance of the well-known lesson that careful checks on the robustness of estimated coefficients are essential. This seems especially true when long-run restrictions are exploited, and when the data possibly need to be detrended to achieve stationarity. Also, as forcefully pointed out by Canova (1998), how such detrending is achieved can matter.

²¹ Faust (1997) and Rudebusch (1998) also discuss the robustness of structural VARs in a similar context, although they do not consider real wage dynamics.
The lack of robustness found here can potentially be due to the inability of the simple trivariate VAR to account for the actual (complex) economic behavior of the labor market. For example, Ramey and Shapiro (1998) show that compositional (sector-specific) effects can lead to quite different wage responses to government spending shocks (a specific type of aggregate demand), depending on how real wages are measured and deflated. This is consistent with the theoretical model developed in their paper, but such subtleties are ruled out in the models considered here. In other words, empirical work on the effects of demand shocks on real wages should be better guided by theory in determining how real wages are to be measured. It also suggests the potential gain from more precisely identifying different sources of aggregate demand shocks (such as shocks to money supply). Finally, the work of Cooley and Dwyer (1998) suggests that better attention to economic theory in determining the statistical specification (given the choice of proxies) can yield more robust estimates of real wage dynamics. Further analysis along these lines will contribute to our understanding of the transmission of aggregate demand shocks.
References


Keating, John W. “Structural Inference With VAR Models that are Identified by Long-Run
Figure 1. Responses to aggregate demand shocks -- Gamber and Joutz proxies

\( w = \text{earnings/deflator}, \ y = \text{real gdp}, \ u = \text{unemployed males} > 19 \)
Figure 2. Responses to aggregate demand shocks -- Spencer proxies

\( w = \) earnings, no overtime//PPI, \( n = \) employment, \( u = \) total unemployment

A: detrending, 4 lags  
B: detrending, 8 lags  
C: no detrending, 4 lags  
D: no detrending, 8 lags
Figure 3. Responses to aggregate demand shocks -- alternative real wage

\( w = \text{earnings} / \text{PPI}, \ \ y = \text{real gdp}, \ u = \text{unemployed males} > 19 \)
Figure 4. Responses to aggregate demand shocks -- alternative real wage

\(w\) = earnings, no overtime/deflator, \(y\) = real gdp, \(u\) = unemployed males>19

A: detrending, 4 lags
B: detrending, 8 lags
C: no detrending, 4 lags
D: no detrending, 8 lags
Figure 5. Responses to aggregate demand shocks -- alternative real wage

\( w = \text{real compensation}, \ y = \text{real gdp}, \ u = \text{unemployed males} > 19 \)
Figure 6. Responses to aggregate demand shocks -- GJ and Spencer variables

All variables detrended using Hodrick/Prescott filter (\(\lambda=1600\))

A: Gamber/Joutz, 4 lags
B: Gamber/Joutz, 8 lags
C: Spencer, 4 lags
D: Spencer, 8 lags
Figure 7. Error variance explained by aggregated demand shocks -- Gamber and Joutz

\[ w = \text{earnings/deflator}, \ y = \text{real gdp}, \ u = \text{unemployed males>19} \]

A: detrending, 4 lags
B: detrending, 8 lags
C: no detrending, 4 lags
D: no detrending, 8 lags
Figure 8. Error variance explained by aggregated demand shocks -- Spencer

\( w = \) earnings, no overtime/ppi, \( n = \) employment, \( u = \) total unemployment

A: detrending, 4 lags
B: detrending, 8 lags
C: no detrending, 4 lags
D: no detrending, 8 lags
Figure 9. Responses to aggregate demand shocks -- nominal GDP

\( w \) = earnings/deflator, \( y \) = real gdp, \( Y \) = nominal gdp, \( P \) = deflator

A: detrending, 4 lags
B: detrending, 8 lags
C: no detrending, 4 lags
D: no detrending, 8 lags
Figure 10. Responses to aggregate demand shocks -- nominal GDP

\( w = \) earnings, no overtime/PPI, \( y = \) real gdp, \( Y = \) nominal gdp, \( P = \) deflator
Figure 11. Responses to aggregate demand shocks -- nominal GDP

\[ w = \text{earnings/PPI}, \ y = \text{real gdp}, \ Y = \text{nominal gdp}, \ P = \text{deflator} \]
Figure 12. Responses to aggregate demand shocks -- nominal GDP

\( w = \text{earnings, no overtime/deflator}, y = \text{real gdp}, Y = \text{nominal gdp, } P = \text{deflator} \)
Figure 13. Responses to aggregate demand shocks -- nominal GDP

\[ w = \text{real compensation}, \ y = \text{real gdp}, \ Y = \text{nominal gdp}, \ P = \text{deflator} \]