Is Sticky Price Adjustment Important for Output Fluctuations?

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Abstract: The paper finds that shocks which have no contemporaneous effect on the price level explain almost all the variance of aggregate output in the short run. Similar results are obtained with sectoral and industry-level data. Seasonally adjusted data and not seasonally adjusted data obtain essentially the same results. A second model identifies shocks that don't affect prices for at least two months. These shocks are significantly more important for aggregate output than shocks which affect the price level immediately or with a one-month delay. A third model finds that most of the variance of aggregate output over the business cycle is explained by shocks which have no contemporaneous effect on the price level and no long-run effect on output. This finding is interpreted as evidence to support the hypothesis that sticky price adjustment is an important factor in causing aggregate demand shocks to have real effects. Economic models in which prices adjust rapidly to clear markets will have difficulty explaining all the empirical results found in this paper.

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(1) Introduction

A cornerstone of Keynesian economic theory and policy analysis is that nominal prices fail to adjust promptly to clear markets.[1] The first generation of sticky price theories simply asserted that prices responded with an arbitrary lag, and this ad hoc assumption yielded disequilibrium in the aggregate economy. Subsequently, New Keynesian models were constructed with the goal to provide rigorous microfoundations for sticky prices.[2] More recently, sticky price adjustment has been derived as an equilibrium phenomenon.[3] Sticky price theories have often been justified by casual observation, but surprisingly little empirical evidence that prices fail to adjust quickly to clear markets. [4]

In a somewhat radical departure from standard econometric practice, Blinder (1994) questions firms about the way prices are determined.[5] This research attempts to discover if sticky price adjustment is a pervasive factor in the modem industrial economy. One important result from Blinder's research is that almost four-fifths of Gross Domestic Product (GDP) in the United States is repriced less than once every three months.[6] Some would interpret such wide-spread sluggish price adjustment as support for Keynesian macroeconomics.

Theoretical models that were used initially to examine Real Business Cycle phenomena have since been modified to allow for sticky prices.[7] For example, Ohanian, Stockman and Kilian (1995) build a two-sector model where the price in one sector does not respond contemporaneously to new information while price adjusts immediately to clear the other sector. This modeling strategy is consistent with Blinder's finding that some firms adjust price rapidly while other firms adjust price with some delay. In Ohanian, Stockman and Kilian money can only have real effects because of sticky prices. They find that the non-neutrality of money with respect to aggregate real output depends on the values of certain structural parameters such as the size of the sticky price sector relative to the flexible price sector. In other words, it is theoretically plausible that prices are sticky in many sectors of the economy (in accord with Blinder's findings), but that flexible-price sectors adjust in such a way as to make the aggregate economy behave essentially like a flexible price system.[8] Therefore an important topic for macroeconomic research is to determine how much output variation is attributable to sticky price adjustment.

This paper uses vector autoregressions to construct empirical measures of the amount of output fluctuation associated with sticky prices. Section 2 presents a bivariate statistical model that identifies two kinds of shocks to output, shocks that affect the price-level contemporaneously and shocks that do not have an immediate effect on prices. The latter shocks are used to measure the role of sticky prices. Estimates of the output variance associated with these shocks are presented in the third section from a variety of United States data. With quarterly and monthly aggregate data, the shocks which have no contemporaneous effect on the price level explain almost all the variance of output in the short run. A similar finding is also obtained in models with sectoral and industry-level data using seasonally adjusted data as well as data that has not been seasonally adjusted.

In Section 4 a model is developed which identifies shocks that have no effect on price for two months, shocks that don't affect price for one month and shocks that contemporaneously affect the price level. This model finds that shocks which don't affect price for two months are much more important for output than the other two shocks combined. Robust empirical findings from Sections 3 and 4 that shocks affecting price with the longest lag are the dominant factor for short-run output fluctuations support the hypothesis that sticky price adjustment plays a quantitatively significant role.

In the fifth section, I decompose output shocks which have no contemporaneous effect on the price level into two components: one which has no long-run effect on the level of output and another which is allowed to have a permanent effect on output. The identification restrictions are motivated by the theory underpinning Blanchard and Quah's (1989) approach to identifying aggregate demand and aggregate supply disturbances. Shocks which have no contemporaneous price-level effect and no long-run output effect are found to be the most important source of fluctuations in output over the business cycle. Impulse responses are consistent with an aggregate demand shock interpretation for these shocks. The empirical evidence in this paper supports the view that sticky price adjustment causes aggregate demand to have real effects. Section 6 concludes by discussing implications of this empirical study for future research.

(2) A Bivariate Empirical Model

The first empirical model uses the logarithm of a price series (P) and the logarithm of a measure of real output (y) to examine the role of output shocks that have no contemporaneous effect on price. This model is written as:

$$P_t = \Theta_{11}(L)\varepsilon_t + \Theta_{12}(L)\gamma_t \tag{1}$$

$$y_t = \Theta_{21}(L)\varepsilon_t + \Theta_{22}(L)\gamma_t \tag{2}$$

where

$$\Theta_{ij}(L) = \sum_{k=0}^{\infty} \Theta_{kij} L^k$$

are the lag polynomials from the moving average representation (MAR) of this model for i=1,2 and j=1,2. The stochastic shocks ε_t and γ_t are orthogonal and serially uncorrelated. Without loss of generality, the empirical model may include deterministic elements which are omitted from (1) and (2). In fact, every VAR has a constant in each equation.

The interpretation of the shocks in a time series model depends on the identification assumptions. This model identifies ε_t as the shock to output that is associated with contemporaneous movement in the price level and γ_t as the shock to output associated with no contemporaneous price response. The statistical decomposition is achieved by restricting the contemporaneous effect of γ on P to equal zero; i.e. by setting Θ_{012}=0. This model requires no restrictions on the dynamic responses of variables to shocks, except that the vector stochastic process is invertible. A Cholesky decomposition of the covariance matrix for VAR residuals with P placed ahead of y in the recursive ordering uniquely identifies this model. Consequently, ε_t

is the one-step forecast error for price. One-step forecast errors are sometimes referred to as innovations in the time series literature.

The model attributes to ε all output fluctuations that are correlated with contemporaneous price movements, leaving for γ any variation in output that is not associated with price contemporaneously. If prices adjust promptly to clear markets, one would expect ε to explain a significant portion of the variance of output in the short run. On the other hand, if prices do not adjust quickly to clear markets, ε should not explain much short-run output variance. Hence, the percentage of output variance associated with γ is interpreted as a measure of the importance of sticky price adjustment for output fluctuations. The dynamic responses of price and output to each shock can be studied with impulse response functions. Should evidence of sticky price adjustment be found, characteristics of the responses to γ may suggest the structural source of shocks which affect the economy through sticky prices.

This bivariate model can be viewed as a purely statistical decomposition. However, a structural interpretation is also available based on the standard aggregate supply and aggregate demand macro model if the short-run aggregate supply curve is flat. Under this structural assumption, the innovations to the price level (ε) would arise from shocks to the short-run aggregate supply curve while the shocks to output that are not associated with contemporaneous price movement (γ) would be attributable to shifts in the aggregate demand curve.

(3) Empirical Results from the Bivariate Model

I select VAR specifications using the Akaike information criterion, and then construct the bivariate decomposition from Section 2. First, quarterly U.S. real GDP and the GDP price deflator are used. Potential data problems suggest a sequence of specifications in which higher-frequency data, less-aggregate data and data that are not seasonally adjusted are used in the bivariate model. The key results are robust to these alternative choices of data.

(3.1) Gross Domestic Product Data

The first bivariate model uses quarterly data measuring output by real chain-weighted GDP and measuring the price level by the chain-weighted GDP deflator.[9] With a maximum number of lags set at 16 quarters, the Akaike information criterion selects a VAR model with 2 lags. Series from the third quarter of 1959 to the second quarter of 1996 are used to estimate this model. Table 1 reports the variance decomposition along with standard errors obtained from 1000 bootstrap replications of the model.[10] By construction, γ has no immediate effect on the price level and ε initially explains all the variance of the price level. Even after two years γ shocks explain only 1 percent of the price variance. However, after 10 years the price variance is split almost equally between the two shocks, and after 25 years γ shocks explain 78 percent of the variance of the price level. Hence, shocks which have no contemporaneous price effect become the dominant source of price variation at long horizons.

While the price level innovation and the shock which has no contemporaneous price effect are each permitted to have an immediate effect on output, price innovations explain virtually none of the output variance in the short run. This finding obtains because the innovations to output and the price level are almost uncorrelated.[11] In fact, price innovations never explain a statistically significant portion of output variance. Consequently, shocks that have no contemporaneous effect on prices are the dominant source of output fluctuations explaining at least 85 percent of output's variance at each point along the variance decomposition.

Figure 1 provides dynamic responses of each variable to each shock. Each impulse response plots the point estimate with a solid line and encloses the 90 percent confidence region with dashed lines. These confidence bounds are generated from the same bootstrap simulations used to construct standard errors for variance decompositions. The price innovation causes an immediate rise in the price level and a decline in output, and both effects are significant in the short-run. Price and output moving in opposite directions suggests that aggregate supply is the dominant source of ε shocks. The shock which has no contemporaneous price-level effect causes a gradual increase in price that becomes statistically significant after 8 quarters. The output response to a γ shock is always positive and significant with the peak response occurring 4 quarters after the shock occurs. This co-movement of price and output is consistent with an aggregate demand shock interpretation.

These impulse responses are broadly consistent with the previously mentioned structural interpretation that some might use to motivate this statistical model. From the variance decomposition we observe that output and price fluctuations are essentially unrelated in the short run; virtually all the short-run price variance is explained by ε and virtually all the short-run output variance is explained by γ. Hence the variance decompositions and impulse responses together suggest that in the short run the price level is set by suppliers and the level of aggregate output is determined by aggregate demand. In other words, these results are consistent with an economy which has a short-run aggregate supply curve that is essentially flat and an aggregate demand curve that is nearly vertical at least in the short run. But, even if one would prefer to interpret this decomposition as a purely statistical model, the impulse responses suggest that aggregate demand is the primary source of shocks which have no contemporaneous effect on the price level. This result is of particular interest because it is theoretically possible that the economy's response to both aggregate supply and aggregate demand shocks is affected by sticky price adjustment. The hump-shaped response pattern of output to γ is also consistent with some views about the dynamic response to aggregate demand.[12] However, a finding from this empirical model that does not bode well for this structural interpretation is the large amount of output variance associated with γ at longer horizons. Most theoretical models predict that aggregate supply is the dominant source of long-run output movements not aggregate demand.

(3.2) Are the results obtained from temporal aggregation bias?

The empirical model with GDP suggests that shocks which have no contemporaneous effect on the price level are most important for output fluctuations. One concern raised by the use of quarterly GDP data is the possibility that aggregating over multiple time periods may smooth out high-frequency comovements between output and price. Total Industrial Production (IP) is a popular alternative measure of aggregate output available at monthly intervals. Measures of aggregate output are not available at a higher frequency.[13] The Producer Price Index (PPI) appears at first to be a good price measure because it is a weighted-average of prices from the industries that produce Total IP. Components of the PPI are also well-matched with components of IP. However, the PPI is not without limitations. The most important problem from the standpoint of this study is that the PPI may be an inadequate measure of transactions prices. Wynne (1995,p.2), for example, argues that price data reported by producers may not be accurate "because of fears the data may be used in antitrust litigation or fall into the hands of competitors." The Consumer Price Index (CPI) measures are thought to be more reliable because the Bureau of Labor Statistics regularly collects posted prices from a large number of stores.

Seasonally adjusted (SA) measures of Total IP and the CPI for All Items for Urban Consumers are used to estimate the aggregate model with monthly data. All data available up to June 1996 are used in this VAR and all subsequent models. Consult the Appendix for the starting date for each combination of monthly series for price and output used in the bivariate model. The Appendix also contains the number of lags chosen by the Akaike information criterion for each model where the maximum number of lags was set at 48 months.

The decomposition for monthly aggregate data is reported in the first column of Table 2 and the impulse responses are in Figure 2. Note that from this point onward each table and figure uses months instead of quarters. There are two reasons why only the variance associated with γ from these bivariate models need be reported. Firstly, it is easy to subtract this variance from 100 percent to calculate the amount of variance attributable to price innovations. Secondly, any VAR model with two shocks obtains numerically identical standard errors for the variance explained by either shock at some point in a particular variable's variance decomposition. Results from Table 1 illustrate both of these ideas.

Variance decompositions of output and price using monthly aggregate data are very similar to results from the quarterly GDP data. Consequently, the monthly aggregate data also find that shocks with no contemporaneous effect on the price level are the dominant factor in output fluctuations. This model also finds impulse responses that are broadly similar to the results with GDP data.[14] Therefore, I conclude that temporal aggregation does not explain the findings with quarterly aggregate data.

(3.3) Are the results obtained from sectoral aggregation bias?

One problem with using Total IP and the CPI for All Items is that these data do not cover exactly the same sectors of the economy. For example, the CPI for All Items includes prices of services and the rental cost of existing housing, neither of which pertain to current industrial production.[15] Total IP includes equipment, materials and intermediate goods that are sold to establishments instead of consumers. However, if Consumer Goods output and the CPI for Commodities from January 1956 to June 1996 are used in the bivariate model, essentially the same results obtain. These data represent the largest component of IP that has a corresponding CPI component.

A key empirical finding with aggregate data is that innovations to price and output are nearly uncorrelated. However, a problem with interpreting this empirical result is the possibility that the aggregate supply and aggregate demand equations may coincidentally yield uncorrelated innovations in the aggregate data. To clarify this point, assume e_{pt} and e_{yt} are the innovations to price and real output from a bivariate VAR model. Suppose that the short-run structure consists of equations for aggregate supply, $e_{pt} = a_s e_{yt} + \tau_{st}$, and aggregate demand, $e_{yt} = -a_d e_{pt} + \tau_{dt}$ where each a_i is a non-negative parameter and each τ_{it} is a structural shock. Assume for convenience that aggregate supply and aggregate demand shocks are uncorrelated. It is easy to write each innovation as a function of the structural disturbances: $\begin{bmatrix} e_{pt} \\ e_{yt} \end{bmatrix} = \begin{bmatrix} 1 & -a_s \\ a_d & 1 \end{bmatrix}^{-1} \begin{bmatrix} \tau_{st} \\ \tau_{dt} \end{bmatrix} = \frac{\begin{bmatrix} 1 & a_s \\ -a_d & 1 \end{bmatrix} \begin{bmatrix} \tau_{st} \\ \tau_{dt} \end{bmatrix}}{(1 + a_s a_d)}$. The covariance between the two innovations is then given by $Ee_{pt}e_{yt} = \frac{a_s \sigma_d^2 - a_d \sigma_s^2}{(1 + a_s a_d)^2}$ where σ_s and σ_d are standard errors for the structural shocks to supply and demand, respectively. This covariance is zero if a_d and a_s are both equal to zero. In other words, a flat aggregate supply curve and a vertical aggregate demand curve would yield uncorrelated innovations to price and output. More generally, however, the covariance between price and output innovations will be zero for any combination of structural parameters such that $a_d \sigma_s^2 = a_s \sigma_d^2$. The empirical finding that innovations to the price level and aggregate output are uncorrelated is, therefore, not sufficient to prove that the short-run aggregate supply curve is flat.

Another problem is that aggregate time series combine output and price data from a variety of economic sectors where firms produce different kinds of products and operate in industries that have diverse market structures. It is possible that short-run movements in output and price are correlated in sectoral data, but that this correlation varies across the sectors in such a way that high frequency movements in aggregate measures of price and output happen to be uncorrelated. The possibility that a significant contemporaneous relationship between price and output is hidden by aggregate time series implies that sectoral price and output data should also be used in the bivariate model.

Total IP is separated into Market Groups. For compatibility with CPI price measures, I focus on groups of consumer goods. Foods, Tobacco Products, Consumer Clothing, Consumer Energy Products, Consumer Autos, Consumer Trucks and Other Consumer Durables are found to have appropriate CPI measures.[16] The first four groups are Consumer Nondurables and the last three are Consumer Durables. The Other Consumer Durables category includes appliances, televisions, air conditioners, carpeting, furniture, and miscellaneous home goods.[17]

Table 2 reports variance decompositions for these 7 sectors. Virtually all the variance of each sector's output over the first month is associated with shocks that have no contemporaneous effect on the price level. Even after 3 months, no statistically significant output variance is explained by price innovations, although this effect is close to being significant for Tobacco. Shocks which have no contemporaneous price effect always explain more than half the variance of output, except for Foods and Trucks. These shocks explain virtually all the output variance for Autos and Clothing. For the first year of each decomposition shocks that have no contemporaneous price effect explain almost none of the price variance. At longer horizons these shocks explain most of the price variance for Clothing, about one-third the price variance for Foods and roughly one-fifth the price variance for Energy Commodities. In the remaining four sectors, essentially all the variance of price is explained by price innovations.[18]

The impulse response functions for these sectors are not reported. A few responses are similar to the results with aggregate data, but in most cases the responses are different. No particularly interesting patterns are observed from these differences.

An advantage of Market Group data is that these measures of production span a large fraction of the output sold to consumers. Unfortunately, each of these groups consists of many different products and so an aggregation bias may still obfuscate important contemporaneous relationships between price and output. Therefore, I proceed to the lowest level of aggregation for which measures of Industrial Production can be appropriately matched with components from the Consumer Price Index data.

I separate these industries into non-food and food categories. Estimates for 3 non-food industries are in Table 3 and the estimates for 6 food industries are in Table 4. The empirical results for Shoes, Automotive Gasoline, Furniture, Cheese, Milk, Beer and Soft Drinks support the main findings from the previous models; shocks which have no contemporaneous price effect explain essentially all of the short-run output variance. The only two exceptions are Beef and Pork, but even in these industries shocks that have no contemporaneous effect on price explain at least 75 percent of the output variance for each of the first three months. Hence, these shocks are the dominant factor in short-run output fluctuations in all cases.

The impulse responses from industry-level data are not reported because they do not yield any noteworthy patterns. This observation from industry-level and sectoral data is consistent with the view that each market is subject to a variety of aggregate and market-specific shocks to which the market may have different structural sensitivities. This empirical work was not designed to identify structural sources of shocks to these different markets, but rather to estimate the amount of output fluctuations associated with shocks that have no contemporaneous effect on prices.

Recall that this section began by showing that uncorrelated innovations to price and output in the aggregate data may obtain from a particular configuration of structural parameters, not necessarily because of sticky prices. Some might also wish to apply this result to the findings with sectoral and industry data. While one can claim that a single model's estimates are explained in this manner, it is preposterous to argue that a fortuitous configuration of structural parameters is the reason price and output innovations are essentially uncorrelated in aggregate data, sectoral data and the data from most of the industries in this study. The finding that high-frequency movements in price and output are typically uncorrelated is inconsistent with the notion that prices adjust quickly to clear consumer goods markets.

(3.4) Are the results obtained from seasonal adjustment bias?

VAR models up to this point have used seasonally adjusted data primarily because this transformation is popular in empirical studies. However, some may view seasonally adjusted data with disdain because this adjustment might disguise or radically alter the dynamic relationships under investigation.[19] For example, it is conceivable that a seasonal adjustment filter might eliminate a high-frequency interrelationship between price and output. If that were the case, the VAR results with SA data would be spurious. To address this potential difficulty, I estimate each of the monthly VAR models using not seasonally adjusted (NSA) data. I use all available NSA data for each combination of P and y. Full samples with NSA data begin in the same month as the SA data or one month earlier, except for Total IP where the NSA data for both series begin January 1919. Each VAR with NSA data includes monthly dummy variables to allow for different seasonal means in price and output. Lag lengths are again chosen by Akaike's information criterion with 48 months selected as the upper bound.

Variance decompositions from VAR models with NSA data are in Tables 5, 6 and 7. Table 5 reports the variance decompositions for Total IP and the 7 Market Groups, Table 6 includes results for the 3 non-food industries and Table 7 contains results for food industries. NSA data for Butter are available along with NSA data for the other 6 food industries.[20] Tables 5, 6 and 7 can be compared with results using SA data found in Tables 2, 3 and 4, respectively. The variance decompositions with NSA data are remarkably similar to results found with SA data. Once again shocks which have no contemporaneous effect on price explain virtually all the short-run variance of output for all models except for the Beef and Pork industries. However, even in these two industries the shocks which have no contemporaneous effect on price are the primary source of short-run output variation.[21]

(3.5) Overview of the results from bivariate models

Virtually all the short-run variance of real GDP is associated with shocks that have no contemporaneous effect on the price level. The same result holds for monthly aggregate data, data from all 7 Market Groups and data from 8 of 10 industries. For both exceptional industries, short-run output fluctuations are primarily determined by shocks which have no contemporaneous effect on the price level.

The results are essentially the same using seasonally adjusted or not seasonally adjusted data.

If prices adjust rapidly to clear markets, one should find that innovations to price and output are correlated and that the innovations to the price level are an important source of output fluctuations. However, in almost every model these two innovations are nearly uncorrelated and the price innovations are an insignificant factor for short-run output fluctuations. Therefore, I interpret these robust empirical findings as evidence that sticky price adjustment is a significant factor in economic adjustments.

(4) Identifying Shocks that have no Effect on the Price Level for Two Months

The next model identifies shocks which do not affect the price level for two months, shocks which have no price effect for one month and shocks which contemporaneously influence prices. The motivation is straightforward; If sticky price adjustment is important for aggregate fluctuations and if most prices are fixed for at least a few months, then shocks which have no effect on price for two months should be a major factor for output. In order to estimate a structural VAR model with three shocks I need to add a third variable to the bivariate system used before. I include the Fed Funds interest rate (R) along with Total IP and the CPI for All Items because interest rates are common to empirical and theoretical macro models. The empirical model can be written as

$$P_t = \Theta_{11}(L)\varepsilon_t + \Theta_{12}(L)\gamma_t + \Theta_{13}(L)\phi_t \tag{4}$$

$$y_t = \Theta_{21}(L)\varepsilon_t + \Theta_{22}(L)\gamma_t + \Theta_{23}(L)\phi_t \tag{5}$$

$$R_t = \Theta_{31}(L)\varepsilon_t + \Theta_{32}(L)\gamma_t + \Theta_{33}(L)\phi_t \tag{6}$$

where the restrictions:

$$\Theta_{013} = \Theta_{113} = 0 \tag{7}$$

identify ϕ_t as a shock which has no effect on price for two months. Keating's (1996) method for identifying VARs by means of dynamic restrictions is used. Let the MAR be written as

$$x_t = \Theta(L)\tau_t \tag{8}$$

where x=(P,y,R)', τ=(ε,γ,ϕ)' and the parameters in $\Theta(L)$ are taken directly from (4), (5) and (6). Premultiply (8) first by $\Theta(L)^{-1}$ and then by Θ_0 to construct the VAR representation

$$\beta(L)x_t = e_t \tag{9}$$

where
$$\beta(L) = \Theta_0\Theta(L)^{-1} \tag{10}$$

and $e_t=\Theta_0\tau_t$ by construction. Let $\beta(L) = (I - \beta_1 L - \beta_2 L^2 -...)$ and $\Theta(L) = (\Theta_0 + \Theta_1 L^1 + \Theta_2 L^2 +...)$, where Θ_i and β_i are 3×3 matrices of the parameters from the MAR and the VAR, respectively. Equation (10) provides an infinite number of identities that map parameters from the MAR into the VAR coefficients, and one of these identities can be written as

$$\Theta_1 = \beta_1\Theta_0 . \tag{11}$$

From (11) I obtain

$$\Theta_{113} = \sum_{j=1}^{3}\beta_{11j}\Theta_{0j3} , \tag{12}$$

which is the key expression for identifying the effects of ϕ. Applying the restrictions from (7) to equation (12) and normalizing ϕ on the interest rate[22] by setting

$$\Theta_{033} = 1 , \tag{13}$$

yields that
$$\Theta_{023} = \frac{-\beta_{113}}{\beta_{112}} . \tag{14}$$

In other words, the contemporaneous response of y (the second variable in x) to ϕ (the third shock in τ) is determined by the ratio of coefficients on the first lag of the interest rate (the third variable) and the first lag of output (the second variable) from the price equation (the first variable) of the VAR. The restriction that $\Theta_{012} = 0$ resembles the restriction used to identify γ in the bivariate models. However, this new model has two shocks which have no contemporaneous effect on the price level; ϕ which has no effect for two months and γ which has no effect for one month. As with other methods of identifying VAR models, these restrictions are applied directly to the relationship between innovations. Once the matrix of contemporaneous coefficients (Θ_0) is obtained, VAR coefficients are used to construct complete dynamic responses to each shock.

The variance decompositions for this model are found in Table 8. Shocks with no price effect for two months are the dominant source of output variance at all points in the decomposition, and these shocks are the primary source of price variation in the long run..[23] The effects of γ in bivariate models with aggregate data have been essentially transferred to ϕ in this trivariate model. Therefore, shocks which that have the slowest effect on price, in general, are the most important source of aggregate output fluctuations, and this provides additional support for the importance of sticky price adjustment.

(5) A Structural Interpretation

While the identifying assumptions in previous models are not necessarily structural, impulse responses from aggregate data suggest that shocks which affect price with the longest lag are primarily associated with aggregate demand. The finding that these shocks explain most of the output variance at long horizons, however, appears inconsistent with an aggregate demand interpretation because most economic theories would not yield such an effect. The most plausible interpretation is that shocks which have no contemporaneous effect on the price level are a mixture of aggregate supply and demand factors, with aggregate demand an important factor.

Clearly the next step is to decompose these shocks into structural components, but this task requires an appropriate set of structural identification restrictions. While one macroeconomic structure acceptable to all macroeconomists does not yet exist and perhaps never will, Blanchard and Quah (1989) have developed a popular approach for identifying the effects of aggregate supply and aggregate demand. Their method is based on the textbook model in which the long-run aggregate supply curve is vertical and aggregate demand factors do not affect aggregate supply in the long run. Under this assumption, their model identifies supply shocks which have permanent output effects and demand shocks which have temporary output effects. Other papers have also used Blanchard and Quah-style models with price data in place of the unemployment rate, and found plausible structural results for many different countries.[24]

My approach is to identify two shocks that have no contemporaneous effect on price. One of these shocks is allowed to have a long-run effect on output and the other is constrained to have no permanent effect on the level of output. To impose long-run restrictions on output, y must be integrated of order one and differenced once in the empirical model. Since it is difficult to reject a unit root in each of the three series, each variable is differenced one time. Long-run restrictions are imposed by constraining the long-run multipliers for shocks. Long-run multipliers are obtained from the sum of coefficients from a MAR derived from differenced data.

The model is written as:

$$\Delta P_t = \Theta_{11}(L)\varepsilon_t + \Theta_{12}(L)\delta_t + \Theta_{13}(L)\omega_t \tag{15}$$

$$\Delta y_t = \Theta_{21}(L)\varepsilon_t + \Theta_{22}(L)\delta_t + \Theta_{23}(L)\omega_t \tag{16}$$

$$\Delta R_t = \Theta_{31}(L)\varepsilon_t + \Theta_{32}(L)\delta_t + \Theta_{33}(L)\omega_t \tag{17}$$

where ω_t is identified by restricting

$$\Theta_{013} = 0 \quad \text{and} \quad \sum_{k=0}^{\infty} \Theta_{k23} = \Theta_{23}(1) = 0\ . \tag{18}$$

The first restriction constrains ω to have no contemporaneous price effect and the second restriction forces this shock to have no long-run output effect.

A combination of contemporaneous restrictions and long-run restrictions is imposed with the VAR coefficients.[25] Equations (8), (9) and (10) continue to apply for this model, although now the MAR is given by (15), (16) and (17), $x=(\Delta P,\Delta y,\Delta R)'$ and $\tau=(\varepsilon,\delta,\omega)'$. The sum of coefficients in the VAR can be written as $\beta(1)$. From equation (10), $\beta(1)$ is equal to a function of the coefficients from the MAR:

$$\beta(1) = \Theta_0 \Theta(1)^{-1} \tag{19}$$

where $\Theta(1)$ is the matrix of long-run multipliers. This equation is more conveniently written as

$$\Theta(1) = b\Theta_0 \quad \text{where} \quad b = \beta(1)^{-1}. \tag{20}$$

From the 9 identities in (20) there is one in particular affected by all restrictions that identify ω:

$$\Theta_{23}(1) = \sum_{j=1}^{3} b_{2j} \Theta_{0j3}. \tag{21}$$

Using the normalization of $\Theta_{033} = 1$ and the two restrictions from (18) in equation (21) yields

$$\Theta_{023} = \frac{-b_{23}}{b_{22}}. \tag{22}$$

The assumption that Θ_{012}=0, restricts δ to have no contemporaneous price level effect. This shock may, however, have a long-run effect on the level of output. Once again there are no restrictions on responses to price innovations.

Variance decompositions for this model are in Table 9 and impulse responses are located in Figure 3. Output temporarily rises and the price level rises permanently in response to ω . These effects support the aggregate demand interpretation. The nominal interest rate also rises and all three of these responses are statistically significant. The δ shock causes an increase in output which is always statistically significant along with a decrease in the price level that is statistically significant for a year or so. Hence, these responses support the aggregate supply interpretation. Over the first year, ω explains at least 74 percent of the output variance. After 2 years this shock explains 55 percent of the output variance and after 6 years only 16 percent. The identification restrictions force this variance to shrink to zero asymptotically.

If the textbook structural model is legitimate, this identification decomposes shocks which have no contemporaneous price-level effect into two structural components. The model finds that shocks which have no contemporaneous price effect and no long-run output effect explain most of the output variance at business cycle frequencies. This shock obtains impulse responses that are consistent with the aggregate demand interpretation. Hence, this model provides additional empirical support for the hypothesis that short-run output fluctuations are largely the result of aggregate demand shocks that buffet an economy in which sticky price adjustment is important.

It is interesting that ω causes output and interest rates to move initially in the same direction. If money supply shocks influence the real economy through a liquidity effect, then ω can not be attributed to money supply. These responses suggest that sticky price adjustment is even more important for the transmission of non-monetary aggregate demand shocks to the real economy than it is for the transmission of money shocks. One should be careful not try to push this argument about monetary and non-monetary aggregate demand shocks too far because the empirical model did not separate aggregate demand into these two components. Nevertheless, it is noteworthy that Sims (1998) presents a variety of models of sticky price adjustment, and in some of these models money supply shocks have a very small effect on the level of output.

A final point worth noting is that the amount of aggregate output variance explained by price innovations at long horizons is sensitive to differencing. In this model with differenced data the price innovations eventually explain a little over half the variance of output, while in models with undifferenced aggregate data the output variance associated with price innovations is always small and statistically insignificant. Nevertheless, in all models with aggregate data, price innovations explain almost none of the short-run aggregate output variance.

(6) Concluding Comments

The principle finding of this paper is that output fluctuations, at least in the short run, are primarily associated with shocks that have no contemporaneous effect on the price level. In models with aggregate time series these shocks appear to be associated with aggregate demand. Business cycle theories that are inconsistent with these robust empirical regularities need to be repaired or replaced. Models of sticky price adjustment are consistent with these findings. For example, theories in which price stickiness is an equilibrium outcome might explain the empirical results as might some of the New Keynesian theories. An important topic for future research is to develop tests which can discriminate between different theories of price stickiness. One theory that is not supported by the results in this paper is that price stickiness at the macro level stems from small amounts of price stickiness at the micro level. The variance decompositions show that the response of price to output innovations is very sluggish in aggregate, sectoral or industry-level data.

Traditional models of flexible price adjustment can not explain the finding that output is primarily determined by shocks that have no effect on price in the short-run. To bolster their view about how prices adjust, some proponents of flexible price adjustment may attack the empirical evidence. They might claim that nominal prices clear markets in less than a month, and therefore that observations on price and output are needed at a higher frequency than the quarterly or monthly times series which are available. Of course, this claim is inconsistent with the evidence from most industries according to Blinder's interviews. But for those flexible-price modelers who ignore or dismiss this inconsistency, a challenging research project remains; the calibration of structural models in which prices adjust promptly to clear markets and yet the innovations to price and output are uncorrelated, output levels respond very slowly to price innovations and prices respond very slowly to output innovations.

While the empirical results in this paper contradict standard models in which prices adjust promptly to all kinds of disturbances, no inference can be drawn from this study about whether or not markets do in fact clear. Markets may, for example, clear in the short run by adjusting delivery lags, by varying the services provided to customers or, more generally, by changing the quality of output. This issue remains as an important unresolved topic for economic research.

Notes

1 . Monetarists often adhered to sticky price models, but did not always reach the same policy conclusions for a variety of reasons

2 . Mankiw and Romer (1991) includes many important papers from this literature.

3 . See Farmer (1991,1992) for two examples of endogenously sticky prices.

4 . Important empirical work on sticky price adjustment includes Blinder(1994), Carlton(1986), Cecchetti (1986), Kashyap (1995), Mills (1927) and Stigler and Kindahl (1970).

5 . Blinder et. al. (1997) builds on Blinder's (1994) earlier work.

6 . Hall, Walsh and Yates (1997) have interviewed United Kingdom firms and obtained similar findings to Blinder in most cases.

7 . See Cooley and Hansen (1995) and their references to this literature.

8 . Caplin and Spulber (1987) present another model with sticky price adjustment in which output is not responsive to nominal disturbances.

9 . These data are from FRED, the Web page data source from the St. Louis Federal Reserve Bank.

10 . Runkle (1987) was the first to use bootstrap methods with VAR models.

11 . Note that if the innovations are uncorrelated, different Cholesky orderings will have absolutely no effect on impulse responses and variance decompositions.

12 . Cochrane (1998), for example, shows that money supply shocks may have this hump-shaped effect.

13 . While long time series of high frequency price and output data for specific goods from particular companies would be ideal for this research, I am unaware of any such data in the public domain.

14 . One minor difference is that the shock which immediately raises the price level is associated with a short-run increase in output that is almost significant, but after about 18 months this response is negative and periodically significant.

15 . Measures of output exist for some service sector industries, but most of these data are highly questionable. Griliches (1994,p.14) argues "we are not even close to a professional agreement on how to define and measure the output of banking, insurance, or the stock market (see Griliches, 1992). Similar difficulties arise in conceptualizing the output of health services, lawyers, and other consultants" .

16 . Output measures for Tobacco Products and Foods are actually taken from Industry Groupings because these data are combined into a single Market Grouping.

17. The price series used with Other Consumer Durables, the CPI for House Furnishings, is a reasonably good match for Other Consumer Durables but not a perfect match.

18. From the variance decompositions, Auto sector output and price movements are essentially unrelated.

19. Miron (1996) shows examples where the use of not seasonably adjusted data is beneficial.

20. Seasonally adjusted data for Butter are available, but the price measure ends in 1986:12.

21. The impulse responses with seasonally adjusted and not seasonally adjusted data tell the same basic story. The only difference is that responses with not seasonally adjusted data are sometimes highly cyclical.

22. Numerically identical results are obtained if we normalize on y.

23. The price and output responses suggest that aggregate demand is the primary source of shocks which have no affect on price for at least two months, although these responses are never significant because the confidence bounds are so wide. Nevertheless, this model still obtains the key finding that the shocks which have the slowest effect on the price level are most important for explaining output variance.

24. Bordo (1993), Karras (1994) and Keating and Nye (1998) are examples. Results from Keating and Nye support the use of these identifying assumptions in post-World War II economies. However, they reject these structural restrictions in pre-World War I data for half of the 10 countries used in this study.

25. Gali (1992) was first to identify VARs with such a combination of identifying restrictions.

Table 1: Variance Decomposition, Chain-Weighted Gross Domestic Product

Variable	Quarter(s) Ahead	Innovations to the Price Level	Shocks with No Effect on Price for 1 Quarter
Output	1	1 (2)	99 (2)
	2	1 (3)	99 (3)
	4	4 (5)	96 (5)
	8	9 (9)	91 (9)
	12	12 (11)	88 (11)
	16	14 (12)	86 (12)
	24	14 (12)	86 (12)
	40	12 (11)	88 (11)
	100	8 (10)	92 (10)
Price	1	100	0
	2	100 (0)	0 (0)
	4	100 (1)	0 (1)
	8	99 (3)	1 (3)
	12	96 (6)	4 (6)
	16	91 (10)	9 (10)
	24	77 (16)	23 (16)
	40	49 (16)	51 (16)
	100	22 (14)	78 (14)

Standard errors are in parentheses. Some standard errors round to zero.

Table 2: Total Industrial Production and Consumer Market Groups, seasonally adjusted data
Variance Explained by Shocks which have No Effect on Price for 1 Month

Variable	Month(s) Ahead	Total IP	Cons. Trucks	Cons. Autos	Other Durables	Cons. Cloths	Cons. Energy	Food	Tobacco	
Output	1	100	100	100	100	99	100	100	97	
		(1)	(2)	(1)	(1)	(1)	(0)	(0)	(3)	
	2	100	100	100	100	99	99	99	90	
		(1)	(2)	(1)	(1)	(1)	(1)	(1)	(7)	
	3	99	97	100	100	100	97	99	86	
		(1)	(3)	(1)	(1)	(1)	(2)	(1)	(9)	
	6	100	98	100	94	100	90	99	78	
		(1)	(3)	(1)	(4)	(1)	(5)	(1)	(11)	
	9	100	98	100	88	100	86	99	77	
		(1)	(4)	(2)	(6)	(1)	(6)	(2)	(11)	
	12	100	96	100	83	100	85	97	77	
		(2)	(4)	(2)	(8)	(2)	(6)	(3)	(10)	
	36	84	85	100	73	99	74	74	74	
		(12)	(7)	(2)	(12)	(4)	(10)	(12)	(11)	
	72	78	73	100	73	99	67	58	73	
		(16)	(10)	(2)	(11)	(4)	(13)	(16)	(11)	
	300	77	40	100	67	99	56	33	72	
		(19)	(17)	(2)	(11)	(6)	(18)	(24)	(12)	
Price	1	0	0	0	0	0	0	0	0	
	2	0	3	0	0	0	0	0	0	
		(0)	(2)	(0)	(0)	(0)	(0)	(0)	(1)	
	3	0	4	0	0	0	0	0	0	
		(0)	(3)	(0)	(0)	(0)	(0)	(0)	(1)	
	6	2	5	0	0	1	1	0	1	
		(2)	(5)	(1)	(1)	(1)	(1)	(1)	(5)	
	9	6	4	1	1	1	2	0	4	
		(4)	(5)	(2)	(1)	(2)	(2)	(1)	(8)	
	12		8	3	1	0	2	2	0	5
		(4)	(6)	(3)	(1)	(3)	(2)	(1)	(11)	
	36	24	1	4	1	21	1	8	3	
		(12)	(7)	(7)	(7)	(12)	(2)	(7)	(13)	
	72	45	1	5	4	52	2	14	3	
		(16)	(7)	(9)	(12)	(18)	(3)	(10)	(13)	
	300	78	0	6	8	83	19	37	3	
		(15)	(8)	(10)	(16)	(20)	(9)	(13)	(13)	

Standard errors are in parentheses. Some standard errors round to zero.

Table 3: Non-Food Industries which Primarily Serve Consumers, seasonally adjusted data
Variance Explained by Shocks which have No Effect on Price for 1 Month

Variable	Month(s) Ahead	Shoes	Automotive Gas	Furniture
Output	1	100	100	99
		(1)	(0)	(1)
	2	100	100	100
		(1)	(1)	(1)
	3	99	97	100
		(1)	(2)	(1)
	6	100	88	100
		(1)	(5)	(1)
	9	100	86	100
		(1)	(5)	(1)
	12	99	86	100
		(2)	(5)	(1)
	36	99	80	100
		(3)	(7)	(1)
	72	97	79	99
		(6)	(8)	(2)
	300	40	80	97
		(13)	(8)	(5)
Price	1	0	0	0
	2	0	0	0
		(0)	(0)	(0)
	3	0	1	1
		(0)	(1)	(1)
	6	0	10	1
		(1)	(5)	(1)
	9	0	18	0
		(1)	(7)	(1)
	12	1	19	1
		(1)	(8)	(2)
	36	4	16	8
		(4)	(7)	(9)
	72	7	34	17
		(7)	(10)	(14)
	300	23	55	27
		(18)	(11)	(19)

Standard errors are in parentheses. Some standard errors round to zero.

Table 4: Food Industries, seasonally adjusted data

Variance Explained by Shocks which have No Effect on Price for 1 Month

Variable	Month(s) Ahead	Beef	Pork	Cheese	Milk	Beer	Soft Drinks	
Output	1	81	92	100	100	100		98
		(4)	(3)	(1)	(1)	(0)	(2)	
	2	76	89	100	100	100		98
		(4)	(4)	(1)	(1)	(1)	(2)	
	3	75	88	99	100	100		98
		(5)	(4)	(1)	(1)	(1)	(2)	
	6	76	85	98	99	98	99	
		(6)	(6)	(2)	(3)	(2)	(2)	
	9	77	84	97	99	98	99	
		(6)	(7)	(4)	(4)	(2)	(2)	
	12	75	87	94	98	99	99	
		(7)	(6)	(7)	(4)	(2)	(2)	
	36	74	76	71	96	99	99	
		(9)	(10)	(17)	(6)	(3)	(4)	
	72	76	73	51	93	99	98	
		(9)	(11)	(20)	(9)	(6)	(7)	
	300		79	60	38	82	99	97
		(9)	(14)	(20)	(16)	(10)	(9)	
Price	1	0	0	0	0	0	0	
	2	2	8	1	0	0	1	
		(1)	(3)	(1)	(0)	(0)	(1)	
	3	3	14	1	1	1	1	
		(1)	(4)	(1)	(1)	(1)	(1)	
	6	5	23	2	3	3	0	
		(3)	(7)	(2)	(3)	(3)	(1)	
	9	8	25	2	5	5	0	
		(5)	(8)	(3)	(5)	(5)	(1)	
	12	10	27	2	6	7	1	
		(5)	(10)	(4)	(6)	(6)	(2)	
	36	9	30	3	16	34	6	
		(5)	(12)	(10)	(11)	(16)	(11)	
	72	9	24	4	25	62	16	
		(9)	(10)	(14)	(14)	(19)	(17)	
	300		54	23	5	36	85	28
		(15)	(16)	(17)	(17)	(18)	(22)	

Standard errors are in parentheses. Some standard errors round to zero.

Table 5: Total Industrial Production and Consumer Market Groups, not seasonally adjusted data
Variance Explained by Shocks which have No Effect on Price for 1 Month

Variable	Month(s) Ahead	Total IP	Cons. Trucks	Cons. Autos	Other Durables	Cons. Cloths	Cons. Energy	Food	Tobacco
Output	1	99	100	100	100	100	100	100	99
		(1)	(1)	(1)	(1)	(0)	(1)	(1)	(1)
	2	99	100	100	100	100	98	100	99
		(1)	(2)	(1)	(1)	(0)	(2)	(1)	(1)
	3	99	99	100	97	100	95	100	99
		(1)	(3)	(1)	(2)	(1)	(3)	(1)	(1)
	6	99	99	98	91	99	88	99	99
		(1)	(3)	(3)	(5)	(2)	(5)	(1)	(1)
	9	99	99	96	84	99	84	99	99
		(1)	(3)	(4)	(7)	(2)	(6)	(1)	(2)
	12	99	98	96	78	97	82	97	99
		(1)	(4)	(5)	(9)	(4)	(6)	(2)	(2)
	36	100	91	96	61	97	76	78	99
		(3)	(5)	(6)	(13)	(5)	(8)	(10)	(2)
	72	100	82	96	60	97	71	66	99
		(5)	(7)	(6)	(13)	(6)	(11)	(14)	(2)
	300	99	52	96	56	96	59	40	99
		(12)	(16)	(6)	(12)	(7)	(17)	(23)	(2)
Price	1	0	0	0	0	0	0	0	0
	2	1	3	1	0	0	1	0	0
		(1)	(2)	(1)	(0)	(0)	(0)	(0)	(0)
	3	3	7	0	1	0	1	0	1
		(1)	(4)	(1)	(1)	(0)	(1)	(0)	(1)
	6	9	11	1	0	0	0	0	3
		(3)	(8)	(2)	(1)	(1)	(1)	(0)	(3)
	9	12	9	1	0	1	0	0	6
		(4)	(8)	(2)	(1)	(2)	(1)	(1)	(4)
	12	14	8	0	1	2	0	0	10
		(5)	(8)	(3)	(2)	(3)	(1)	(1)	(6)
	36	15	4	3	5	16	0	4	24
		(9)	(8)	(7)	(10)	(11)	(2)	(5)	(13)
	72	21	3	8	14	41	1	8	31
		(13)	(8)	(11)	(15)	(18)	(4)	(8)	(16)
	300	65	2	11	22	86	18	31	35
		(21)	(9)	(14)	(18)	(20)	(9)	(13)	(18)

Standard errors are in parentheses. Some standard errors round to zero.

Table 6: Non-Food Industries which Primarily Serve Consumers, not seasonally adjusted data, Variance Explained by Shocks which have No Effect on Price for 1 Month

Variable	Month(s) Ahead	Shoes	Automotive Gas	Furniture
Output	1	100	98	99
		(0)	(1)	(1)
	2	100	99	99
		(1)	(1)	(1)
	3	100	98	99
		(1)	(1)	(1)
	6	99	90	97
		(1)	(5)	(3)
	9	99	89	90
		(2)	(5)	(6)
	12	99	88	86
		(2)	(6)	(8)
	36	97	84	80
		(4)	(8)	(10)
	72	97	83	80
		(6)	(9)	(10)
	300	38	83	80
		(16)	(9)	(10)
price	1	0	0	0
	2	0	0	0
		(0)	(0)	(0)
	3	0	0	0
		(1)	(0)	(1)
	6	1	3	0
		(1)	(2)	(1)
	9	0	3	1
		(1)	(3)	(2)
	12	1	3	1
		(2)	(3)	(2)
	36	4	5	17
		(6)	(7)	(13)
	72	9	22	38
		(10)	(13)	(18)
	300	25	43	56
		(20)	(15)	(21)

Standard errors are in parentheses. Some standard errors round to zero.

Table 7: Food Industries, not seasonally adjusted data,
Variance Explained by Shocks which have No Effect on Price for 1 Month

Variable	Month(s) Ahead	Beef	Pork	Butter	Cheese	Milk	Beer	Soft Drinks	
Output	1	80	90	100		99	99	99	98
		(4)	(3)	(1)	(1)	(1)	(1)	(2)	
	2	76	89	100		99	98	98	98
		(5)	(3)	(1)	(1)	(2)	(2)	(2)	
	3	74	88	99	97	98	98	98	
		(5)	(4)	(1)	(2)	(2)	(2)	(2)	
	6	74	85	99	97	99	98	99	
		(6)	(5)	(2)	(4)	(3)	(2)	(2)	
	9	70	84	98	94	99	98	99	
		(7)	(6)	(3)	(6)	(3)	(2)	(2)	
	12	67	86	94	91	99	97	99	
		(7)	(6)	(4)	(8)	(3)	(2)	(2)	
	36	56	82	72	57	99	96	99	
		(10)	(8)	(10)	(14)	(4)	(5)	(4)	
	72	55	80	68	42	98	94	98	
		(11)	(8)	(12)	(15)	(5)	(7)	(7)	
	300	59	69	67	34	93	89	96	
		(11)	(12)	(12)	(15)	(12)	(13)	(8)	
Price	1	0	0	0	0	0	0	0	
	2	2	9	1	0	0	0	2	
		(1)	(3)	(1)	(0)	(0)	(0)	(2)	
	3	3	17	3	0	1	1	2	
		(1)	(4)	(2)	(1)	(1)	(1)	(1)	
	6	6	25	11	0	6	4	1	
		(3)	(7)	(4)	(1)	(4)	(3)	(1)	
	9	6	25	16	0	9	6	1	
		(4)	(8)	(6)	(2)	(6)	(5)	(1)	
	12	6	27	16	0	12	8	1	
		(4)	(9)	(7)	(3)	(8)	(6)	(2)	
	36	4	30	28	2	25	28	8	
		(3)	(11)	(14)	(9)	(14)	(16)	(11)	
	72	5	24	66	3	32	48	20	
		(7)	(10)	(15)	(11)	(17)	(20)	(17)	
	300	44	24	80	4	39	66	32	
		(12)	(16)	(13)	(12)	(20)	(22)	(22)	

Standard errors are in parentheses. Some standard errors round to zero.

Table 8: Variance Decomposition for IP, CPI and Fed Funds Rate, seasonally adjusted data
VAR Model in Levels

Variable	Month(s) Ahead	Innovations to the Price Level	Shocks with No Effect on Price for 1 Month	Shocks with No Effect on Price for 2 Months
Price	1	100	0	0
	2	99 (1)	1 (1)	0
	3	95 (2)	5 (2)	0 (0)
	6	83 (5)	17 (6)	0 (2)
	9	79 (7)	21 (7)	0 (3)
	12	76 (8)	24 (9)	0 (4)
	24	65 (12)	32 (13)	3 (8)
	36	55 (16)	36 (16)	9 (13)
	48	47 (17)	36 (18)	17 (16)
	72	35 (17)	30 (18)	34 (19)
	120	23 (14)	20 (16)	57 (18)
	180	19 (13)	15 (16)	66 (19)
	300	16 (13)	10 (18)	74 (20)
Output	1	2 (1)	11 (23)	87 (23)
	2	1 (1)	13 (23)	86 (23)
	3	1 (1)	15 (24)	84 (24)
	6	1 (1)	14 (23)	85 (23)
	9	1 (2)	12 (22)	87 (22)
	12	1 (2)	10 (21)	89 (21)
	24	3 (5)	6 (17)	91 (17)
	36	5 (6)	7 (16)	88 (16)
	48	7 (7)	11 (16)	82 (17)
	72	7 (8)	19 (17)	73 (17)
	120	8 (8)	23 (18)	70 (18)
	180	9 (7)	21 (17)	70 (17)
	300	9 (7)	18 (17)	73 (18)
Interest Rate	1	2 (2)	96 (18)	2 (18)
	2	2 (2)	97 (17)	1 (17)
	3	2 (2)	97 (16)	1 (16)
	6	1 (1)	97 (17)	2 (17)
	9	1 (2)	94 (17)	4 (17)
	12	1 (3)	93 (18)	6 (18)
	24	1 (5)	89 (19)	10 (19)
	36	1 (6)	85 (20)	13 (20)
	48	1 (6)	82 (19)	17 (19)
	72	2 (6)	78 (18)	20 (18)
	120	3 (7)	76 (18)	20 (17)
	180	3 (7)	76 (18)	20 (17)
	300	3 (7)	76 (17)	20 (17)

Variances may not sum to 100% due to rounding. Standard errors are in parentheses. Some standard errors round to zero.

Table 9: Variance Decomposition for IP, CPI and Fed Funds Rate, seasonally adjusted data
VAR Model in First Differences

Variable	Month(s) Ahead	Innovations to the Price Level	Shocks with No Price Effect for 1 Month: Shocks which Have a Long-Run Effect on Output	Shocks which Do Not Have a Long-Run Effect on Output
Price	1	100	0	0
	2	99 (1)	0 (0)	0 (0)
	3	95 (2)	2 (2)	2 (2)
	6	84 (5)	6 (6)	10 (5)
	9	80 (6)	8 (7)	13 (6)
	12	76 (8)	9 (8)	15 (7)
	24	66 (10)	11 (11)	23 (10)
	36	63 (11)	11 (11)	26 (12)
	48	61 (12)	11 (12)	28 (12)
	72	59 (12)	11 (12)	30 (13)
	120	57 (12)	11 (12)	32 (13)
	180	57 (13)	11 (12)	32 (13)
	300	56 (13)	11 (12)	33 (13)
Output	1	2 (2)	22 (27)	76 (27)
	2	1 (1)	20 (27)	79 (27)
	3	1 (1)	17 (26)	82 (26)
	6	1 (1)	18 (26)	81 (26)
	9	2 (2)	20 (26)	78 (26)
	12	4 (4)	22 (26)	74 (26)
	24	14 (8)	31 (24)	55 (21)
	36	25 (11)	37 (21)	38 (16)
	48	34 (13)	39 (19)	27 (12)
	72	43 (14)	41 (17)	16 (7)
	120	51 (15)	41 (16)	8 (3)
	180	54 (15)	41 (16)	5 (2)
	300	57 (15)	41 (15)	3 (1)
Interest Rate	1	2 (2)	56 (29)	42 (29)
	2	2 (2)	50 (28)	48 (28)
	3	2 (2)	43 (27)	55 (28)
	6	1 (2)	36 (26)	63 (26)
	9	1 (2)	31 (24)	68 (24)
	12	1 (2)	27 (23)	72 (23)
	24	0 (4)	20 (21)	80 (21)
	36	1 (6)	17 (21)	82 (20)
	48	1 (8)	16 (20)	83 (20)
	72	2 (11)	15 (20)	84 (21)
	120	3 (14)	13 (19)	84 (21)
	180	4 (15)	12 (19)	84 (22)
	180	4 (15)	12 (19)	84 (22)

Variances may not sum to 100% due to rounding. Standard errors are in parentheses. Some standard errors round to zero.

Appendix: Specifications for Bivariate Time Series Models with Monthly Data

	Price and Output Series			Lags	
Model Name	CPI Measure	IP Measure (SIC code)	Date	S	N
Total IP	All Items	Total Index	47:1	33	27
Consumer Trucks	New Trucks	Consumer Trucks (371pt)	84:1	4	5
Consumer Autos	New Autos	Consumer Autos (371pt)	72:1	2	15
Other Durables	Housefurnishings	Other Consumer Durables	67:1	5	7
Consumer Clothing	Apparel Commodities	Consumer Clothing	56:1	8	19
Consumer Energy	Energy Commodities	Consumer Energy Products	57:1	9	16
Food	Food	Food (20)	47:1	25	23
Tobacco	Tobacco & Smoking Products	Tobacco Products (21)	86:1	2	4
Shoes	Footwear	Shoes (314)	54:1	15	27
Automotive Gas	Gasoline	Automotive Gas (291pt)	67:1	13	13
Furniture	Furniture & Bedding	Household Furniture (251)	69:1	3	9
Beef	Beef & Veal	Beef (201pt)	54:1	11	12
Pork	Pork	Pork (201pt)	54:1	26	23
Butter	Butter	Butter (2021)	54:1	n/a	23
Cheese	Cheese	Cheese (2022)	78:1	3	4
Milk	Fresh Milk & Cream	Milk & Miscellaneous Dairy Products (2026)	78:1	4	3
Beer	Beer & Ale at Home	Beer & Ale (2082,3)	69:1	9	9
Soft Drinks	Carbonated Drinks	Soft Drinks (2086,7)	78:1	3	3

This appendix reports for each model the price series, the output series, the DATE both seasonally adjusted (SA) series begin (except for Butter where the model is estimated only with not seasonally adjusted, NSA, data), lags in the VAR for the model with SA data (column S) and for the VAR with NSA data (column N). Lags were chosen by the Akaike Information Criterion. In all cases the starting date with NSA data is the same as with SA data or one month earlier, except for Total IP where the NSA data begin January of

1919 (i.e. 19:1).

References

Blanchard, Olivier J. and Danny Quah (1989) "The dynamic effects of aggregate demand and supply disturbances," American Economic Review, 79: 655-673.

Blinder, Alan S. (1994) "On sticky prices: Academic theories meet the real world," in Monetary Policy, ed. N.G. Mankiw, 117-50.

Blinder, Alan S., Elie R. D. Canetti, David E. Lebow, and Jeremy B. Rudd (1997) Asking About Prices: A New Approach to Understanding Price Stickiness, Russell Sage Foundation, New York.

Bordo, Michael D. (1993) "The gold standard, Bretton Woods and other monetary regimes: A historical appraisal," in Dimensions of Monetary Policy, Federal Reserve Bank of St. Louis, 123-191.

Caplin, Andrew S. and Daniel F. Spulber (1987) “Menu costs and the neutrality of money” Quarterly Journal of Economics 102(4), November 1987, 703-25.

Carlton, Dennis W. (1986) "The rigidity of prices," American Economic Review, 76:637-658.

Cecchetti, Steven G. (1986) "The frequency of price adjustment: A study of the newsstand prices of magazines," Journal of Econometrics, 31:255-274.

Cochrane, John H. (1998) "What do VARs mean?: Measuring the output effects of money" Journal of Monetary Economics 41, 277-300.

Cooley, Thomas and Gary Hansen (1995) "Money and the business cycle," in Frontiers of Business Cycle Research, ed. T. Cooley.

Farmer, Roger E. A. (1991) "Sticky prices," Economic Journal, 101:1369-1379.

Farmer, Roger E. A. (1992) "Nominal price stickiness as a rational expectations equilibrium," Journal of Economic Dynamics and Control, 16:317-337.

Gali, Jordi (1992) "How well does the IS-LM model fit postwar U.S. data," Quarterly Journal of Economics, 57:709-38.

Griliches, Zvi (1992) "Introduction," Output Measurement in the Service Sectors, ed. Z Griliches, NBER Studies in Income and Wealth, Vol 56. Chicago: University of Chicago Press, 1-22.

Griliches, Zvi (1994) "Productivity, R&D and the data constraint," American Economic Review 84, 1-23.

Hall, Simon, Mark Walsh and Anthony Yates (1997) “How do U.K. companies set prices?” Bank of England Working Paper.

Karras, George (1994) "Aggregate demand and supply shocks in Europe: 1860-1987," The Journal of European Economic History, 22:79-98.

Kashyap, Anil K. (1995) "Sticky prices: New evidence from retail catalogs," Quarterly Journal of Economics, 110:245-74.

Keating, John W. (1996) "Using dynamic restrictions to identify vector autoregressions."

Keating, John W. and John V. Nye (1998) "Permanent and transitory shocks to real output: Estimates from nineteenth century and postwar economies" Journal of Money, Credit, and Banking 30, 231-251.

Mankiw, N. Gregory and David Romer (1991) New Keynesian Economics, MIT Press, Cambridge.

Mills, Frederick C. (1927) The Behavior of Prices, National Bureau of Economic Research, New York.

Miron, Jeffrey A. (1996) The Economics of Seasonal Cycles, MIT Press, Cambridge.

Ohanian, Lee E., Alan C. Stockman and Lutz Kilian (1995) "The effects of real and monetary shocks in a business cycle model with some sticky prices," Journal of Money, Credit and Banking 27:1210-1234.

Runkle, David E. (1987) "Vector autoregressions and reality," Journal of Business and Economic Statistics, 5:437-54.

Sims, Christopher A. (1998) “Stickiness” forthcoming in the Carnegie-Rochester Conference Series on Public Policy.

Stigler George J. and James K. Kindahl (1970) The Behavior of Industrial Prices, National Bureau of Economic Research, New York.

Wynne, Mark (1995) "Sticky prices: What is the evidence?," Federal Reserve Bank of Dallas, Economic Review, First Quarter, 1-12.