The Interest Rate Sensitivity of Texas Industry

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Our analysis suggests that interest rate movements affect the composition of Texas employment rather than its level.

A key factor in forecasting a region's growth is anticipating how the region will respond to changes in national policy. One important way that national policy affects a region is through real interest rates. Our analysis shows that changes in real interest rates can influence the Texas economy.

The linkage between changes in federal policy and real interest rates has been the subject of much economic research. Many fiscal policies have been shown to have considerable influence on effective real interest rates. For example, Robert Hall and Alvin Rabushka estimate that scrapping corporate and individual income taxes and replacing them with a flat tax on consumption would cut U.S. interest rates by more than 20 percent (Hall and Rabushka 1995). On the other side of the policy equation, many economists believe shifts in monetary policy can temporarily alter real short-term interest rates.[1]

Forecasting the regional consequences of such policy changes, therefore, requires good estimates of the interest rate sensitivity of regional industries. If most Texas industries are highly sensitive to interest rate changes, interest rates may be a primary channel through which policy affects the region. On the other hand, if Texas industries are insensitive to interest rate changes, the interest rate effects of policy are relatively unimportant to regional analysis. Furthermore, if some Texas industries are sensitive to interest rate changes while other industries are not, the pattern of interest rate sensitivity among industries may shed light on the compositional effects of policy change.

There is a modest literature on the extent to which industries respond to interest rate changes. Ceglowski (1989) finds that most U.S. industries are not sensitive to changes in interest rates, but that construction and some construction-related manufacturing (lumber and wood products and furniture and fixtures) are highly sensitive. Ceglowski finds evidence of moderate interest sensitivity for industries that produce transportation equipment, chemicals, textiles, and rubber and plastics. A casual analysis of industry sensitivity in the United Kingdom also indicates above-average interest sensitivity in the transportation equipment, chemicals, and textiles industries (Lonie et al. 1990). Given the central role of employment data in regional analysis, it is unfortunate that neither of these studies estimates employment responses.

We contribute to this literature by examining the sensitivity of Texas industry employment to changes in real short-term interest rates. We find that most Texas industries are insensitive to changes in real interest rates, but that a few industries, notably construction, apparel, nonelectrical machinery, and primary metals are sensitive to interest rate movements. Moreover, we find that Texas total nonagricultural employment is not sensitive to changes in real interest rates. As such, our analysis suggests that real interest rate movements influence the composition of Texas employment rather than its level.[2]

Analytical framework and estimation

We use a vector autoregressive (VAR) model to assess interest rate sensitivity. A VAR model is a system of reduced-form equations wherein the interaction among several variables is used to forecast each individual variable. Each endogenous variable is represented as a function of past values of itself and past values of all the other variables in the system.

Our system consists of five endogenous variables that were chosen to represent the major influences on Texas industry employment. The five variables are the real price of oil (which reflects the influence of the prominent energy industry), the real short-term interest rate, aggregate U.S. employment (which reflects the influence of national business cycles), aggregate Texas employment (which reflects the influence of regional business cycles), and Texas employment in the industry under evaluation.[3] We estimate this system for each industry for which employment data are available.

The VAR approach is particularly well-suited to an analysis of interest rate sensitivity for a number of reasons. First, the VAR approach allows us to examine the timing as well as the magnitude of a variable's response to a systemic shock. Therefore, we can be more precise in our estimates of the regional effects of interest rate changes. Second, the VAR approach imposes no a priori restrictions on the system's structure; rather, the approach allows the data to determine the results. Such a nonstructural approach is preferable whenever economic theory provides little guidance as to the exact nature of the relationship among variables in the system. Although the nonstructural approach prevents the inference of causality, it generates reliable estimates of the response of sectoral employment to changes in interest rates. Furthermore, because the VAR approach estimates reduced-form relationships, the channels through which interest rates affect sectoral employment need not be explicitly modeled. Finally, estimating the interest rate sensitivity of employment in a VAR system with a Choleski decomposition for the errors allows us to trace movements in employment that arise either directly from interest rate changes or indirectly through the influence of interest rates on the other included variables.

The data

The monthly data for this analysis come from a variety of sources and span the period from January 1980 to November 1995. We use refiners' acquisition cost to measure the oil price and the interest paid on three-month U.S. Treasury bills to measure the interest rate. In both cases, we adjust for inflation using the consumer price index. Employment data for the United States and Texas come from the Bureau of Labor Statistics and are seasonally adjusted using the Berger–Phillips two-step method.[4] Our measures of sectoral employment include each of the nine industry divisions—mining, construction, manufacturing, TCPU (transportation, communications, and public utilities), wholesale trade, retail trade, FIRE (finance, insurance, and real estate), services, and government—as well as the thirty-nine major industry groups within those divisions for which complete employment data are available.

Because a VAR system can be sensitive to the stationarity of the data series, we test for stationarity using augmented Dickey–Fuller tests. The first difference of the natural log is stationary for all but three of the data series (employment in chemicals manufacturing, FIRE, and depository institutions), and the second difference of the natural log is stationary for those three series.[5] Therefore, we transform the employment and price series accordingly.[6] Following convention, we did not transform the real interest rate variable.

The appropriate specification of the VAR system also critically depends on the number of lags. If the system has too few lags, the researcher has omitted valuable information and the estimation may be biased. If the system has too many lags, the researcher has included avoidable noise, and the estimation will be inefficient (but should be unbiased). We use the Akaike information criterion (AIC) and the Schwarz criterion (SC) to suggest the appropriate lag length.[7] The AIC indicates that the appropriate specification would include at least twelve lags of the variables in the system; the SC indicates that no more than two lags would be necessary. Unfortunately, a likelihood ratio test does not systematically favor the two-lag specification over the twelve-lag specification (or vice versa).[8] Therefore, in the interest of comparability, we choose to err on the side of unbiased but possibly inefficient estimation. All variables in the system are estimated as a function of twelve lags of themselves and twelve lags of each of the other variables.[9]

Assessment strategies

We use two strategies to assess the relationship between interest rate innovations and industry employment. The first strategy is to test for a direct relationship between employment changes and lagged movements in the interest rate variable using Granger-causality tests. In this context, a Granger-causality test examines the hypothesis that the interest rate coefficients in the industry employment equation are jointly zero. If we can reject the hypothesis that all of the coefficients are jointly zero, movements in interest rates are said to Granger-cause movements in employment.[10] The second strategy uses impulse response functions to capture the direct and indirect relationship between employment and interest rates. Impulse response functions trace over time how an independent and unexpected shock to one variable in the VAR system affects another.

We use a Choleski decomposition to trace the effects of a one-time shock to interest rates on employment in each of the sectors. The Choleski technique decomposes the residual (μ_i) from each equation in the VAR system into a linear combination of residuals from the other equations (μ_j) and an orthogonal element (ν_i). We specified a decomposition that allows a one-way contemporaneous relationship between interest rates and the Texas sectoral employment variables.[11] The structure is as follows:

$$(1) \quad \mu_{oil} = \nu_{oil},$$

$$(2) \quad \mu_r = c_{21}\mu_{oil} + \nu_r,$$

$$(3) \quad \mu_{US} = c_{31}\mu_{oil} + c_{32}\mu_r + \nu_{US},$$

$$(4) \quad \mu_{TX} = c_{41}\mu_{oil} + c_{42}\mu_r + c_{43}\mu_{US} + \nu_{TX},$$

$$(5) \quad \mu_{ind} = c_{51}\mu_{oil} + c_{52}\mu_r + c_{53}\mu_{US} + c_{54}\mu_{TX} + \nu_{ind},$$

where μ_{oil} represents the residual from the real oil price equation, μ_r represents the residual from the real interest rate equation, μ_{US} represents the residual from the aggregate U.S. employment equation, μ_{TX} represents the residual from the aggregate Texas employment equation, and μ_{ind} represents the residual from the Texas industry employment equation.

The above structure implies that unexpected changes in oil prices (μ_{oil}) do not contemporaneously arise from any of our specified variables. Similarly, unexpected changes in real interest rates (μ_r) do not contemporaneously arise from any of the employment variables but can be contemporaneously affected by innovations in oil prices (μ_{oil}). Unexpected changes in oil prices and interest rates contemporaneously affect unexpected changes in aggregate U.S. employment (μ_{US}), but μ_{US} affects oil prices and interest rates only in subsequent periods. Similarly, current innovations in total Texas nonagricultural employment (μ_{TX}) are affected by current innovations in oil prices, interest rates, and U.S. employment but not by current innovations in the sectoral employment variables (μ_{ind}). Although innovations in sectoral employment affect Texas total employment, they are not contemporaneous—they work their effects through the system over time.

We used the estimated coefficients of the VAR system of equations and Monte Carlo integration with 1,000 replications to compute confidence bands for the impulse response functions. The methodology follows Kloek and Van Dijk (1978) with the coefficient draws taken directly from the estimated posterior distribution of the coefficients. This methodology yields one-standard-deviation confidence bands for the impulse response functions of the variables in the model.[12]

These confidence bands can be used to distinguish where the impulse response functions differ significantly from zero. Whenever the lower bound on the impulse response function is positive, we consider the impulse to be significantly positive. Whenever the upper bound on the impulse response is negative, we consider the impulse to be significantly negative. Rather than show the confidence bands directly, for simplicity we report only significant impulse responses.

Results

Our assessment strategies offer two ways to look at the interest sensitivity of Texas industry. Tables 1 and 2 present both the Granger-causality tests and the cumulative impulse responses. In all cases, the impulse responses represent the cumulative percentage change in industry employment associated with a one-percentage-point increase in the real interest rate at the beginning of the time period. Table 1 presents results for aggregate Texas employment and the nine broad industry divisions,

Table 1
The Cumulative Employment Response of Industry Divisions to an Increase of 100 Basis Points in the Real Interest Rate
(Percent change in employment)

Industry division	3-month response	6-month response	12-month response	24-month response	36-month response	60-month response
Total	.	.	.	.	.	.
Mining	.	.	.	.	.	.
* Construction	–.26	–.37	–.53	–.64	–.65	.
** Manufacturing	.	.	–.11	–.30	–.29	–.31
** TCPU	.	.	.	–.19	–.24	–.24
* Wholesale trade	.	.	.	–.18	–.24	–.25
Retail trade	.	.	.	.	.	.
FIRE	.	.	.	.	.	.
Services[a]	.	.	.	.	.	.
* Government	–.06	–.00	–.07	–.08	–.09	–.10

NOTE: A missing value indicates that the interest rate sensitivity is indistinguishable from zero. The symbols on the left indicate that innovations in the real interest rate Granger-cause innovations in employment at the 5-percent level (**) or 10-percent level (*). The symbol "a" indicates an industry that we evaluate using two-standard-deviation confidence bands for the impulse responses.

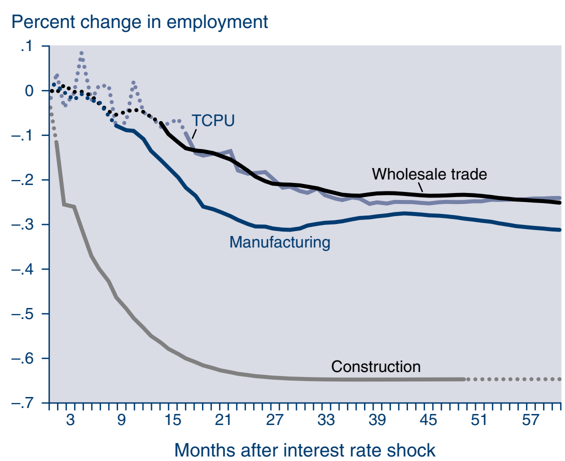
while Table 2 presents results for major industry groups within those divisions.

The data in Table 1 support three general conclusions about interest rate sensitivity. First, the Granger-causality tests and impulse responses both indicate aggregate Texas employment is not systematically influenced by changes in real short-term interest rates.[13] Second, both approaches also suggest that individual industries can be influenced by interest rate movements. We find that changes in real short-term interest rates Granger-cause employment changes in construction, manufacturing, government, and the service-producing industries that distribute goods (TCPU and wholesale trade). The impulse responses also indicate significant effects on employment in these industries. Finally, the relatively modest impulse responses suggest that no Texas industries are highly sensitive to movements in real short-term interest rates.

Consistent with conventional wisdom, the construction industry shows the quickest and strongest initial response to an interest rate shock. Within three months after an unanticipated, one-percentage-point increase in real short-term interest rates, construction employment in Texas decreases by 0.26 percent. Over the next three quarters, construction employment declines by another 0.26 percent. The peak cumulative effect of a 0.65-percent decline in construction employment is reached thirty-seven months after the initial shock.

As Figure 1 illustrates, an interest rate shock elicites a slower and weaker employment response from the manufacturing sector than from the construction sector. It takes nine months for an interest rate shock to affect manufacturing employment, and when it does, the reaction

Figure 1
Employment Response Of Private Industry Divisions



NOTE: Dotted line indicates that the impulse response is not significant.

Table 2

Cumulative Employment Response of Major Industry Groups to an Increase of 100 Basis Points in the Real Interest Rate

(Percent change in employment)

Major Industry Groups

Industry	3-month response	6-month response	12-month response	24-month response	36-month response	60-month response
Manufacturing						
** Nonelectrical machinery	.	.	–.31	–.92	–1.05	–1.17
* Primary metals	.	.	–.60	–.93	–1.04	–1.16
Apparel	–.13	–.16	–.37	–.70	–.77	–.95
** Fabricated metals	.	.	–.28	–.64	–.60	–.70
Lumber and wood	.	.	.	.	.	–.64
** Rubber	.	.	.	–.32	–.37	–.32
* Petroleum and coal[a]	.	.	.	.	.	.
** Printing[a]	.	.	.	.	.	.
Miscellaneous manufacturing[a]	.	.	.	–.37	.	.
Leather[a]	.	.	.	–.85	.	.
Textiles	.	.	.	–.31	.	.
Chemicals	.	.	.	.	.	.03
Transportation equipment	.	.11	.25	.40	.67	1.08
TCPU						
* Communications	.	.	.	–.40	–.44	–.54
Railroads	.	.	.	–.48	–.62	–.63
Air transportation[a]	.31	.34	.38	.	.	.
FIRE						
Depository institutions	.	.	.	–.03	–.04	.
Services						
** Health	–.02	–.05	–.08	–.11	–.13	.
Educational services	.	.	.	.20	.33	.47
** Personal	.	.	.12	.18	.21	.23
** Hotels	.14	.18	.28	.38	.46	.55
Government						
** Federal	.	.	.21	.30	.42	.55
* State	–.12	–.11	–.17	–.22	–.21	.
Local	.	.	–.09	–.12	–.14	.

NOTE: Only those industries for which we could detect significant interest rate sensitivity at the indicated intervals are reported. The symbols on the left indicate that innovations in the real interest rate Granger-cause innovations in employment at the 5-percent level (**) or 10-percent level (*). The symbol "a" indicates an industry that we evaluate using two-standard-deviation confidence bands for the impulse responses.

is comparatively modest. According to the impulse response functions, the manufacturing sector's peak cumulative response to an interest rate shock is less than half that of the construction sector.

In turn, the employment response of the distribution industries is weaker and slower than that of the manufacturing sector. Wholesale trade responds in fifteen months and TCPU in eighteen months. In both cases, the magnitude of the response is weaker than in manufacturing.

While the data in Table 1 are informative, there is still substantial variation within the industry divisions. Table 2 presents the estimates for major industry groups wherein we could detect systematic interest rate effects.[14] We could detect Granger causality in twelve of the thirty-nine industries for which we had complete data. We could detect significant impulse responses in twenty-two of the thirty-nine industries. Significant impulse responses in the absence of Granger causality imply either that the relationship between interest rates and industry employment is contemporaneous or that the relationship is indirect and works through the influence of interest rate movements on other variables in the VAR system.

The manufacturing industry varies dramatically with respect to both the timing and intensity of the employment response. For example, although manufacturing as a whole responds to an interest rate shock much more slowly and weakly than the construction industry, the apparel manufacturing industry responds as rapidly and builds over time to a peak response that greatly exceeds the construction industry response. Furthermore, the peak response of nonelectrical machinery, primary metals, fabricated metals, and transportation equipment manufacturing is stronger than the peak response of the construction industry.[15]

Somewhat surprisingly, only half of the manufacturing industries that are commonly related to construction activity demonstrate significant interest rate sensitivity. We cannot detect a systematic relationship between interest rate movements and changes in employment for furniture and fixtures, or stone, clay, and glass products. However, fabricated metals, and lumber and wood products demonstrate comparatively strong interest rate sensitivity. In both cases, the peak employment response is at least as strong as that of the construction industry, but appears only after a substantial lag. Lumber and wood products employment takes nearly four years to respond to an interest rate shock.

Our analysis of TCPU suggests that the industry division's sensitivity to interest rate shocks comes from the transportation and communications components: utilities are not interest sensitive by either assessment strategy. We find that communications and railroad transportation are particularly sensitive to interest rate movements. The impulse responses indicate these industries are more than twice as sensitive to interest rate movements as is aggregate TCPU, although the timing of the response is very similar.

Interestingly, although we could not detect interest rate sensitivity in the FIRE or services divisions, we find that five of their component industries are sensitive to movements in interest rates. Increases in real short-term interest rates have a negative impact on employment in depository institutions and health services but a positive impact on employment in personal services, hotels, and educational services. The positive interest rate response for personal services and hotels is consistent with Ceglowski (1989). Because most interest-sensitive industries seem to respond to an interest rate increase by decreasing employment, apparent gains for the educational services industry may reflect an increased demand for education by workers displaced from those industries.

Finally, our analysis of the government sector reveals mixed results. Higher real interest rates precede increases in federal government employment but decreases in state and local government employment. The negative effect on state government is immediate and Granger causal: the negative effect on local government is lagged and not Granger causal. Interestingly, the employment effects are strongest at the federal level and decline in intensity with the level of government.

Conclusions

Our analysis suggests that interest rate movements affect the composition of Texas employment rather than its level. We find that changes in real short-term interest rates do not predict changes in aggregate Texas employment, but do predict changes in sectoral Texas employment. In particular, we find that unanticipated increases in real short-term interest rates lead moderate employment decreases in construction, manufacturing, and the service-producing industries that distribute goods.

As such, our analysis suggests that real short-term interest rates are not a primary channel through which national policy affects Texas employment. However, our analysis does suggest that interest rate movements can be important to regional analysis because they can have compositional effects on employment.

Notes

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1 Movements in nominal interest rates need not imply similar movements in real interest rates.

2 Our finding that employment is insensitive to changes in real short-term interest rates need not imply that

output is also insensitive. If firms substitute labor for capital, rising interest rates could lower output without necessarily reducing employment.

[3] In exploratory analysis for Texas as a whole, we also incorporated a real long-term interest rate (the ten-year Treasury bond rate deflated by the Federal Reserve Bank of Philadelphia's Index of ten-year inflation expectations). A block-exogeneity test indicated that the long-term interest rate did not add any information not already captured by the short-term interest rate. Therefore, we did not include real long-term interest rates as a variable in our analysis.

[4] For a description of the Berger–Phillips method, see Berger and Phillips (1994). The real interest rate and real oil price series had no significant seasonal pattern and, therefore, were not seasonally adjusted.

[5] The construction employment series was not stationary for any plausible degree of differencing, either with or without the logarithmic transformation. However, when we restrict the sample to the period after 1985, the logarithmic series was first-difference stationary. Given the dramatic effects on the construction industry of the Tax Reform Act of 1986, it seems plausible to so restrict the sample. Therefore, the sample used for analysis of the construction industry spans the period from January 1986 to November 1995.

[6] Differencing the data makes the series stationary but reduces the information used to estimate the VAR. One might recover some of this information in an error-correction model by exploiting a long-run cointegrating relationship among the regressors. However, reliable long-run relationships are difficult to detect in short time series (Campbell and Perron 1991). Therefore, we did not employ an error-correction model.

[7] For a further discussion of the model-selection criteria, see Mills (1990) or Kennedy (1992).

[8] For twenty-three of the forty-eight industries or major industry groups, we can reject the hypothesis that the coefficients on lags three through twelve are jointly zero across all five variables and all five equations in the system. For all of the systems, we cannot reject the hypothesis that the coefficients on a thirteenth lag would be jointly zero across all five variables in all five equations. We also cannot reject the hypothesis that the coefficients on lags thirteen through twenty-four are jointly zero across all five variables and all five equations in each system.

[9] Because the construction industry is evaluated over a shorter time period, it may require a different lag structure than the rest of the analysis. The AIC indicates that three lags would be appropriate for analysis of the construction industry; the SC indicates that only one lag is necessary. Because a likelihood ratio test favors three lags, we estimate construction industry employment as a function of three lags of itself and three lags of each of the other variables.

[10] We should note that the relationship is causal only in a temporal sense. Rejecting the hypothesis implies that movements in interest rates systematically precede movements in employment and can be used to predict movements in employment. However, this need not imply that movements in interest rates induce movements in employment.

[11] If the covariance among the residuals is sufficiently high, the ordering of the dependent variables can affect the results. In our opinion, the ordering employed here reflects the most plausible transmission relationship among the variables. Furthermore, exploratory analysis suggests that variations in ordering have little qualitative impact on the results.

[12] However, because it increases our uncertainty about the estimation, we use a two-standard-deviation confidence band for the impulse response whenever we cannot reject at the 10-percent level of significance the hypothesis that the coefficients on all of the variables in the industry employment equation are jointly zero.

[13] Texas' employment insensitivity is consistent with work by Carlino and DeFina (1996) that finds that personal income is less sensitive to changes in short-term interest rates in the Southwest census region (which includes Texas) than in the nation as a whole.

[14] Complete data were not available for a number of Texas industries. Data were available but the interest rate sensitivity was indistinguishable from zero for the following industries: oil and gas extraction; nonmetallic minerals extraction; furniture and fixtures; food and kindred products; paper and allied products; stone, clay, and glass; electronics and electrical equipment; instruments; utilities; apparel stores; auto dealers; food stores; general-merchandise stores; building-materials stores; and amusements.

[15] The positive employment effect on transportation equipment manufacturing seems anomalous, but it is consistent with previous work by Peter Kretzmer (1985), which finds a similar short-term effect from unanticipated money shocks.

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