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Energy price deregulation has reduced regional disparities in residential energy expenditures. Simulation results from a state-level model of the United States suggest that additional energy price deregulation, such as the deregulation of bulk electric power, would further reduce differences in average per capita expenditures across states. Consumers in the Northeast would have the largest decreases in expenditures, while consumers in the Northwest could see some increases.

The strongest overall influence on fluctuations in the Texas unemployment rate is the U.S. business cycle. The state's unemployment rate is also significantly affected by the Mexican business cycle and by cyclical fluctuations peculiar to Texas. Two additional factors, however, mean that the state's unemployment rate can rise even when overall economic activity is expanding. First, permanent shifts in the relative demands for labor among economic sectors can lead to temporary increases in the unemployment rate during business cycle upswings. Second, when shifts in the state's industrial structure lead to rising employment volatility, the result on average is a higher unemployment rate.

Distributional Implications of Reducing Interstate Energy Price Differences

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Since the 1973-74 oil embargo, the distributional effect of energy price shocks has been uneven across regions of the United States. Because of differences in the mix and quantity of fuels demanded by residential consumers in different states, the ability to adjust behavior to changing energy market conditions has been unequal. Furthermore, regional disparities have been exacerbated by the existence of federal and state regulations that have tended to keep fuel costs from equalizing across regions.

With the deregulation of oil in the late 1970s and the deregulation of most natural gas accomplished by 1985, some of the regulatory barriers to fuel price equalization have been removed. These events, in addition to increasing interest in deregulation of bulk electric power transmission, suggest that large disparities in regional fuel prices may be reduced in the foreseeable future—at least to the extent that regulated prices have prevented competition. States that presently face high fuel prices due to restricted market entry are likely to have falling energy prices under deregulation as a result of increased competition. On the other hand, states that have had low prices may have higher prices as energy producers in those areas widen their product markets.

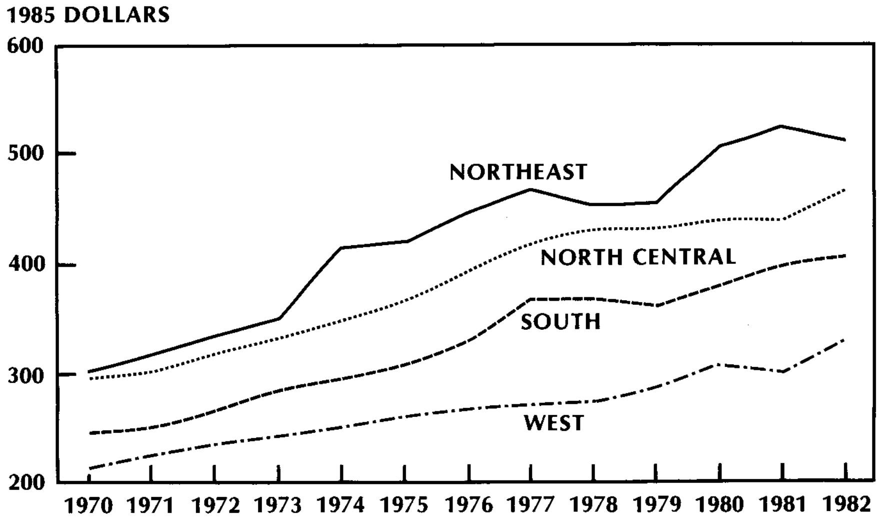
The purpose of this study is to simulate the effects that narrowing natural gas and electricity regional price differentials would have on the distribution of residential energy expenditures across states.[1] Using a model of state residential energy consumption for electricity, natural gas, and petroleum, scenarios are developed to examine the response of residential energy consumption to a reduction in regional price differences attributable to deregulation.[2]

In general, the results indicate that deregulation of natural gas will benefit eastern and northwestern consumers at the expense of consumers in the middle and western parts of the country. If bulk electric power is also deregulated, the gains to the East Coast rise, but the benefits of natural gas deregulation for the Northwest are greatly outweighed by rising electricity prices.

Expenditure and price trends

The extent of past regional expenditure variations can be seen in Chart 1. Real per capita expenditures for 1970

Chart 1
Real Per Capita Residential Energy Expenditures



SOURCES OF PRIMARY DATA: U.S. Department of Commerce.
U.S. Department of Energy.

through 1982 are shown for four major regions of the continental United States.[3] Not surprisingly, the Northeast consistently had the highest expenditures, while the West and South had the lowest. All the regions had growing real energy expenditures over the period.

The Northeast also faced the largest rise in energy costs following the 1973-74 oil embargo and the 1979-80 oil price increase. As seen in Chart 1, per capita energy expenditures changed relatively little in the other regions, but costs jumped rapidly in the Northeast.

The greater responsiveness of expenditures in the Northeast to changes in oil prices is largely a result of differences between this region and others in the type of fuel consumed. The Northeast has relied less heavily on electricity than have the other regions, as exhibited in Chart 2, and has relied more heavily on oil and natural gas. This greater reliance on oil and gas has made that region more susceptible to changes in oil and gas prices. Although the Northeast has been reducing its reliance on natural gas and oil by switching to electricity, it still has the smallest share of electricity among the regions. Furthermore, most of the electricity in the Northeast is generated by oil and nuclear fuels, linking electricity costs more closely to oil prices. The North Central region, in contrast, has relied heavily on electricity generated by burning coal, which is less closely tied to oil price movements.

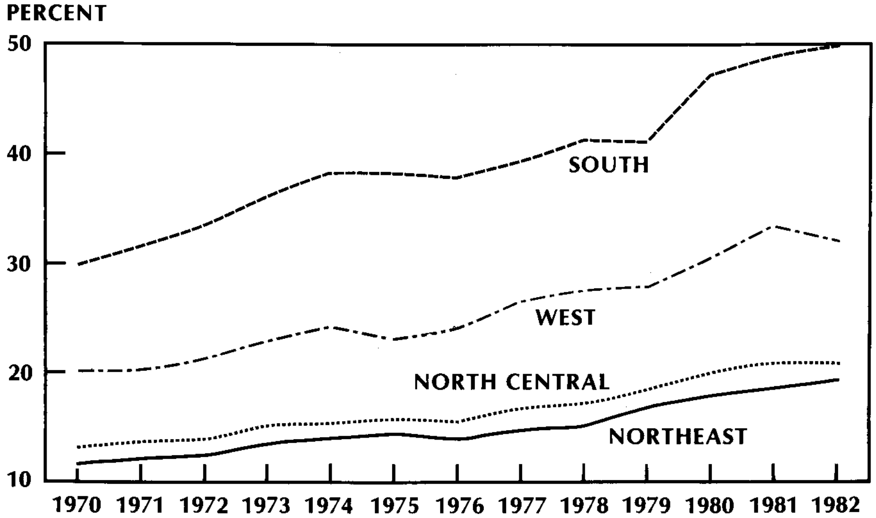
These differences in fuel expenditures and fuel shares are the result of several factors. Geographical factors have been important in the fuel selection process. Access to coal in the North Central region, oil in the South, and abundant hydroelectric power in the West encouraged use of those resources in the respective regions. The Northeast made use of oil because of the relatively low cost of transporting that fuel.

Demographics also have played a role. Newer structures, most of which are in the South and West, have relied more on electricity and natural gas (instead of heating oil) for heating and cooling. Furthermore, expansion of air-conditioning powered by electricity has occurred more rapidly in the warmer regions of the country.

The role of regulation

An additional factor important in determining differences in fuel expenditures and fuel shares across regions has been energy price regulation. This is particularly true in the case of natural gas, the regulation of which led to distortions in the price and availability of the fuel. Before the Natural Gas Policy Act of 1978 (NGPA), only gas sold through interstate pipelines was assigned a regulated price. The NGPA did not

Chart 2
Share of Residential Energy Consumption Provided by Electricity



SOURCE OF PRIMARY DATA: U.S. Department of Energy.

immediately deregulate prices but, instead, retained an elaborate schedule of wellhead prices that were based on the age of the field, depth of well, and whether the natural gas was committed to interstate or intrastate sales before 1978. Consequently, prices in different states depended on the relative proportions of low-cost and high-cost gas that gas distributors in the states had under contract.

The effects of regulation in this regard have also been important for the electricity market. Regulations by public utility commissions and the Federal Energy Regulatory Commission determine rates of return for utilities and govern the sale of power outside the immediate region of utilities. Public utility commissions also limit construction of new power generation facilities.

Since 1978, energy prices increasingly have been deregulated. Oil price controls were phased out between 1978 and 1981. In 1985, most natural gas was released from price controls, and attempts to release the remaining categories of controlled gas from regulation have continued. Recently, interest has emerged in deregulating portions of the electric utility industry.[4] Rulings favoring the sale of cogenerated power and developing capacity in long-distance transmission have raised the possibility that electricity will be sold with market-determined prices, at least in regional markets and perhaps in a national power grid.

Deregulation of energy prices is likely to have distributional consequences on residential energy expenditures across states. Insofar as current price differences reflect regulatory inefficiencies that have kept prices (adjusted for transportation costs) from equalizing across regions, deregulation should affect the regional distribution of energy prices and expenditures by reducing regional energy price differentials.

Modeling residential energy consumption

To explore the effect of changes in energy prices on residential consumers in different states, it is first necessary to model the relationship between energy prices and residential energy consumption. In this section, equations relating consumption of electricity, natural gas, and petroleum to energy prices and other variables are derived. Later sections describe the estimation of these equations and use the estimates to model the effect of energy price deregulation.

A large body of empirical and theoretical literature exists to explain the determinants of residential energy consumption. Because of the difficulty and expense in changing energy-using capital equipment at the residential level, consumption usually is best modeled as a lagged adjustment process. A typical consumer is expected to react slowly to changes in energy prices, causing long-run elasticities to be considerably larger than short-run elasticities.

Specification of the consumption equations for residential consumers is derived from previous research.[5] The consumption equations for electricity, natural gas, and petroleum are expressed as follows:

$$(1.1) \quad ELEC_{jt} = a_{10} + a_{11}ELEC_{jt-1} + a_{12}PRELEC_{jt} + a_{13}PRGAS_{jt} + a_{14}HEAT_{jt} + a_{15}COOL_{jt} + \varepsilon_{Ejt},$$

$$(1.2) \quad NGAS_{jt} = a_{20} + a_{21}NGAS_{jt-1} + a_{22}PRGAS_{jt} + a_{23}PRELEC_{jt} + a_{24}HEAT_{jt} + \varepsilon_{Gjt},$$

$$(1.3) \quad PETR_{jt} = a_{30} + a_{31}PETR_{jt-1} + a_{32}PRPETR_{jt} + a_{33}PRGAS_{jt} + a_{34}HEAT_{jt} + \varepsilon_{Pjt},$$

where

$ELEC$ = per capita electricity consumption in state j
$NGAS$ = per capita natural gas consumption in state j
$PETR$ = per capita petroleum consumption in state j
$PRELEC$ = price of electricity in state j
$PRGAS$ = price of natural gas in state j
$PRPETR$ = price of petroleum in state j
$HEAT$ = reported heating degree-days for state j (in thousands)
$COOL$ = reported cooling degree-days for state j (in thousands)
t = time index for successive years.

All fuels are measured in millions of British thermal units (Btu), and average fuel prices are expressed in 1967 dollars per million Btu after being deflated by the nonfuel consumer price index. Annual energy consumption and price data for each of the lower 48 states are taken from the U.S. Department of Energy (DOE) State Energy Price and Expenditure Data System, covering the years 1970-82. All variables other than heating and cooling degree-days are used in logarithmic form.

The model represented by equations 1.1 through 1.3 differs in certain key respects from models in many other studies of residential energy consumption. First, given the high degree of multicollinearity between fuel prices and that each fuel often faces only one primary competitor, the consumption equation for each fuel includes only the own-price variable and the price of the fuel's major substitute. During the 1970-82 period, natural gas gained considerable market share from both electricity and petroleum. Consequently, the price of natural gas is used as the substitute price in the electricity and petroleum consumption equations, while the price of electricity is used as the substitute price for natural gas consumption.

Second, heating and cooling data are not equally important in explaining consumption of different fuels. Both heating and cooling degree-days were found to be statistically important in explaining electricity demand, but cooling data were not statistically important for natural gas or petroleum demand. The apparent insignificance of cooling data for natural gas and petroleum reflects, in large part, the dominant role of electricity in air-conditioning. Consequently, the final equations for the two fuels do not include cooling degree-days.

Third, per capita income is often used in residential energy demand studies but is not included here. The simulations presented in this article employ the assumption that residential energy consumption is a necessity and is not significantly affected by differences in per capita income across states (which tend to be small) or changes in average income over the time span of the sample. Exclusion of income from the model may be important, but when a variety of techniques were used, per capita income failed to provide significant explanatory power to the model.[6] While the lack of significance may appear surprising, it is not without precedent in energy demand studies.[7]

The price and quantity data taken from the DOE data set have the advantage of including periods of both increasing and decreasing real energy costs. Furthermore, the data exhibit substantial price and consumption variability across individual states and over time, making the estimation of price coefficients in the model more precise.

Residential consumption parameter estimates

Before the parameters in equations 1.1 through 1.3 were estimated, the equations were first tested for residual autocorrelation on a state-by-state basis. Given the lagged dependent variable, the presence of autocorrelation would render the estimates biased and inconsistent. Only 3 cases out of 144 revealed significant first-order positive autocorrelation at the 5-percent significance level. Therefore, the absence of autocorrelation in the errors was assumed in the pooled regressions.

Parameter estimates are obtained from a feasible generalized least squares regression procedure that pools the state-level data for the 12 time periods. A new procedure, described in the Appendix, was used for efficiently extracting information about the structure of the variance-covariance matrix. The procedure estimates a block

Table 1
REGIONAL CLASSIFICATION OF STATES

West	North Central	South	Northeast
Block 1	Block 4	Block 7	Block 10
Arizona	Minnesota	Arkansas	Maine
California	North Dakota	Louisiana	Massachusetts
Nevada	South Dakota	Oklahoma	New Hampshire
New Mexico	Wisconsin	Texas	Vermont
Block 2	Block 5	Block 8	Block 11
Idaho	Illinois	Alabama	Connecticut
Montana	Iowa	Florida	New Jersey
Oregon	Missouri	Georgia	New York
Washington	Nebraska	Mississippi	Pennsylvania
Block 3	Block 6	Block 9	Block 12
Colorado	Indiana	North Carolina	Delaware
Kansas	Kentucky	South Carolina	Maryland
Utah	Michigan	Tennessee	Rhode Island
Wyoming	Ohio	Virginia	West Virginia

diagonal error covariance structure that assumes that disturbances in states in the same regional block are related while errors in different regional blocks are not correlated. As discussed in the Appendix, traditional methods for the pooled estimation fail to use the available information efficiently.

The regional breakdown used in forming the disturbance covariance matrix is presented in Table 1. Covariances between disturbances in states within the same block were estimated, while errors in different blocks were assumed to be uncorrelated. The covariance estimates were then used to generate the final generalized least squares parameter estimates for equations 1.1 to 1.3.

All parameters, shown in Table 2, have the expected signs and are statistically significant. Also, the implied elasticities are within the range of estimates commonly reported by other researchers.

As shown by the coefficients on the lagged dependent variables, consumers take a long time to adjust to changes in energy prices. Reaction to a permanent increase in the exogenous variable would be only 50 percent complete after 6.6 years in the case of electricity and after 40.2 years and 10.7 years for natural gas and petroleum, respectively.[8] Consequently, changes in consumption are expected to occur slowly, especially in the case of natural gas consumption.

As shown in the lower panel of Table 2, the long-run price elasticities of consumption are generally high, reflecting the adjustment of households' capital stock to changes in energy costs. The short-run elasticities, on the other hand, indicate little response of consumption to price changes.[9]

The weather variables indicate sensitivity of consumption to temperature fluctuations. Electricity consumption rose in response to increases in both heating and cooling degree-days, while natural gas and petroleum consumption rose with increases in heating degree-days.

Although the results of the estimation are generally consistent with those of other studies, it is important to note that data limitations require such estimates to be treated with caution. Some preliminary evidence suggests that the parameters may not be stable over the whole time period. Behavioral changes in response to shortages generated by price controls and the large price movements in the 1970s may have increased the price elasticities of residential consumers. These effects, although not large, suggest that gains and losses to consumers resulting from deregulation may accrue more rapidly than indicated in the simulation experiments reported below.[10]

Table 2
ESTIMATED RESIDENTIAL ENERGY CONSUMPTION PARAMETERS

Variable	Electricity	Natural gas	Petroleum
	Dependent variables		
Intercept	-.0833 (-4.09)	-.0490 (-1.25)	-.7037 (-9.88)
Lagged dependent variable	.9006 (118.14)	.9829 (240.94)	.9372 (118.72)
Electricity price	-.1099 (-12.69)	.0358 (3.59)	
Natural gas price	.0164 (3.65)	-.0355 (-3.63)	.0639 (4.23)
Petroleum price			-.2601 (-12.45)
Heating	.1327 (10.72)	.0710 (3.69)	.1573 (4.60)
Cooling	.4926 (13.13)		
R^2	.98	.98	.97
Implied long-run elasticity			
Own price	-1.11	-2.08	-4.14
Cross price	.16	2.09	1.02

NOTE: Figures in parentheses are asymptotic *t* ratios.

Estimating price differentials

The consumption equations presented above can be used to simulate changes in energy consumption patterns, across states and among fuels, that result from changes in energy prices. Although it is assumed that the consumption equation parameters are identical for residential consumers in different states, regional consumption patterns and expenditures differ in the model because fuel prices and climate vary across states and because demands for energy sources involve long periods of adjustment. In this section, a set of equations is developed to model fuel price differentials in different states.

The forecasting model for price differentials is shown in Table 3. Percentage deviations for each state from average fuel prices across states are assumed to be determined by two factors. First, a constant is estimated for each state through the use of dummy variables. This constant represents a structural difference in fuel prices estimated from data for 1970 through 1982. Second, it is assumed that the process of adjusting price differentials through changes in the supply of or demand for different fuels takes time. Consequently, price differentials are assumed to have a lagged adjustment formulation.

The equation for petroleum price differentials includes two additional terms in order to capture the structural changes after 1978 that resulted from petroleum price deregulation. The first term, δ_1, is included to reflect any uniform percentage change across states in the magnitudes or

Table 3
STRUCTURAL DIFFERENCES IN FUEL PRICES AMONG STATES

Equation	Estimated relationships
2.1 . . .	$P_{e,i,t} = \alpha_i + .7392{*}P_{e,i,t-1}, \quad R^2 = .97.$
2.2 . . .	$P_{n,i,t} = \beta_i + .6422{*}P_{n,i,t-1}, \quad R^2 = .94.$
2.3 . . .	$P_{p,i,t} = \gamma_i + .0098{*}P_{p,i,t-1} - .86{*}D_t{*}\gamma_i + .32{*}D_t{*}P_{p,i,t-1}, \quad R^2 = .71.$

Variable definitions

P_e = percentage deviation from mean electricity price.
P_n = percentage deviation from mean natural gas price.
P_p = percentage deviation from mean petroleum price.
i = the state.
t = the year.
D = 0 before 1979 and 1 thereafter.

State	α_i	β_i	γ_i	State	α_i	β_i	γ_i
West				**South**			
Block 1				Block 7			
Arizona	3.47	-0.74	23.18	Arkansas	-1.10	-15.03	7.06
California	2.27	-8.63	23.80	Louisiana	-4.34	-7.25	31.96
Nevada	-4.82	-.62	10.45	Oklahoma	-3.69	-15.14	1.30
New Mexico	3.37	-9.31	9.05	Texas	-.90	-4.41	6.37
Block 2				Block 8			
Idaho	-17.15	4.49	3.03	Alabama	-2.97	-1.11	21.90
Montana	-12.58	-10.84	3.76	Florida	2.00	10.03	34.86
Oregon	-15.31	8.29	-12.11	Georgia	-2.63	-4.39	19.30
Washington	-25.07	6.33	-13.18	Mississippi	-1.96	-6.01	18.15
Block 3				Block 9			
Colorado	-1.37	-8.77	1.05	North Carolina	-1.60	2.17	-13.55
Kansas	-.70	-15.17	-3.80	South Carolina	-1.90	3.36	-3.75
Utah	-.89	-12.97	8.98	Tennessee	-9.14	-9.75	6.43
Wyoming	-9.44	-13.20	9.54	Virginia	1.18	4.51	-16.24
North Central				**Northeast**			
Block 4				Block 10			
Minnesota	-1.22	-4.06	-9.77	Maine	2.28	22.76	-12.40
North Dakota	-3.95	-5.97	-3.68	Massachusetts	9.06	15.45	-15.65
South Dakota	-3.24	-7.52	-3.25	New Hampshire	7.50	8.48	-12.22
Wisconsin	-.14	-.44	-14.12	Vermont	1.64	11.74	-10.59
Block 5				Block 11			
Illinois	3.86	-4.89	-11.48	Connecticut	8.46	16.89	-14.02
Iowa	.81	-7.10	-1.01	New Jersey	12.16	10.22	-15.65
Missouri	-1.13	-5.06	-.47	New York	12.23	8.50	-17.41
Nebraska	-5.61	-12.36	.05	Pennsylvania	4.80	-.29	-18.26
Block 6				Block 12			
Indiana	-3.01	-7.02	-10.65	Delaware	9.20	7.06	-13.99
Kentucky	-6.36	-11.09	12.41	Maryland	3.87	4.75	-15.33
Michigan	1.56	-5.34	-19.99	Rhode Island	9.79	14.61	-15.40
Ohio	1.49	-5.45	-16.00	West Virginia	-2.64	-5.71	-4.90

NOTE: Percentage deviation of price from mean is approximated by 100 times the difference in the logarithms of actual price and average price.

Table 4
PROJECTION OF MEAN ENERGY PRICES

Equation	Estimated relationships
3.1 . . .	$\ln(PELEC_t) = \underset{(-3.51)}{-1.29} + \underset{(3.02)}{.4450} \ln(PELEC_{t-1}) + \underset{(4.21)}{.0838} \ln(PCRUDE_t),$
	$R^2 = .92$; Durbin's h statistic $= .58$.
3.2 . . .	$\ln(PNATC_t) = \underset{(-.31)}{-.16} + \underset{(6.15)}{.8889} \ln(PNATC_{t-1}) + \underset{(1.80)}{.0967} \ln(PCRUDE_t),$
	$R^2 = .96$; Durbin's h statistic $= -.83$.
3.3 . . .	$\ln(PPETR_t) = \underset{(-16.55)}{-2.28} + \underset{(11.26)}{.5330} \ln(PCRUDE_t),$
	$R^2 = .93$; Durbin-Watson statistic $= 1.63$.

Variable definitions

PCRUDE = real price of crude oil at time *t*.
PELEC = real mean price of electricity for residential consumers.
PNATC = real mean price of natural gas for residential consumers.
PPETR = real mean price of petroleum for residential consumers.

NOTE: Figures in parentheses are asymptotic *t* ratios except those in equation 3.3, which are *t* ratios adjusted for degrees of freedom.
When testing for the alternative of positive first-order autoregressive errors, the critical value at the 5-percent level of significance in the Durbin *h* test is 1.645.
The upper bound and lower bound at the 5-percent level of significance in the Durbin-Watson test are .971 and 1.331, respectively.

directions of regional petroleum price differentials. The second additional term, δ_2, is included to capture any shift in the lagged adjustment parameter. The petroleum price deviation equation can be written as

$$(2) \qquad P_{i,t} = \gamma_i + \delta_1 \gamma_i D_t + \beta P_{i,t-1} + \delta_2 {}^* D_t {}^* P_{i,t-1} + \varepsilon_{i,t},$$

where $P_{i,t}$ is the petroleum price deviation for state i in period t, γ_i is the constant term for state i, D_t is a binary variable having a value of 1 after 1978 and 0 otherwise, and $\varepsilon_{i,t}$ represents the unobserved equation error. Notice that the equation is nonlinear because of the multiplicative interaction between δ_1 and the constant terms for each state.

The three equations in Table 3 were estimated as a system of seemingly unrelated regressions, using an iterative nonlinear procedure.[11] Several results in the table are noteworthy. First, electricity prices tend to be lower than average in the West and South and higher than average in the Northeast. These results reflect the availability of low-cost hydroelectric power in the West and the high cost of producing electricity in the Northeast with nuclear power and petroleum.

Second, the structure of prices reflects the competitiveness of suppliers in different regions. Areas with more than average shares of consumption of a particular fuel are observed to have lower than average prices for that fuel. For example, petroleum prices were lower than average for residential consumers in the Northeast. Because most energy transportation involves decreasing average unit costs at low volumes, natural monopolies tend to emerge in areas that use little of the particular fuel. As consumption rises, incentives for entry by other suppliers increase. Resulting competitive pressure reduces average prices for the fuel.[12]

Third, the estimated values of δ_1 and δ_2 in the petroleum price differential equation are of special interest. The estimates imply that petroleum price deregulation resulted in a 79-percent decrease in the long-run absolute value of the petroleum price differential in each state.[13] This result is consistent with the views expressed earlier concerning the dampening effect of deregulation on regional energy price differences.

The equations in Table 3 yield projections of price differentials for each state that deviate from a mean price path. Given a forecast of mean prices for each period, the equations in Table 3 can be used to calculate the percentage deviation of each fuel price from that mean to arrive at a state-specific fuel price.

Simulation design

The equations in Table 3 provide a convenient method for testing the effects of deregulation. By reducing the magnitude of the constant terms and the lagged adjustment parameter in a given price equation, price differentials across states can be proportionately lowered. By reducing the intercept for each state by a constant percentage, prices could continue to differ across states—reflecting transportation costs—but the differences would be squeezed. Simultaneously reducing the value of the coefficient on the lagged dependent variable would allow more rapid adjustments in price differentials.

Furthermore, it is assumed that the estimated effects of petroleum price deregulation, as indicated by δ_1 and δ_2 in the petroleum price differential equation, can be applied to the cases of natural gas and electricity price deregulation. Therefore, in the simulations of the effects of natural gas and electricity deregulation presented later, the constant terms in the equations for natural gas and electricity price differentials are reduced by 86 percent, reflecting the estimate of δ_1, and coefficients on the lagged dependent variables are set at 0.33, reflecting the value of the lagged adjustment parameter in the petroleum price equation after petroleum price deregulation.

Several important qualifications deserve mention at this point. First, the simulation strategy assumes that the effect of deregulation on state price differentials is similar in the case of all fuels. Although important differences are likely to exist in these effects, such differences are ignored to keep the model tractable and because obvious alternative specifications are lacking. Second, it is conceivable that the oil price shock of 1979 resulted in a decline in petroleum price differentials between states. Because δ_1 and δ_2 are assumed to measure only regulatory effects and cannot separate out the effect of the price shock on conservation, the simulation results could be overstating the effects of deregulation.

Forecasts of mean energy prices are accomplished with the use of the equations presented in Table 4, which were estimated by ordinary least squares. It is assumed that crude oil prices are exogenously determined. It is also assumed that all other fuel prices are ultimately driven by crude oil price movements. As observed in the recent oil price decline, petroleum product prices fell rapidly, and downward pressure was observed on natural gas and electricity prices. Because of the direct physical relationship between crude oil and petroleum products, the full effect of crude oil prices on petroleum product prices is assumed to occur in a single year. Electricity and natural gas prices also change with oil prices, but the process takes more time—particularly in the case of natural gas, where the large coefficient on the lagged dependent variable reflects the long-term nature of natural gas contracts.

Three scenarios are considered in examining the potential effect of deregulation. First, a base case is developed. Crude oil prices are assumed to follow their historical values through 1985 and then to take on a value of $15 per barrel in 1986. That price is assumed to remain constant, in real terms, through the year 2000.[14] The equations in Table 4 translate this exogenously determined crude oil price path into paths for the mean price of each of the residential fuels. These paths, combined with forecasts provided by the equations in Table 3 of the deviations from mean in the price for each of the three fuels, produce state-specific projections for residential fuel prices through the year 2000. Finally, these price projections are translated into projections for consumption of each of the three fuels in all 48 states by using equations 1.1 through 1.3 and the coefficients in Table 2. The heating and cooling variables are set at their mean values in the simulation for all periods.

In the second simulation, the effects of deregulation of natural gas prices are examined.[15] The simulation procedure is identical to the procedure used in the base case, except the constants listed in Table 3 are reduced by 86 percent in the natural gas price deviation equation and the coefficient on the lagged dependent variable in this equation is set at 0.33.

In the third simulation, bulk electricity deregulation is proxied by reducing the constants for each state in the electricity price deviation equation by 86 percent and setting the coefficient on the lagged dependent variable at 0.33. Because natural gas prices were deregulated in 1985, the previously mentioned modifications to the natural gas price deviation equation associated with simulating natural gas deregulation are again employed.

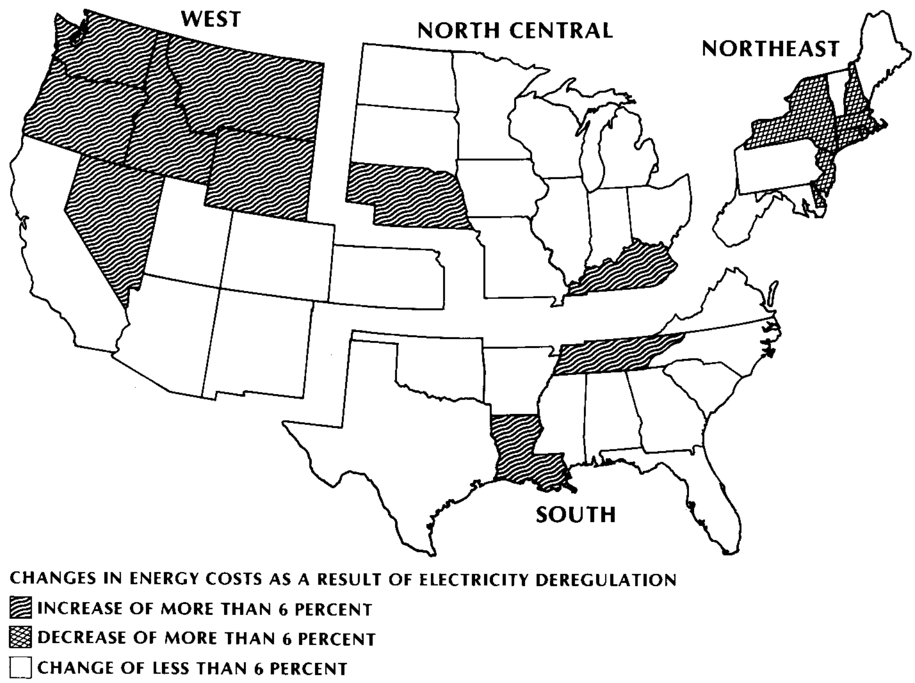
Consequently, comparison of scenarios 1 and 2 allows evaluation of the expected effect of past deregulation of natural gas prices. Comparison of scenarios 2 and 3 factors in the additional distributional effects that might occur if electricity is also deregulated.[16]

Table 5
EFFECT OF ENERGY PRICE DEREGULATION ON RESIDENTIAL ENERGY EXPENDITURES
(Percentage changes in total expenditures)

State	Energy prices deregulated: Electricity, natural gas	Energy prices deregulated: Natural gas	State	Energy prices deregulated: Electricity, natural gas	Energy prices deregulated: Natural gas
West			**South**		
Block 1			Block 7		
Arizona	-4.57	0.30	Arkansas	10.77	9.20
California	4.04	7.13	Louisiana	9.93	3.61
Nevada	6.95	.39	Oklahoma	15.27	9.86
New Mexico	3.04	7.30	Texas	3.24	2.17
Block 2			Block 8		
Idaho	24.44	-2.20	Alabama	4.66	.55
Montana	26.18	8.62	Florida	-5.54	-2.52
Oregon	17.79	-4.26	Georgia	6.19	2.47
Washington	36.48	-3.17	Mississippi	5.64	2.83
Block 3			Block 9		
Colorado	9.23	7.56	North Carolina	1.28	-.92
Kansas	13.25	12.42	South Carolina	1.50	-1.29
Utah	12.90	11.80	Tennessee	19.06	4.45
Wyoming	24.08	11.31	Virginia	-3.77	-2.32
North Central			**Northeast**		
Block 4			Block 10		
Minnesota	4.78	3.34	Maine	-12.12	-9.98
North Dakota	9.06	4.00	Massachusetts	-19.39	-11.58
South Dakota	8.98	4.93	New Hampshire	-11.98	-4.56
Wisconsin	.45	.32	Vermont	-7.13	-5.47
Block 5			Block 11		
Illinois	.29	4.79	Connecticut	-18.43	-10.60
Iowa	4.78	5.72	New Jersey	-19.16	-7.90
Missouri	5.36	3.80	New York	-18.19	-6.78
Nebraska	17.90	10.07	Pennsylvania	-4.89	.25
Block 6			Block 12		
Indiana	9.61	5.79	Delaware	-14.07	-4.24
Kentucky	16.27	7.20	Maryland	-7.43	-3.15
Michigan	3.75	5.34	Rhode Island	-19.47	-10.84
Ohio	3.09	4.91	West Virginia	7.80	4.20

NOTE: Expenditures are defined as the discounted real value of per capita consumer spending on residential electricity, natural gas, and petroleum from 1986 through the year 2000.

Effects of Electricity Deregulation



Simulation results

Results from the simulation experiments are presented in Table 5. For each state, the present discounted value of real energy expenditures for 1986 through 2000 is calculated under the three scenarios, using a real discount rate of 4 percent. This discounted value of expenditures will be referred to simply as expenditures. Differences in expenditures between the two deregulation scenarios and the base case are then reported in the table for each state.

As shown in Table 5, deregulation of gas prices alone results in higher expenditures for 31 states and lower expenditures for the remaining 17 states modeled. The major gainers are in the Northeast, where natural gas prices fall under deregulation in most states. In contrast, the largest losers are in the North Central areas and the energy-producing areas of the West (California, New Mexico, and most of Block 3) and South (Block 7 in particular), where natural gas prices rise and cause total expenditures to rise.

Deregulating electricity as well as natural gas results in 14 states having lower costs and the remaining 34 facing higher costs, as shown in Table 5. Gains to the Northeast from natural gas deregulation are strengthened by electricity deregulation, while gains in the Northwest (mostly Block 2 states) are dramatically reversed.

To understand the changes from the scenario in which only natural gas is deregulated, it is helpful to look at the incremental effects of electricity deregulation. Winners and losers from deregulating electricity and gas, instead of only gas, are shown in the accompanying map. Apparently, major gainers are in the Northeast, while the largest losers are in the Northwest. In the Northeast, states rely on high-cost nuclear or petroleum-fired generators, and electricity deregulation results in lower electricity costs. In the Northwest, electricity deregulation has a large positive impact on electricity prices. This area, especially Washington, has had low electricity prices as a consequence of plentiful low-cost hydroelectric power.

In general, the results confirm the view that residential consumers in energy-producing areas stand to lose the most from deregulation. Conversely, consumers in energy-importing areas can be expected to enjoy lower costs.

Such conclusions, however, depend on important assumptions used in the model. In particular, the assumption that mean price paths are not affected by the regulatory environment may bias the results. Modeling the influence of regulations on the supply of energy is subject to considerable uncertainty. Nevertheless, it is usually assumed that deregulation will lead to greater supply at lower prices than would be forthcoming under a regulated environment. In support of this view, a recent study concludes that the average price of electricity is 33 percent lower with competition than with a monopoly structure.[17] If mean prices are indeed reduced by deregulation, losses reported in the simulations would be overstated and gains would be understated. The pattern of relative losers and gainers, however, would be largely unaffected.

In light of these considerations, additional simulations were conducted to lower the mean price for a deregulated fuel by 33 percent in each period while also altering regional price differentials in the manner described above. After incorporation of the assumption that deregulation reduces mean prices as well as state differentials around those mean prices, deregulation of natural gas prices alone results in lower expenditures for all 48 states, while deregulation of gas and electricity prices results in lower expenditures for every state except Washington. For Washington, expenditures rise 8.17 percent, in contrast to 36.48 percent when only regional price effects are allowed for in the simulations. Although every state except Washington has a decrease in expenditures in this new round of simulations, the decrease is larger for states identified as posting decreases in expenditures in Table 5.

Conclusions

Several important conclusions emerge from the simulation results. First, deregulation is likely to lead to measurable distributional effects on expenditures by residential consumers. Consumers in the Northeast have the most to gain by such legislation, while those in the West have the most to lose, especially if electricity prices are deregulated.

Second, and in contrast, producers of electricity in the West have the most to gain by deregulating bulk power transmissions. Because of their cost advantages, sellers of bulk electric power in the Northwest could increase profits by selling in a national market, while those in the Northeast would see lower profits.

From a public policy perspective, a deregulated environment is likely to exhibit far less dramatic distributional consequences in response to future energy price shocks. Unlike the situation in the 1970s, when lack of price movement caused shortages in some fuels that imposed severe hardships on certain regions, prices can be expected to be much more responsive to changes in world oil prices. Also, increased competition among fuels will probably provide a mechanism to limit price movements in any one fuel. In general, the impact of an energy price shock can be expected to have a more even effect on residential consumers throughout the nation than was the case with regulated prices.

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1. Residential energy consumption covers fuels used in the home for space heating, cooking, and power. It does not include consumption outside the home, such as gasoline for transportation.

2. The incidence of changes in energy costs considered in this article is limited to effects on direct expenditures of residential consumers. Other distributional consequences, such as effects on income and wealth, are outside the scope of this study. For a recent examination of the effect of changes in natural gas price deregulation on the regional distribution of wealth, see Joseph P. Kalt and Robert A. Leone, "Regional Effects of Energy Price Decontrol: The Roles of Interregional Trade, Stockholding, and Microeconomic Incidence," *Rand Journal of Economics* 17 (Summer 1986): 201-13.

3. Nominal expenditures were adjusted for inflation by using the nonfuel consumer price index.

4. See Paul L. Joskow and Richard Schmalensee, *Markets for Power: An Analysis of Electric Utility Deregulation* (Cambridge: MIT Press, 1983).

5. See Roger H. Dunstan and Ronald H. Schmidt, "Structural Changes in Residential Energy Demand" (Federal Reserve Bank of Dallas, April 1986, Photocopy).

6. See Dunstan and Schmidt, "Structural Changes in Residential Energy Demand."

7. See James G. Beierlein, James W. Dunn, and James C. McConnon, Jr., "The Demand for Electricity and Natural Gas in the Northeastern United States," *Review of Economics and Statistics* 63 (August 1981): 403-8.

8. These figures are calculated as $T = \ln(.5)/\ln(\beta)$, where β is the estimated coefficient on the lagged dependent variable.

9. The short-run elasticities are equal to δ, and the long-run elasticities are equal to $\delta/(1 - \beta)$, where δ is the coefficient on the respective price variables and β is the coefficient on the lagged dependent variable.

10. For a discussion of possible changes in the structural parameters, see Dunstan and Schmidt, "Structural Changes in Residential Energy Demand."

11. For a discussion of the iterative generalized least squares procedure used, see SAS Institute Inc., *SAS/ETS User's Guide, Version 5 Edition* (Cary, N.C.: SAS Institute Inc., 1984), 505-50.

12. The lower than average prices for the fuel in areas that are heavier users indicate two forces at work. First, as a causal factor, lower costs encourage the consumption of that fuel. Second, because some degree of monopoly power exists in the residential energy market, more intensive use of one particular fuel encourages more competition in the areas to bid away the monopoly rent.

13. The long-run price deviation for a particular state is calculated as $\theta/(1-\beta)$, where θ is the estimated constant term for the state and β is the estimated lagged adjustment parameter. The estimated interactive terms show that after deregulation, each of the constant terms in the petroleum price deviation equation was reduced by 86 percent while the value of the lagged adjustment parameter increased from 0.01 to 0.33. The combined effect of these changes on the long-run price deviations for each state is then easily calculated.

14. Because of the design of the experiments, the results are invariant to the path specified for crude oil prices. Allowing higher oil prices, for example, increases the present value of total expenditures significantly for all states, but the percentage differences in expenditures *between* scenarios are not affected.

15. The simulation strategy captures only the effects of narrowing price differentials across states. Other possible consequences of deregulation, including other changes in the consumer and market behavior modeled by the parameter estimates of the various equations used in the simulations, are not addressed.

16. The simulation methodology does not allow for asymmetries in the effects of deregulation on energy prices in low-cost and high-cost areas. For example, it could be argued that although high-cost areas would have reductions in prices as barriers to entry are removed and low-cost producers expand their product markets under deregulation, low-cost areas would not have increases in prices, or at least not of the same magnitude. Upward pressure on prices in low-cost areas, stemming from suppliers widening their product markets into high-cost areas, could be offset by increases in supply. Insofar as such considerations are pertinent, the simulated effects of deregulation on expenditures in energy-producing areas should be viewed as upper bounds.

17. See Walter J. Primeaux, Jr., "Estimate of the Price Effect of Competition: The Case of Electricity," *Resources and Energy* 7 (December 1985): 325-40.

Appendix

Pooled Estimation with a Block Covariance Structure

Estimation of parameters for residential energy consumption equations typically assumes that the disturbances can be specified in the structure of an error components model. An error components model assumes that the variance of the disturbance is the same for all states, that the correlation between disturbances for a given state across time is unchanged no matter how far apart in time the disturbances are, and that the contemporaneous covariance of disturbances across states is the same for all states.[1]

Formally, the error components model assumes the following relationships among disturbances:

(A.1)
$$\begin{aligned} E(e_{it}) &= 0, \\ E(e_{it}e_{js}) &= 0 \text{ for } i \neq j \text{ and } t \neq s, \\ &= \sigma^2 \text{ for } i = j \text{ and } t = s, \\ &= \sigma_\lambda^2 \text{ for } i = j \text{ and } t \neq s, \\ &= \sigma_\mu^2 \text{ for } i \neq j \text{ and } t = s, \end{aligned}$$

where i and j are states and t and s are time periods.

The main computational advantage of the error components model derives from the strict set of assumptions imposed on the disturbance structure. Only three parameters need to be estimated to complete the variance-covariance matrix. This is a particular advantage for the current application, given the limited number of time series observations available. The weakness of the error components model for the present study, however, is that the model forces the disturbance covariances among all states to be the same and, so, ignores information about regional similarities and differences.

An alternative approach is to allow disturbance covariances and variances to differ for each state, using the estimation method described by Arnold Zellner and Richard Parks.[2] Under this methodology, separate covariances are estimated for each pair of cross sections. However, not all disturbance variances and covariances can be estimated for a pooled regression where the number of cross sections is larger than the number of time series observations. In such cases, the estimated full disturbance variance-covariance matrix is singular.[3]

This estimation problem presents itself in the study here because only 12 time series observations are used for each of the 48 states. The usual procedure in such cases is to estimate separate disturbance variances for each state and to assume that there is no correlation of the disturbances across states. This "heteroskedasticity" model fails, however, to capture many of the important correlations among states.

An alternative method, used in the study here, improves on the heteroskedasticity model by grouping the states in regional blocks with the following disturbance structure:

(A.2)
$$\begin{aligned} E(e_{ivt}) &= 0, \\ E(e_{ivt}e_{jws}) &= 0 \text{ for } t \neq s, \\ &= \sigma_i^2 \text{ for } i = j, \\ &= \sigma_{ij} \text{ for } i \neq j \text{ and } v = w, \\ &= 0 \text{ for } v \neq w, \end{aligned}$$

where v and w are the regions to which states i and j belong. The disturbance structure in (A.2) allows variances to differ across states and assumes that disturbances in states within the same region are correlated but errors in states in different regions are not correlated.

Inclusion of nonzero correlations between states in the same region results in parameter estimates that are significantly more efficient (that is, they have smaller variances) than those in the heteroskedasticity model, as long as the disturbances in these states are actually contemporaneously correlated. Furthermore, this technique incorporates considerably more information in the variance-covariance matrix than does the error components model, which has only three estimated parameters. Insofar as the correlations of disturbances across states depend on identifiable factors, such as the geographical proximity of states (that is, the correlation between disturbances in Washington and Oregon is probably greater than that between disturbances in Washington and Georgia), the block covariance structure in (A.2) is less restrictive than the structure in (A.1).

In this study, the states were divided into 12 regional blocks, each containing 4 states. Theoretically, estimation would have been possible if the states were divided into 4 regional blocks, each containing 12 states. This strategy would have allowed estimation of a greater number of covariance terms than the one employing 12 regional blocks. However, estimation of disturbance covariance terms for states in which the disturbances are actually not correlated results in a decrease in efficiency for estimates of the effects of the explanatory variables on energy consumption.[4] Therefore, only covariance terms that are, on the basis of prior economic information, likely to be significantly different from zero should be estimated.

Energy consumption not explained by the model is likely to be correlated only among states with similar energy industry structures. States exhibiting these similarities tend to be small in number and closely situated geographically, such as the electricity-producing states of the Northwest.

Pretests of the significance levels of the estimated disturbance correlations across states confirmed these priors, revealing that the disturbances were, in most cases, highly correlated across states only within small geographical regions. Therefore, the states were grouped according to regional similarities, and only four states were included in each region. The regional breakdown is presented in Table 1 in the preceding text.

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1. For a discussion of the error components model, see Thomas B. Fomby, R. Carter Hill, and Stanley R. Johnson, *Advanced Econometric Methods* (New York: Springer-Verlag, 1984), 334-36.

2. See Arnold Zellner, "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias," *Journal of the American Statistical Association* 57 (June 1962): 348-68; and Richard W. Parks, "Efficient Estimation of a System of Regression Equations When Disturbances Are Both Serially and Contemporaneously Correlated," *Journal of the American Statistical Association* 62 (June 1967): 500-509.

3. See Henri Theil, *Principles of Econometrics* (New York: John Wiley & Sons, 1971), 310.

4. See Fomby, Hill, and Johnson, *Advanced Econometric Methods*, 164-66, for a discussion of issues related to this consideration.

Understanding the Texas Unemployment Rate

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Even though the Texas economy expanded rapidly during the 1970s and early 1980s, the state's average unemployment rate rose. At the same time, however, the U.S. unemployment rate rose faster than the state's, causing the ratio of the Texas unemployment rate to the nation's to fall. Despite this decline, both Texas' and the nation's series generally moved up and down at about the same time.

These various facets of the state's unemployment rate raise questions about the nature of Texas' growth during this period. Why did the average unemployment rate in Texas increase? Was it because Texas' economic growth was accompanied by growing instability in demand for labor? Or was increasing U.S. joblessness simply pushing workers displaced in other parts of the nation into the Texas job market rapidly enough that the state could not absorb its new immigrants into the workforce? Further, was unemployment in Texas linked to economic events in Mexico and to resultant increases in immigration?

In attempting to answer these questions, this paper assesses the effects of aggregate business cycle fluctuations in the United States and Mexico upon the match between Texas jobs and Texas workers available. Also shown is that even when the overall U.S. economy is growing, permanent shifts in the relative demands for labor by each economic sector in the nation can increase the unemployment rate in Texas. In addition, the paper examines the response of Texas' aggregate output to world economic events, together with the impact on the state's unemployment rate. Attention is given to the impact of changes in the Texas industrial structure upon the volatility of employment in the state. The analysis here links increasing employment volatility to a rising average unemployment rate in Texas.

These influences are captured in a single-equation model that is able to explain a large portion of the total variation in the Texas unemployment rate. Using the estimation derived from the model for the sample period (1970.I-1981.IV), the Texas unemployment rate was simulated for later periods.

The model demonstrates that aggregate business cycle fluctuations in Mexico and in the United States have significant impacts on fluctuations in the Texas unemployment rate. Fluctuations in aggregate output in Texas likewise strongly affect the state's unemployment. Over the sample period, a measure of fluctuations in U.S. aggregate output was shown to explain more variation in the Texas unemployment rate than did any other explanatory variable considered.

Permanent U.S. realignments of relative demand for labor among industries were found to strongly affect the rate of unemployment in Texas. Even when national economic growth is occurring, if a U.S industry goes into a long-term decline, some of its laid-off workers are likely to swell the ranks of the unemployed in Texas.

Although the shift in Texas' industrial structure from a low-employment volatility to a higher one also affected the state's average unemployment rate, this transformation had the smallest impact on unemployment variation of any factor considered during the sample period.

Although the sample period was characterized by high rates of economic growth in Texas, out-of-sample predictions show that much of the state's unemployment variation during both the economic downturn of 1982 and the subsequent economic weakness of 1983 is captured by this model.

Texas employment and unemployment in the 1970s and 1980s

During the 1970s and early 1980s, the economy of Texas grew faster than that of the nation, with the Texas gross state product growing slightly more than twice as fast as U.S. gross national product for the 1970-80 period.[1] For the same period, nonagricultural employment in Texas grew one and two-thirds as fast as that for the United States. As Texas' employment rose during this period, the state's population also expanded more rapidly than the national population in a ratio of 27.1 percent to 11.4 percent.

The takeoff in Texas growth was part of a transformation of the industrial structure of the United States which occurred because of realignments in the prices of various goods and services. In Texas, the most obvious realignment was the rapid rise in energy prices relative to others. Texas was well equipped to benefit from this realignment, not only because of its energy reserves but also because of its human capital.

Even in 1970, Texas had a relatively high proportion of total employment in oil and gas extraction, oilfield equipment, and other energy-related industries. In comparison to Texas' 5.1 percent of total U.S. nonagricultural employment, the state showed a 36.0-percent share of U.S. oil and gas extraction employment and a 65.7-percent share of U.S. oilfield equipment employment. In addition, the state still had a potential for further development of its energy resources, as well as a well-developed set of extraction and extraction-related industries capable of serving world markets.

The state experienced not only a rapid overall growth in employment but also a shift in the shares of employment by industry. For the decade 1970-80, the share of total nonagricultural employment in Texas due to oil and gas extraction rose from 2.7 percent to 4.0 percent, and that for oilfield equipment increased from 0.8 percent to 1.1 percent, while the share of nonagricultural employment in food products manufacturing fell from 2.3 percent to 1.7 percent.

Significant shifts in employment shares also occurred in other states and in nonenergy sectors. The share of durable goods employment in the United States fell, while the shares of services and of mining employment rose. Overall, the decade of the 1970s was particularly susceptible to extended sectoral shifts of employment for both Texas and the United States.

While Texas employment and population grew rapidly during this period, the average unemployment rate for Texas rose. As Chart 1 shows, for both Texas and the nation, the average unemployment rate for the period 1976-80 was clearly above the average for 1970-75. Nevertheless, the U.S. average unemployment rate rose more rapidly than that of Texas. With the rapid rise of industries nationally—with disproportionately large shares of employment in Texas—the unemployment rate for the state fell relative to that of the nation (see Chart 2). The Texas unemployment rate relative to the national rate fluctuated a good deal during the 1970s and 1980s, but this ratio generally declined during the 1970s.

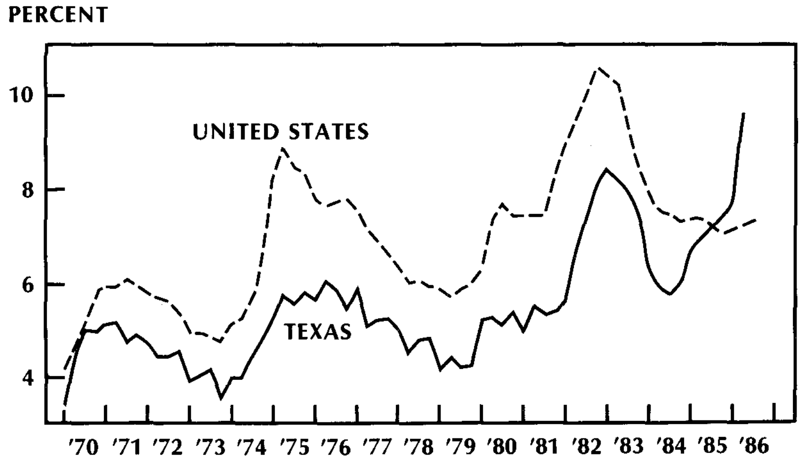
Despite the perception of some that the state of Texas was "recession-proof" during this period, unemployment rates moved more or less in tandem with the nation. Chart 1 demonstrates that while Texas' unemployment rate remained below the nation's until 1984, the movement in the Texas rate generally reflected national economic patterns, including unemployment shifts up or down, though with a lag.

Why unemployment rates change

Changes in the natural rate. The causes of unemployment rate changes are complex. Some unemployment is always present—even in periods of economic growth—because of fluctuations in demand for individual products and in the cost of inputs to production. Economists have defined this rate of unavoidable unemployment as the "natural rate" of unemployment.[2]

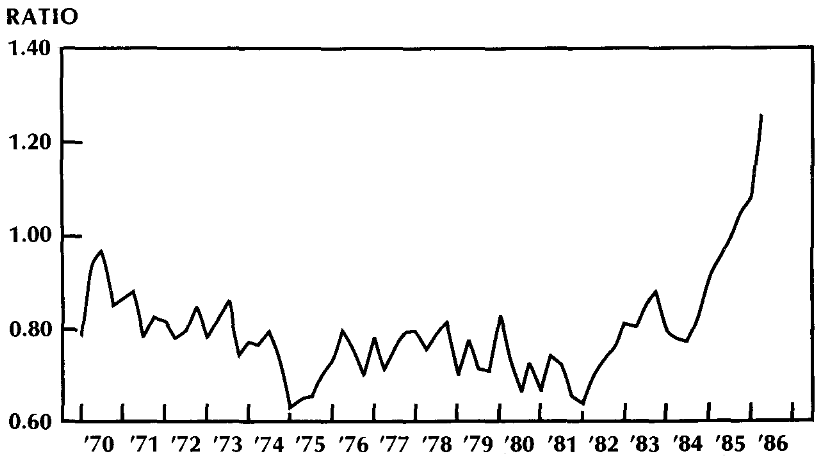
The natural rate may be defined also in terms of its relationship to wage changes as one at which there is neither upward nor downward pressure on the rate of change in wages. Because the rate of increase in wages moves closely with the overall rate of inflation, it is not unusual to consider the natural rate of unemployment as having neither upward nor downward pressure on the rate of inflation. Many

Chart 1
Texas and U.S. Unemployment Rates



SOURCE OF PRIMARY DATA: U.S. Department of Labor.

Chart 2
Ratio of Texas to U.S. Unemployment Rates



SOURCE OF PRIMARY DATA: U.S. Department of Labor.

economists traditionally have viewed fluctuations in the overall unemployment rate as deviations from a natural rate that varies little over time.[3] That is, when sales slump overall, workers are laid off and the jobless rate rises; and when sales rise, some of the jobless are hired, and the unemployment rate falls. These movements in the unemployment rate are seen as the normal and expected results of upswings and downswings in the business cycle. But if the natural rate has not changed, a particular ratio of actual to potential GNP will be associated with some particular rate of unemployment. For example, the unemployment rate that occurs when actual GNP equals potential GNP will be about the same, no matter when this event occurs.

Some economists recently have begun to offer a different explanation for unemployment rate fluctuations, although the concept is also linked to the idea of a natural rate. They claim that a portion of what traditionally have been considered cyclical movements in the unemployment rate are actually fluctuations in the natural rate.[4]

In one version of this explanation, the natural rate rises when permanent shifts in relative labor demands across economic sectors induce workers from one industry to seek jobs in another. Transitory, rather than permanent, shifts in relative demands for labor across sectors are normal characteristics of the business cycle, but the stress on the permanent component of such shifts is important. For example, an aggregate cyclical downswing usually has a more profound impact on capital goods industry employment than on services employment. The consequence of a cyclically generated decline in the capital goods share of overall employment is, technically speaking, a sectoral shift. But this is simply a result of the particular way in which an overall economic downturn generally hits a certain industry—capital goods. In this case, though unemployment may rise because of job losses in capital goods, this increase does not signal a change in the natural rate of unemployment. It only marks the the rise of overall unemployment to a point above the natural rate. (We refer to sectoral shifts that are normal to the business cycle as "transitory" because when the economic downswing ends and the upswing gets under way, the industry in question will regain its former share of workers.)

When a sectoral shift is permanent, however, workers who have lost their jobs because of weakness in a given industry will not be rehired in that industry. A permanent shift thus persists in the face of aggregate growth or declines.

A permanent sectoral shift in demand for labor affects the unemployment rate because the job search process is time-consuming and costly. If an industry undergoes a permanent downturn, its laid-off workers require time to find and take new jobs. When workers have skills that are not easily transferable from one firm or industry to others, they may be slow to take employment in other sectors of the economy. The most quickly available new job may not use the skills which the worker developed in his old firm and thus may pay a lower wage rate than the employee formerly received.

A permanent sectoral shift in demand for labor causes a temporary increase in the natural rate of unemployment. This increase in the overall rate of unemployment is independent of the traditional, aggregate demand-generated effects of the business cycle. It is possible, then, to have economic growth and rising unemployment at the same time. Overall economic growth does not preclude a permanent downshift in the demand for one industry's products or the sudden rise of another's. Because they disrupt the traditional relationship between a given rate of economic growth and a given rate of unemployment, permanent sectoral shifts are seen as temporarily altering the natural rate of unemployment rather than the cyclical rate.[5]

Thus far, only the temporary effects of a permanent sectoral shift have been discussed. A permanent sectoral shift, however, can have both permanent and temporary effects. When a permanent sectoral shift induces workers to seek new jobs, its unemployment effect is over when all searchers find work. Thus, this effect is temporary. The more permanent effect of a sectoral shift is a changed industrial structure. This change in industrial structure may also have a significant effect upon a state's patterns of unemployment fluctuations. Specifically, such a change can affect the unemployment effects of the business cycle. Paradoxically, the permanent effect of a sectoral shift can be a change in the cyclical patterns of unemployment itself.

Changes in employment variability. As is well recognized, differences in industrial structures—either over time or across states—can correspond to differences in average unemployment rates. Because the demands for capital goods tend to fluctuate more than those for services, a capital goods worker may be more likely to work overtime than a service worker during an upswing in the business cycle. For the same reason, during a downswing, a capital goods worker might be more likely to be unemployed than would a service worker. Furthermore, because of the relatively great heights of upswings and the depths of downswings in capital goods industries, the average period of time unemployed over the business cycle is likely to be greater for workers in these industries than for those in service industries. A capital goods firm may compensate workers at a higher rate than does a service firm, given comparable skill levels, in order to adjust for their relatively high risk of being unemployed. Even so, the introduction of capital goods industries into a region—or expansion within it—may, other things being equal, result in a higher average rate of unemployment. In general, the states dominated by industries with high employment variation are also likely to have higher average unemployment rates than those whose industries have low employment variation.

When there are several industries in a state, the timing of their individual employment variations is also linked to the state's average unemployment rate. If all industries in a state lay off workers at the same time, it is particularly difficult for workers from one industry to find jobs in another within the state. The average unemployment rate in such states is likely to be higher than in those where some industries are tending to lay off workers at times when other local industries are adding to their workforces. It is common to refer to states with industries whose downswings tend to occur simultaneously as having high employment covariance.

States with both high employment variance and high employment covariance are said to have high *employment portfolio variance*. Differences in the degree of employment portfolio variance not only can occur across states at a point in time but also may differ within a state over time. When industries with a high variance or covariance grow more rapidly than industries with low variance or covariance, the portfolio variance of the state will rise. As the portfolio variance of a state rises, so does its average unemployment rate.

Because these explanations of unemployment rate fluctuations are general, they must be tailored to the particularities of the Texas experience. In the following section, these explanations are related to the fluctuations of the Texas unemployment rate during recent years.

Explaining the Texas unemployment rate

The Texas economy is a small, open economy affected by national and world events. As an open economy within the United States, the state is naturally affected by fluctuations in income and output that occur in the larger, national economy. Because of its geographic location and industrial structure, the Texas economy is also influenced by economic growth and contraction in Mexico. Nevertheless, Texas' industrial mix, legal structure, and portfolio of natural and human resources make it sufficiently different from either the rest of the United States or Mexico that the state's economic fluctuations are not identical with those of either. The Texas unemployment rate thus is influenced by fluctuations in the aggregate supply of, and demand for, goods and services in the United States and in Mexico as well as by those that occur within the state itself.

U.S. aggregate business cycle fluctuations and Texas unemployment

U.S. aggregate business cycle fluctuations have a strong effect on Texas' unemployment. When upturns in the U.S. business cycle occur, this expansion generally pushes up demand for Texas' products, thus fueling employment increases. But if the labor force does not expand in the state faster than the increase in employment, the unemployment rate falls.

Even if growth in the United States occurs but does not result in increased demand for Texas' particular mix of products, unemployment can fall in Texas because U.S. expansion also increases demands for labor in areas of the country outside Texas. In this case, workers outside Texas become less prone to leave other portions of the United States to seek work in Texas. Conversely, Texas workers become more prone to leave the state for jobs elsewhere. Even if the demand for labor does not change in Texas because of U.S. economic growth, the supply of labor will. In sum, when U.S. aggregate output growth occurs, both supply and demand effects are likely to lower the unemployment rate in Texas.

Similar effects of Mexican aggregate output fluctuations

Similar arguments apply to Mexico's impact on Texas unemployment. Mexico shares a border of more than a thousand miles with Texas. Mexican consumers come to Texas to buy a wide array of Texas consumer goods and services. Mexico imports oilfield equipment and other Texas-made capital goods, as well as Texas agricultural products. Thus, not only Mexican demand for goods and services but flows of Mexican labor influence the Texas unemployment rate. The length and porosity of Texas' border with Mexico also mean that the arrival and departure of Mexican workers, both legal and illegal, are daily events of considerable magnitude. When economic growth occurs in Mexico, the expansion generally means an increase in demand for Texas products and a consequent increase in the demand for labor in Texas. Again, the state's unemployment rate will fall unless the labor supply increases more rapidly than the upturn in Texas employment.

Even if upturns in Mexican income and output do not translate into an increase in demand for Texas' output, they do imply an expansion in the demand for labor in Mexico. Then, if the supply of Mexican workers to Texas diminishes, other things being equal, the Texas labor force also declines. The Texas unemployment rate thus could still fall. In the event of a downturn in the Mexican economy—and reduced employment opportunities—more Mexican workers would come to Texas. But if the Texas labor demand were insufficient to absorb the increase, the Texas unemployment rate would rise.

Aggregate output fluctuations in Texas

An additional aggregate effect is specific to Texas. Texas' endowment of natural resources, its institutional structure, the characteristics of its labor force, and the extent and nature of its entrepreneurship all provide comparative advantages for some types of products but not for others. In part, because the portfolio of industries in which Texas has a comparative advantage is different from that of the United States or Mexico, the state's individual components of overall aggregate output are different. Consequently, the Texas business cycle does not coincide exactly with those either of the United States or Mexico. For example, Texas can be in the growth portion of its cycle while the United States is in a slump. Conversely, while the U.S. aggregate output is growing, the particular attributes that characterize the Texas economy can put it in the recessionary portion of its cycle.

To account fully, therefore, for the influence of business cycles on the Texas unemployment rate, it is necessary to model both the Texas business cycle and the aggregate U.S. and Mexican business cycles. The usefulness of considering the state's business cycle as separate from the nation's has become particularly evident in 1986 when the aggregate growth for the United States has been accompanied by aggregate declines in Texas output.

Permanent sectoral shifts affecting Texas unemployment

If the sectoral shift theorists are correct, the influence of U.S. economic events upon the Texas unemployment rate is not limited to national aggregate fluctuations. Even in periods of economic growth, national permanent sectoral shifts can result in a rising U.S. unemployment rate. When changes in costs, tastes, or technologies force long-lived rearrangements of the distribution of demand for labor among industries, these changes are likely to affect such distributions throughout the country. In the wake of a permanent sectoral shift, displaced workers search for employment in industries where they have not worked before. In their search, some of these workers are likely to move across state boundaries, and in Texas they cannot always immediately find jobs. With a national permanent sectoral shift, then, the unemployment rate in Texas could rise.

Employment portfolio variance increases in Texas

Finally, growth in portfolio variance is linked to the long-term increases in the average Texas unemployment rate. During the 1970s and early 1980s, changes in the industrial structure of the Texas economy resulted in steadily rising employment portfolio variance. While Texas employment grew overall, some volatile industries such as oilfield equipment and construction grew especially rapidly. In addition, this growth was particularly strong among industries whose employment patterns were highly covariant with one another. That is, during the 1970s and early 1980s—as the Texas economy became less diversified—employment became increasingly unstable.

A model of Texas unemployment

A quarterly linear regression model was used to test the significance of the relationship between the Texas unemployment rate and three general types of influences: (1) aggregate output fluctuations, including those of Texas, the United States, and Mexico; (2) national permanent sectoral shifts in labor demand; and (3) Texas portfolio variance.

The sample period 1970.I-1981.IV begins with 1970 because of changes that occurred in that year in the procedure for estimating the Texas unemployment rate. Specifically, 1970 marks the beginning of the use of the Census Bureau's Current Population Survey to derive estimates of the Texas unemployment rate. Formerly, estimates were derived from unemployment insurance statistics. The period ends with 1981 because the calculation procedures for the permanent sectoral shift variable require 16 quarters of observations past the regression sample. This means that to estimate the permanent sectoral shift variable through 1981.IV, it was necessary to have employment data through 1985.IV.

In order to estimate the effects of aggregate output fluctuations in the United States, Mexico, and Texas upon the Texas unemployment rate, measures of aggregate "gaps" were used as variables in the regression equation. The aggregate gaps for the United States, Mexico, and Texas may each be considered as the percentage difference between the potential level of output at full employment and the actual level of aggregate output. Other things being equal, as actual output falls farther below potential output for the United States, Mexico, or Texas, the state's unemployment rate is expected to rise. Likewise, if actual output rises toward or above the estimates of potential output, the Texas unemployment rate is expected to fall. The relation between each gap variable and the Texas unemployment rate thus is expected to be negative. Discussions of the procedures for calculating such gaps appear in subsequent paragraphs.

GNP gap data provided by the Federal Reserve Bank of St. Louis were used to capture the influence of U.S. business cycle fluctuations upon Texas unemployment. This variable is measured as potential real GNP in the United States minus actual real GNP expressed as a percentage of real GNP.[6] Because gap variables are not readily available for Texas or Mexico, it was necessary to create Texas and Mexican gap variables.[7]

Although economic theory allows linking fluctuations in these gap variables to changes in the Texas unemployment, it provides little about the exact timing of these relationships. In the beginning of an economic downturn, firms commonly are reluctant to fire their employees. Though they may cut employee hours, firms often prefer to keep their workers during a downturn because of the firm-specific skills they have developed. Hiring new workers after an upturn in the business cycle also can mean that additional training costs will be incurred. Also, when employees are laid off in one state, they may seek other jobs there before fanning out to other parts of the country. As a result of these factors, lags can be expected between downturns in U.S., Texas, or Mexican output and in increases in the Texas unemployment rate. On the other hand, it is difficult to know *a priori* which particular lag relationship that the fluctuations in each of these variables would have to the Texas unemployment rate.

Two separate selection criteria were used in order to specify optimal lag configurations for the aggregate gaps of the United States, Mexico, and Texas in the regression. These measures included the Akaike Information Criterion and the MSE_p Criterion.[8] Both approaches to selection of lags resulted in the same lag configuration, which included contemporaneous values for the U.S., Mexican, and Texas gaps. In the equation selected by both criteria, the lagged variables included lags of one and three quarters for the Texas gap, lags of one and four quarters for the U.S. gap, and a four-quarter lag for the Mexican gap.[9]

The model accounts for permanent U.S. sectoral shifts through an estimation procedure that is described mathematically in Appendix A. In brief, this variable is a measure of the permanent component of the difference between a series of past employment distributions by sector and a series by sector that occurs for an extended period after the observation point in question. If the observation point is 1981.IV, for example, this variable measures the permanent component of the difference between a weighted average of sectoral employment distributions occurring as far back as 1977.IV, with a similar average of sectoral distributions of employment occurring as far ahead as 1985.IV. A large change in these distributions over time is interpreted as meaning that a significant number of workers have been induced to seek work in industries different from the ones in which they have most recently been employed. Permanent sectoral employment shifts are expected to be positively related to changes in the Texas unemployment rate.[10]

Also considered was the role of employment portfolio variance in explaining the Texas unemployment rate. The measure used to construct the variable (see Appendix B) is a matrix of the U.S. employment portfolio variance adjusted to consider the employment share-weights particular to the state of Texas in each quarter of the observation period. As noted in previous sections of this discussion, increases in the estimates of portfolio variance are expected to be related positively to increases in the Texas unemployment rate.

Although the gap variables in the equation were lagged, neither the permanent sectoral shift nor the portfolio variance variables were lagged because fluctuations in these variables—even in their contemporaneous form—reflect long-term changes in economic structure. It should also be noted that in other studies in which conceptually similar or comparable variables have been used, lags in such variables were either not significant or not used.

Estimation results

The results of the regression analysis are reported in Table 1. Results for the gap variables are reported in terms of the summed coefficient values. The equation was able to explain 85.99 percent of the variation in the Texas unemployment rate over the sample period.

The sum of the contemporaneous and lagged values of U.S. GNP gap coefficients was negative and significant at the 0.0003 level. Those for Texas and Mexico were also of the expected negative sign and significant at the 0.0027 and 0.0062 levels, respectively. Significance levels in the cases of U.S., Texas, and Mexican gaps were estimated using *F*-tests of joint significance.

The coefficient of the permanent sectoral shift variable is positive, as was hypothesized. As estimated on the basis of a *t*-test, the coefficient value was significant at the 0.0386 level. Permanent U.S. sectoral shifts apparently have acted upon the Texas unemployment rate in the expected way. That is, as permanent sectoral shifts occur nationally, displaced workers sometimes come to Texas to find work and are not always immediately successful in their job searches.

Table 1
REGRESSION RESULTS FOR A QUARTERLY MODEL OF UNEMPLOYMENT IN TEXAS[1]

Variable	Parameter estimate	t- or F-statistic	Significance level
Intercept	−2.749671	−1.961 (t)	.0575
Mexican GDP gap	−3.466021	5.85 (F)	.0062
Texas portfolio variance[2]	1.391644	4.599 (t)	.0001
Texas GSP gap	−1.829559	5.67 (F)	.0027
U.S. sectoral employment shift[3]	0.908656	2.145 (t)	.0386
U.S. GNP gap	−15.648165	8.02 (F)	.0003

R^2 = .8599.
R^2 adjusted = .8221.
DW = 1.70.
F = 22.72.
$RMSE$ = .2689.
First-order autocorrelation = .142.

1. The dependent variable is the quarterly average Texas unemployment rate.
2. Observations were multiplied times 10^4 for convenience of reporting coefficients and standard errors.
3. Observations were multiplied times 10^2 for convenience of reporting coefficients and standard errors.

SOURCES OF PRIMARY DATA: Baylor University Forecasting Services, Professor M. Ray Perryman.
International Monetary Fund.
U.S. Bureau of Labor Statistics.
U.S. Department of Commerce.

Table 2
TOTAL DIRECT AND INDIRECT CONTRIBUTION OF EACH EXPLANATORY VARIABLE TO TOTAL VARIATION IN THE ESTIMATED TEXAS UNEMPLOYMENT RATE

Variable	Percent
Mexican GDP gap	20.65
U.S. GNP gap	37.87
Texas GSP gap	7.53
Texas portfolio variance	6.53
U.S. sectoral employment shift	27.42
Total	100.00

SOURCES OF PRIMARY DATA: Baylor University Forecasting Services, Professor M. Ray Perryman.
International Monetary Fund.
U.S. Bureau of Labor Statistics.
U.S. Department of Commerce.

The coefficient of the Texas portfolio variance expression was positive and significant at the 0.0001 level. Because the value of this variable rose steadily during the sample period, it appears to have played a role in explaining the secular increase in the Texas unemployment rate during the sample period. The restructuring of the Texas economy during this period apparently injected a degree of employment instability that had not formerly been seen in the state.

While the results of the regression equation show that all of the variables had statistically significant explanatory power, this finding offers little information as to the relative importance of each variable in explaining the Texas unemployment rate. Because of the complicated nature of some of the variables, particularly those depicting permanent U.S. sectoral employment shifts and Texas portfolio variance, the interpretation of even the coefficient elasticities is not straightforward.

To assess the economic significance of each of the independent variables, the average percentage change in the model's predicted value due to each independent variable was estimated (see Table 2).[11] This estimation procedure captures the total contribution provided by a given variable, both indirectly through its influence on other variables in the equation and directly through its influence on the Texas unemployment rate. Essentially, this procedure involves calculating each variable's share of within-sample unemployment rate variation estimated by the total model in each quarter and averaging each share over the sample period. The dominant variable was the U.S. GNP gap, in which—as estimated by the model—variations over the sample period accounted for 37.87 percent of the Texas unemployment rate fluctuations. Second in dominance was the permanent sectoral employment shift variable, which accounted for 27.42 percent of the fluctuations in the estimated unemployment rate. The total effect of the Mexican gross domestic gap variable accounted for 20.65 percent of the unemployment rate fluctuations, while variations in the Texas gross state product gap accounted for only 7.53 percent of estimated unemployment rate fluctuations.

This latter estimation requires some care in interpretation. A number of variables that affect the Texas unemployment rate also may be expected to influence the Texas gross state product gap. These variables include the U.S. and Mexican GNP gaps. The impacts of these two variables on the Texas unemployment rate may be both direct and indirect—through their impacts on the Texas gross state product gap. The measure of the proportion of total estimated unemployment captures both the direct and indirect effects of these variables. As a result, the Texas gross state product gap may be said to account for 7.53 percent of unemployment rate fluctuations—net of the portion of its overall variation that is linked to the U.S. GNP gap and the Mexican GDP gap.

The smallest impact of fluctuations in any variable on variations in the Texas unemployment rate, as estimated by the model, was that of Texas employment portfolio variance—6.53 percent. It should be noted that the elasticity of the portfolio variance variable was the largest of any of the variables in the equation. Nevertheless, fluctuations in the value of this variable over the sample period were so small that it accounted for only a relatively small portion of total estimated variation.

Out-of-sample estimations of the model

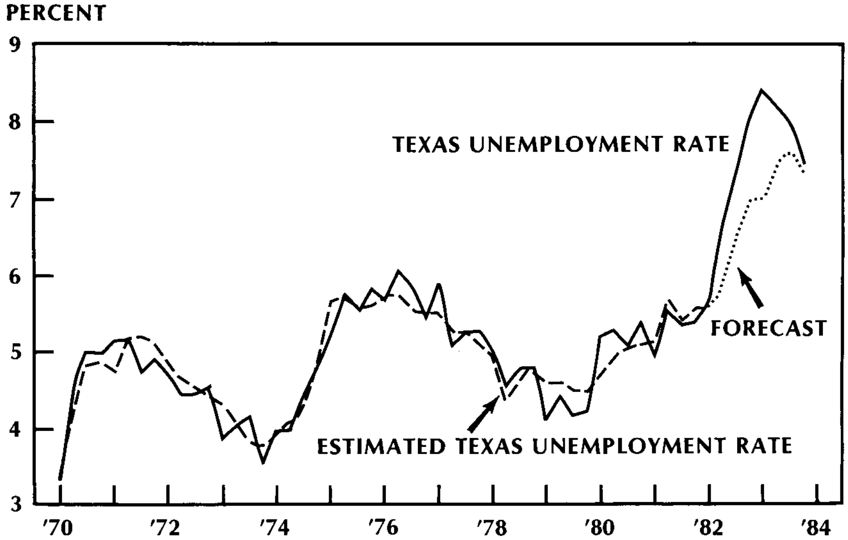
During the sample period for which this model was estimated, Texas grew rapidly. Indeed, one reason that the state's unemployment rate rose during this period was attributable to labor supply effects rather than demand effects. In the wake of the 1973 and 1979 oil price shocks, for example, unemployment in Texas grew—not because employment was falling but because the labor supply was increasing faster than total employment.

In the second quarter of 1982, shortly after the end of the sample period, Texas fell into a recession that had already commenced in the United States. The decline in Texas was a response to growing weakness in the U.S. economy, together with a drop in oil prices that induced a reduction in oil and gas drilling activity and a major downturn in Mexico. Oil prices had peaked in 1980.IV, reaching an average on-the-spot market price of $38.63 per barrel. By 1981.IV, spot prices had fallen 12.8 percent to an average price of $33.68 per barrel. By 1982.IV, prices were averaging $31.75. Partially in response to the repercussions of this decline, the Texas gross state product fell 4.2 percent between 1982.I and 1982.IV, while the Mexican gross domestic product dropped 6.2 percent. The unemployment rate in Texas rose from an average of 5.4 percent in 1981.IV to 8.4 percent in 1983.I.

In order to test the predictive power of the model, out-of-sample predictions of the Texas unemployment rate were performed for each quarter of the period 1982.I-1983.IV.[12] Recognizing the difference between Texas' economic experience within the sample period and what occurred in the out-of-sample period, we considered that the prediction would prove a rigorous test of the model's validity.

Chart 3 depicts both in-sample and out-of-sample predictions of the Texas unemployment rate, together with the actual values of the unemployment rate for the period 1970.I-1983.IV. The predicted values generally move in a direction that is consistent with actual values. Nevertheless,

Chart 3
Texas Unemployment Rate vs. Estimated Texas Unemployment Rate for the Period 1970.I-1983.IV



SOURCE OF PRIMARY DATA: U.S. Department of Labor.

the predicted values fall far short of reaching the peaks posted by the actual unemployment values. The most extreme error occurred in 1983.I, when the predicted value was 6.9 percent and the actual value was 8.4 percent. By 1983.IV, however, the predicted and actual values had converged and differed by only 0.2 percentage points. Some of the error in the predicted values can be attributed to the out-of-sample permanent sectoral shift variable being measured with error, for reasons described in footnote 11. For the entire out-of-sample prediction period, however, the correlation between the real and predicted fluctuations in Texas unemployment rates was 87 percent.

Conclusions

The above findings help to answer in some detail the questions posed at the beginning of this paper. Was Texas' economic growth accompanied by growing instability in demand for labor? Or was increasing U.S. joblessness simply pushing workers displaced in other parts of the nation into the Texas job market at such a high rate that the state could not absorb its new immigrants into the workforce?

The results of the regression equation suggest affirmative answers to both questions, because the coefficients for variables that accommodate these two concepts were significant. These two explanations are not mutually exclusive, however. The increasing value of Texas employment portfolio variance over time attests to the rising instability of labor demand in the Texas economy. Consistent with the displaced-worker argument is the evidence of a strong influence of fluctuations in the U.S. GNP gap on the Texas unemployment rate, together with Texas' rapid employment growth often being accompanied by an even more rapid expansion in the labor force.

Were fluctuations in unemployment in Texas significantly linked to events in Mexico? The regression results clearly suggest that they were. When the rate of change in Mexican gross domestic product fell below its trend rate of growth, the Texas unemployment rate was shown to increase. A particularly striking finding is not simply that fluctuations in Mexico help to explain fluctuations in the Texas unemployment rate but that such a large portion of total Texas unemployment rate fluctuations can be explained by a Mexican variable.

Furthermore, this model is able to provide some answers for other questions that could be raised in response to remarks in preceding sections of this paper. For example, permanent national sectoral shifts appear to have supply effects that can raise the Texas unemployment rate even when overall U.S. growth is positive. The U.S. permanent sectoral employment shift variable was shown to have significant explanatory power in the model, despite the inclusion of the U.S. GNP gap.

Finally, it can be asked what this model means for the future of unemployment in Texas. The model suggests that aggregate economic events in the United States have an extremely strong impact on Texas but that much of this impact occurs with a substantial lag. When oil price declines shock Texas, they negatively impact the state quickly and powerfully. These effects ultimately may be moderated by increases in U.S. demand and output. These moderating responses, however, occur with a considerable lag after the price decline. They are the result of the lagged growth reaction of the U.S. economy to such a decline and of the lagged impact of that national growth on the Texas unemployment rate. Pulling from the other direction, however, are the unemployment effects of a continued weakness in the Mexican economy. While Mexico's influence on Texas employment is not as strong as that of the United States, it still exerts an important influence on the state's labor markets. As long as economic weakness occurs in Mexico, this problem will temper the positive effects for Texas of U.S. growth.

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1. Estimates of the Texas gross state product are regularly published by, and are available from, Professor M. Ray Perryman, Baylor University Forecasting Services (Waco, Texas). The authors are grateful for the use of these data.

2. For a discussion of the fundamentals of the traditional natural rate theory, see Robert J. Gordon, *Macroeconomics* (Boston: Little, Brown and Co., 1978), 212-15.

3. This somewhat different emphasis in interpreting the natural rate or nonaccelerating inflation rate of unemployment stems from attempts to examine the stability of the Phillips Curve relationship. See, for example, Milton Friedman, "The Role of Monetary Policy," *The American Economic Review* 58 (March 1968): 1-17; and Edmund S. Phelps, "Introduction: The New Microeconomics in Employment and Inflation Theory," in Edmund S. Phelps, ed., *Microeconomic Foundations of Employment and Inflation Theory* (New York: W. W. Norton and Co., Inc., 1970), 1-23. It should be noted that even in the earliest casting of this approach to the analysis of the natural rate, clear statements appear indicating that the natural rate is not immutable. For example, fluctuations in real minimum wages and in the strength of labor unions are cited in Friedman (see above) as causes of fluctuations in the natural rate. Researchers who focus on the unemployment rate/price relationship commonly estimate the natural rate for different periods and find some variation over time. (See A. Steven Englander and Cornelis A. Los, "The Stability of the Phillips Curve and Its Implications for the 1980s," Research Paper, Federal Reserve Bank of New York, January 1983. Englander and Los also note four survey articles dealing with this topic, each of which cites a plethora of other research papers on the subject. Also see three publications by Robert J. Gordon: "Inflation, Flexible Exchange Rates, and the Natural Rate of Unemployment," in Martin Neil Baily, ed., *Workers, Jobs, and Inflation* [Washington, D.C.: The Brookings Institution, 1982], 89-152; "Unemployment and Potential Output in the 1980s," in William C. Brainard and George C. Perry, eds., *Brookings Papers on Economic Activity*, vol. 2 [Washington, D.C.: The Brookings Institution, 1984], 537-64; and "Understanding Inflation in the 1980s," in William C. Brainard and George C. Perry, eds., *Brookings Papers on Economic Activity*, vol. 1 [Washington, D.C.: The Brookings Institution, 1985], 263-99.) In many cases, however, these studies find the natural rate to be fairly stable over time. Gordon (1985, see above) finds the natural rate to have ranged between 5.8 percent and 6.0 percent over the period 1971-84, and in an earlier paper (1982, see above) he finds no significant change in the natural rate between the 1950s and the late 1970s except for movements associated with long-term demographic trends. Arthur M. Okun, in *The Political Economy of Prosperity* (Washington, D.C.: The Brookings Institution, 1970), 136, cites two approaches to analyzing the relationship between aggregate economic activity and the unemployment rate. One approach involves comparing changes in the ratio of potential to actual aggregate economic output with changes in the unemployment rate. The other addresses the relation between the level of the ratio of the potential to actual aggregate economic output and the level of the unemployment rate. This second approach—which uses levels but assumes "the trend of output growth at constant unemployment rates"—is the focus of my discussion in the text which follows.

4. The theoretical foundations of the aspects of the "variable" natural rate approach that are addressed in this paper lie in a series of arguments in which changes in the unemployment rate may occur without any aggregate fluctuations. In these models, increases in the stochastic variability of labor demands, either between industrial sectors or in the aggregate, result in increased equilibrium unemployment and job mobility. (See, for example, Phelps, ed., *Microeconomic Foundations of Employment and Inflation Theory*.) In competitive models where search is costly and occurs among spatially distinct "islands," a perceived change in the distribution of labor demand among markets increases the amount of search unemployment resulting from the option price character of the reservation wage. In another model, where search costs are constant, increased variance in the distribution of sectoral demands increases the return to search. As a result of this increase, the equilibrium amount of search unemployment rises. (See Robert E. Lucas, Jr., and Edward C. Prescott, "Equilibrium Search and Unemployment," *Journal of Economic Theory* 7 [February 1974]: 188-209.)

5. An example of the early empirical development of the notion of sectoral shifts is in David M. Lilien, "Sectoral Shifts and Cyclical Unemployment," *Journal of Political Economy* 90 (August 1982): 777-93. Lilien's work, however, did not include attempts to separate the effects of permanent sectoral shifts from the transitory component that later work suggested was simply an effect of the business cycle. An attempt to separate permanent from transitory components of sectoral shifts appears in George R. Neumann and Robert H. Topel, "Employment Risk, Sectoral Shifts and Unemployment," Research Paper, Economics Research Center, NORC, supported by the U.S. Department of Labor, Office of the Assistant Secretary for Policy, January 1984; rev., October 1984.

Neumann and Topel's paper, however, is not alone in criticizing Lilien's approach as capturing the detailed impacts of the business cycle. For a paper that begins with a similar criticism but develops an argument in opposition to that of Neumann and Topel, see Katherine G. Abraham and Lawrence F. Katz, "Cyclical Unemployment: Sectoral Shifts or Aggregate Disturbances?" Working Paper No. 1410, NBER Working Paper Series (Cambridge, Mass.: National Bureau of Economic Research, July 1984); this paper has been published by the authors under the same title in the *Journal of Political Economy* 94 (June 1986): 507-22. Abraham and Katz build upon their critique of Lilien by attempting to show that aggregate fluctuations are the major explainers of unemployment rate fluctuations. Abraham and Katz, however, do not distinguish between the roles of permanent and transitory sectoral shifts. Although the controversy surrounding the role of aggregate fluctuations versus sectoral shifts is not the focus of the present paper, the controversy is important. To the extent that sectoral shifts—rather than aggregate fluctuations—determine variations in unemployment, the power of national aggregate fiscal policy is diminished as a tool for reducing joblessness.

6. The application of the U.S. GNP gap to explain unemployment rates is based on a version of Okun's Law, which essentially suggests that a decline in aggregate demand will show up as an increase in GNP gap. According to Okun's approach, the drop in aggregate demand is seen as reducing the demand for labor and thus increasing unemployment (see, for example, Okun, *The Political Economy of Prosperity*). The actual procedure for estimation of GNP gap as used in the present paper, however, is found in Robert H. Rasche and John A. Tatom, "Energy Resources and Potential GNP," Federal Reserve Bank of St. Louis, *Review* 59 (June 1977): 10-24.

7. To derive a Texas gap variable, the natural log of real gross state product was regressed on a quadratic time trend, and the predicted values were used as a proxy for potential gross state product for Texas. This variable minus estimates of the natural log of the actual real GSP served as the gap variable for Texas. The real GSP estimates were provided by Professor Perryman of Baylor University Forecasting Services. For deriving a Mexican gap variable, real annual gross domestic product data from the Mexican government were used. Because these data were not quarterly, they were expressed quarterly by means of the Chow-Lin Procedure. (See Gregory C. Chow and An-loh Lin, "Best Linear Unbiased Interpolation, Distribution, and Extrapolation of Time Series by Related Series," *The Review of Economics and Statistics* 53 [November 1971]: 372-75.) Changes in annual Mexican industrial production indexes were related to changes in Mexican gross domestic product. Quarterly Mexican industrial production indexes, readily available from the Banco de Mexico, were used to estimate quarterly real Mexican gross domestic product. The natural log of Mexican GDP was then regressed on a quadratic time trend, and the predicted value was used as a proxy for potential Mexican GDP. Subtracting estimates of actual quarterly Mexican GDP from this proxy for potential GDP produced a measure of Mexican GDP gap.

8. The Akaike Information Criterion was used (as described in George G. Judge, William E. Griffiths, Carter Hill, and Tsoung-Chao Lee, *The Theory and Practice of Econometrics* [New York: John Wiley and Sons, 1980]). A full explanation of the MSE_p Criterion, as used in the present paper, appears in John Neter and William Wasserman, *Applied Linear Statistical Models: Regressions, Analysis of Variance, and Experimental Designs* (Homewood, Ill.: Richard D. Irwin, Inc., 1974). According to these selection processes, regressions were performed for all combinations of lags from zero to five for each of the three gaps. It should be noted that the set of all combinations of lags includes combinations in which distant lags are included but nearer lags are excluded. Thus, a fourth-quarter lag may appear even when first, second, and third-quarter lags are not included. In addition, these procedures do not constrain all lag lengths for all lagged variables to be identical.

9. A method of lag-length selection in which intermediate lags are retained was also applied. Under this procedure, the lags on the variables were simultaneously increased until the minimum mean square error was achieved, given the constraint that no intervening lags were allowed to be deleted. Under this method, four lags were chosen as optimal for each of the three gap variables. The resulting mean square error was slightly higher than in the model in which intermediate lags were not included, and the out-of-sample estimations from the four-lags model were slightly less accurate than in the model for which results appear in the table.
   Because the reported model leaves out some intermediate lags, its dynamic multipliers are not smooth. However, as the explanatory contribution made through the inclusion of intermediate lags is essentially insignificant, the alternative model changes this result very little. Also, little change in the dynamic multipliers was realized through the application of Almon lag structures, an approach that was also tried. The lag configurations of the reported model (and even of the unreported models) are consistent with the notion not only that gap variables have both labor demand and labor supply impacts but also that the bulk of each of these two classes of impacts occurs at different times and, in terms of timing, that they may be relatively discrete events.

10. It is reasonable to hypothesize that permanent sectoral shifts in Mexico would also affect the unemployment rate in Texas. Anecdotal evidence reveals that such permanent shifts occurred in Mexico during the 1970s. Mexican labor data, however, that over the observation period were consistent, reliable, and applicable to the estimation of a Mexican permanent sectoral employment shift variable were unavailable. Construction of a Mexican permanent shift variable was attempted by using labor data extrapolated by the Mexican government from information gathered during past census years. The resulting variable did not, however, provide significant explanatory power.

11. This procedure estimates the contribution that fluctuations in each variable—in both contemporaneous and lagged form—have made collectively to fluctuations in the Texas unemployment rate over the sample period. This estimation was accomplished by taking the absolute value of the change in the Texas unemployment rate predicted by a given variable, dividing it by the sum of these predicted changes for each quarter in the sample, and then averaging each variable's contribution to predicted variation for the entire sample period.

12. All explanatory variables but one were available in their standard forms for the out-of-sample period. In order to construct out-of-sample predictions, it was necessary to estimate values for the permanent sectoral employment shift. A measure of the permanent sectoral shift was not available in its standard form out of sample because 16 quarters of employment data observations past the end of the sample period were required to estimate this variable. Thus, to estimate the standard permanent sectoral shift variable for 1983.IV, employment data through 1987.IV would be required. In order to estimate permanent sectoral shifts through 1983.IV, a separate variable was created that required only eight observations after the sample period. To estimate the standard permanent shift variable out of sample, past values of perma-

nent shift were regressed on values of the eight-quarter permanent shift approximation. Once the relationship between these two variables had been estimated, it was used to simulate the standard permanent shift variable over the prediction period.

Appendix A

Portfolio Variance

The employment portfolio variance may be defined as the summation of variances and covariances of employment within and across industries, weighted by measures of long-run employment shares. Since it represents such a summation, the portfolio variance may be disaggregated into the sum of the individual employment variances multiplied by the squares of the share weights of the individual employment sectors and an appropriately weighted sum of the employment covariances. This latter pair of summations can be expressed mathematically, as follows, where σ_j^2 represents the employment variance of industry j; σ_{ij} represents the covariance of employment between industry i and industry j; and s_i and s_j represent the respective long-term employment share-weights of industry i and industry j:

$$\sigma_p = \sum_j s_j^2 \sigma_j^2 + \sum_{i \neq j} \sum_{j \neq i} s_i \, s_j \, \sigma_{ij}.$$

Every industry thus contributes to the regional portfolio variance, not only through the first term on the right-hand side of the equation but also through the weighted sum of all the covariances with the other industries in the portfolio.

Employment was disaggregated by 27 standard industrial classifications (SICs) for the United States. However, single-digit SICs were used in all industries except mining and manufacturing. In manufacturing, two-digit SICs were applied, except in nonelectrical machinery. Here, the importance of oilfield equipment manufacturing to Texas was taken into consideration. Oilfield equipment, a three-digit SIC, was disaggregated from the rest of nonelectrical machinery. Likewise, in the mining classification, oil and gas extraction was separated out. Based on these data, a relative variance-covariance matrix was estimated for the sample period 1970-81. More specifically, a variance-covariance matrix was estimated from the residuals of employment around an estimate based on a quadratic time trend standardized with respect to the mean of each series. Thus, each element of the matrix includes a relative covariance of the following form:

$$\bar{\sigma}_{ij} = [T-2]^{-1}[\bar{E}_i \bar{E}_j]^{-1} \sum (E_{it} - \hat{E}_{it})(E_{jt} - \hat{E}_{jt}).$$

Here, E_{it} and E_{jt} represent the observed levels of employment in industries i and j, respectively, during quarter t; while $\hat{E}_{it}$ and $\hat{E}_{jt}$ represent the expected levels of employment in industries i and j for month t given by an estimate based on a quadratic time trend for each industry; and $\bar{E}_i$ and $\bar{E}_j$ represent the arithmetic means of the individual industry time series.

This matrix can be condensed to a variable describing the employment variance for a given region by applying region-specific weights to the portfolio variance formula as noted in the first equation and substituting $\bar{\sigma}_{ij}$ from the second equation into the first equation in place of σ_{ij}. In sum, σ_p offers a measure of employment variance for a geographic region under analysis based on the industrial structure (as reflected in the weights) of the region but using a national matrix (for the components of $\bar{\sigma}_{ij}$).

As weights, estimates were used of the relative proportions of quarterly employment (again based on quadratic time trends) in each of the industries represented within SICs described for the state of Texas. Thus, the weights s_i and s_j are taken to be expected proportions of employment in industries i and j in Texas. In the report on the regression results, σ_p is referred to as Texas Portfolio Variance, and fluctuations in this variable are expected to be related positively to fluctuations in the unemployment rate.

Appendix B

Permanent Sectoral Employment Shifts

Neumann and Topel[1] develop a permanent sectoral shift variable using Euclidian lengths. They begin by generating a variable, $\delta\tilde{e}_t$, that represents the difference between moving averages of future and past vectors of employment shares at each time t. This variable, which is taken as a measure of the direction of permanent change in the sectoral distribution of employment, is generated as follows. In any quarter, $e_t = (e_{1t} \ldots e_{nt})$ be the vector of employment shares across n industry groups. Then the direction of permanent change in this distribution is the vector

$$\Delta\tilde{e}_t = \sum_{j=1}^{J} \beta_j e_{t+j} - \sum_{j=1}^{J} \beta_j e_{t-1},$$

where $\sum_{j=1}^{J} \beta_j = 1$. In practice, $J = 16$ quarters, with smoothly declining weights $\beta_j = (.9)^j/(7.33)$.

While the preceding measure defines the direction of permanent change, the actual difference between the current employment distribution and the conformable past distribution is defined as the vector

$$\Delta e_t = e_t - \sum_{j=1}^{J} \beta_j \, e_{t-j}.$$

Because this vector has both permanent and transitory components, a consideration of the permanent component of this actual change requires disaggregation of the permanent and transitory components. A permanent component of such a reallocation in each period is defined as the least squares projection of the actual difference between the current employment distribution and the past distribution onto the vector $\Delta\tilde{e}_t$. That is, the permanent component of a change in distribution is the portion of the actual change that can be explained by changes in the difference between moving averages of future and past vectors of employment shares at each t. Where Δe_t denotes the vector representing the actual difference between the current employment distribution and the conformable past distribution, then the vector of permanent changes in employment shares can be expressed as

$$\Delta e_t^P = [\Delta\tilde{e}_t{}' \, \Delta e_t / \Delta\tilde{e}_t{}' \, \Delta\tilde{e}_t] \Delta\tilde{e}_t.$$

Finally, the size of the permanent shock to the distribution of employment was measured by using the Euclidean length of Δe_t^P:

$$\|\Delta e_t^P\| = [(\Delta\tilde{e}_t \Delta e_t)/(\Delta\tilde{e}_t{}' \, \Delta\tilde{e}_t)^{1/2}].$$

This left-hand-side variable is referred to as SHIFT, and changes here are expected to be positively related to changes in unemployment rates. In this model, industries are disaggregated by the same 27-industry configuration as that used in the portfolio variance estimate. The result is a disaggregation that includes all nonagricultural wage and salary employment in the United States.

1. George R. Neumann and Robert H. Topel, "Employment Risk, Sectoral Shifts and Unemployment," Research Paper, Economic Research Center, NORC, supported by the U.S. Department of Labor, Office of the Assistant Secretary for Policy, January 1984; revised, October 1984.

ANNOUNCEMENT

NEW STATISTICAL RELEASE

Federal Reserve Bank of Dallas

Trade-Weighted Value of the Dollar

Beginning in January 1987 the Federal Reserve Bank of Dallas will publish a monthly statistical release on the trade-weighted value of the dollar. The release will contain monthly updates on the X-131 nominal exchange rate index (see the September 1986 issue of this *Review)* as well as a comparable real (inflation-adjusted) exchange rate index.

In addition to these broad-based measures of the dollar's foreign exchange value, subindexes will be reported which show both the nominal and real value of the dollar relative to the currencies of specific countries or groups of countries—specifically Europe, the Western Hemisphere (excluding Canada), the Pacific Newly Industrialized Countries, Japan, Canada, and the rest of the world. Brief graphical summaries also will be provided.

The annual subscription fee is $48.00. Those interested should send a check or money order to:

Dollar Index
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