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Economic Review

Federal Reserve Bank of Dallas
November 1982

During the past 12 years the monetary aggregates continued to foreshadow changes in business conditions, although the relationship of money growth to current and future real activity was weak. The broader aggregates, especially M2, proved more reliable than M1 as forecasting guides.

Low price levels, coupled with high unemployment rates and high concentrations of both Mexican-Americans and workers in low-skill occupations, account for depressed earnings along the border. This conclusion is based on analysis of data contained in the 1970 Census. The findings suggest that policy should emphasize training and education along the border and that the effect of illegal immigration from Mexico is not confined to the border alone.

Monetary Aggregates as Indicators of General Economic Activity

*By James G. Hoehn**

Economic forecasters rely on leading indicators, which are variables whose movements foreshadow trends in general business activity. Monetary measures are now widely used as such indicators. This use is evident in the financial press, where notable forecasters are frequently quoted on the significance of monetary data, and in the construction of the Commerce Department's index of leading indicators.

This article reviews the record from the events of the 1970's up to March 1982. Simple inspection of the tendency of the monetary aggregates to lead the business cycle yields no firm conclusions but suggests that M2 and M3 served as more reliable indicators than M1. It also warns against expecting monetary deceleration in the few months in the immediate vicinity of a business cycle peak. Statistical tests verify that M2 and M3 could serve as valuable indicators of the course of output in the months ahead. Forecast errors for the Commerce Department's monthly index of roughly coincident indicators can be reduced by as much as one-tenth by analyzing trends in these two aggregates. On the other hand, the relationship between M1 and future real activity was weak.[1]

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Money leads the economy

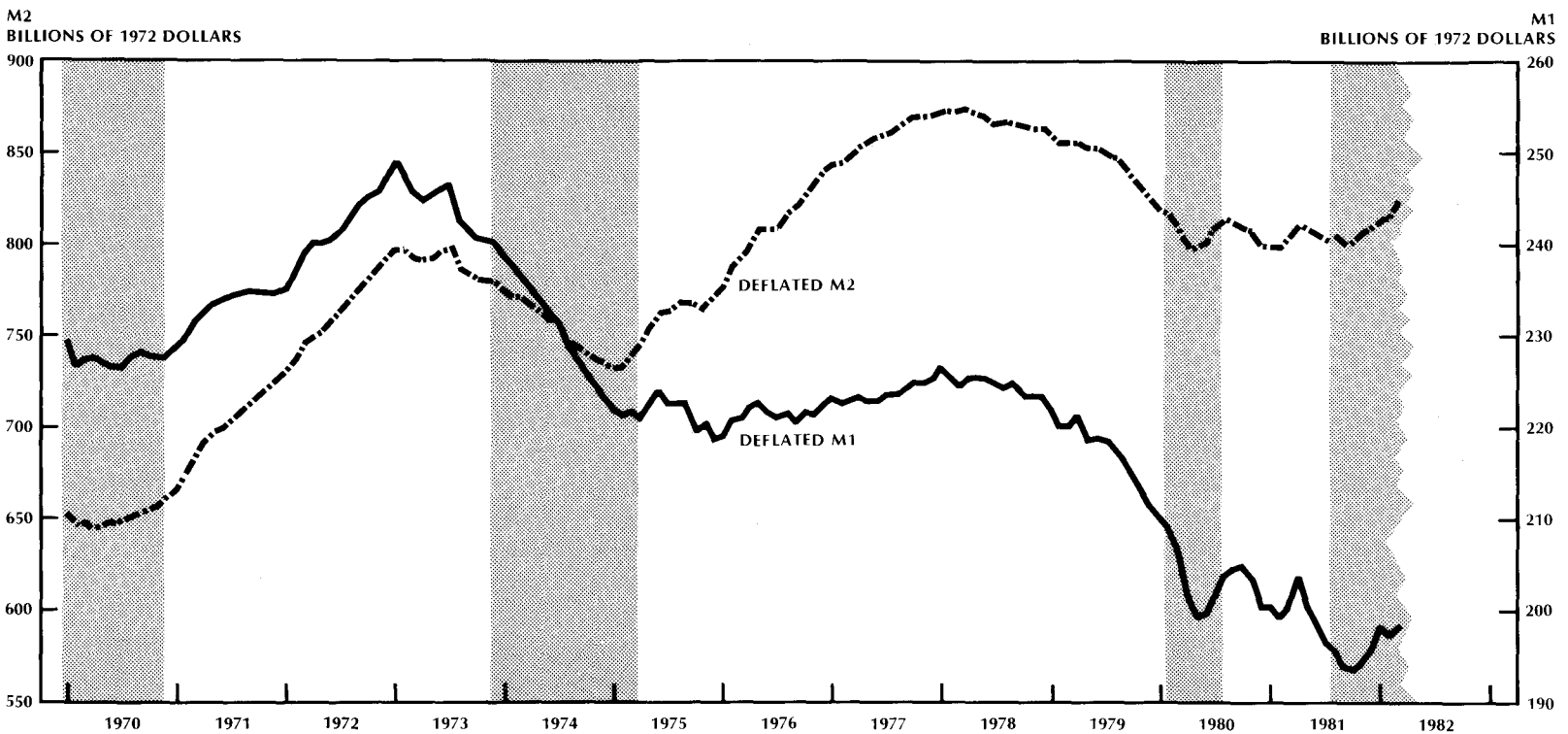
Business cycle analysis seeks to identify turning points in the economy and describe the typical behavior of specific economic indicators in relation to these points. This approach serves as the basic point of departure for more rigorous analyses.

Monetary measures have previously been found to grow more rapidly during economic expansions than during contractions. This pattern is observed for the 1970's as well (Table 1). For each of the current definitions of money, the rate of growth rose in each expansion and fell in each contraction. During expansions, M1 growth averaged 7.2 percent at an annual rate, compared with 5.0 percent during con-

1. This does not imply that M1 is the inferior guide for policy. The target is chosen on the basis of its relationship with nominal income and its controllability. M1 is generally viewed as superior to the broader aggregates on both counts. See Patrick J. Lawler, "The Large Monetary Aggregates as Intermediate Policy Targets," *Voice of the Federal Reserve Bank of Dallas*, November 1981, pp. 1-13.

FIGURE 1

M1 and M2, Deflated by the Consumer Price Index



NOTE: Shaded areas indicate economic recessions as dated by the National Bureau of Economic Research.
SOURCE: U.S. Department of Commerce, Bureau of Economic Analysis.

Table 1
GROWTH RATES OF MONETARY AGGREGATES AND A MEASURE OF BUSINESS ACTIVITY

	Monetary aggregates			Index of roughly coincident indicators
	M1	M2	M3	
	Compound annual rates of change (Percent)			
1969-70 contraction . . .	5.2	5.6	9.8	-6.0
1970-73 expansion	7.0	11.3	13.6	7.2
1973-75 contraction . . .	4.5	6.8	8.5	-10.2
1975-80 expansion	7.2	10.7	10.9	5.6
1980 contraction	3.2	9.3	9.8	-12.7
1980-81 expansion	7.9	9.7	12.0	4.5
1981— contraction[1]	7.3	9.7	9.9	-10.4

1. To March 1982.
SOURCES OF PRIMARY DATA:
Board of Governors, Federal Reserve System.
U.S. Department of Commerce, Bureau of Economic Analysis.

tractions. M2 showed an identical 43-percent increase in growth from contraction to expansion. M3 displayed less sensitivity to the business cycle. Its growth rate during expansions was only 28 percent higher than in contractions.

Business cycle analysts classify series as leading, lagging, or coincident. A leading series can be especially useful, for it tends to indicate turning points in economic activity in advance of their occurrence. Most useful of all are the series that lead by a relatively stable period of time.

Money has been identified as a leading series with a quite variable lead time. Evidence from U.S. business cycles through the 1950's indicates that money growth typically reached its peak 16 months ahead of business activity, but the lead ranged from 6 to 29 months. At troughs, money led by an average of 12 months, with a range of 4 to 22 months.[2]

A serious shortcoming of using visual inspection to identify peaks and troughs in money growth is its subjectivity, which permits different analysts to find different patterns, with no nonarbitrary criterion for choosing among them. An exhaustive search among a large number of conceivable rules could be made to test the reliability of the patterns, but devoting such effort to this approach would be ill-advised when more powerful statistical methods, such as those discussed in later sections, are available.

One investigator did elaborate a well-specified, and therefore testable, rule of thumb for identifying the onset of economic contraction from monetary deceleration. It worked reliably through 1972, but the relationship broke down in the subsequent decade.[3] The failure of an unambiguous and apparently reasonable rule of thumb to produce a con-

2. See Milton Friedman, *A Program for Monetary Stability* (New York: Fordham University Press, 1960), p. 87. Friedman finds the lags shorter in the early 1980's (see "Defining 'Monetarism,' " *Newsweek*, July 12, 1982, p. 64).

3. William Poole ("The Relationship of Monetary Decelerations to Business Cycle Peaks: Another Look at the Evidence," *Journal of Finance* 30 [June 1975]:697-712) defined a monetary deceleration essentially as a drop in money, either M1 or M2, to 3 or 4 percent below the steepest 24-month logarithmic least squares growth trend established during the economic expansion. A study of the 1908-72 period led him to the firm conclusion that a "business cycle peak will be identified within plus or minus 5 months of the month of significant deceleration" in the money stock. A test for the 1973, 1980, and 1981 peaks fails to confirm the hypothesis. The 3-percent deceleration criterion was met by the M1 money measure eight months after the 1973 peak and three months after the 1980 peak. The 4-percent criterion was fulfilled 11 months and 4 months after these respective peaks. Neither condition has yet been fulfilled for the 1981 peak. Thus, the criterion was "successful" only for the 1980 peak, but even then, the six-month recession was at least half over by the time of the signal. M2 gave qualitatively similar results.

sistent forecasting record makes it less likely that a useful one can be identified.

With these caveats in mind, examining the cyclical behavior of money growth is nevertheless instructive. M2, deflated by the consumer price index, has a long-established place among the 12 components of the Commerce Department's index of leading indicators.[4] Since 1970, deflated M2 has consistently peaked and bottomed ahead of the general business cycle. But the lead time varied, and it was particularly long at the 1980 and 1981 cycle peaks. Deflated M1 actually lagged the economy at the 1975 trough, by nine months, but led at all other turning points. Money measures, like most leading indicators, display lead times at troughs that are shorter and less variable than at peaks.

Whether using a deflated money series could have helped a forecaster improve his predictions during the 1970's is unclear, for he could not have identified peaks and troughs in money with much confidence until well after their occurrence. Furthermore, he might have expected the rapid decline in both deflated money series that commenced in 1978 and steepened in 1979 to have indicated a recession long before it actually arrived in 1980. Finally, both deflated money series have become erratic in recent years, making cycle peaks and troughs harder to identify.

Another instructive way of assessing the leading character of money examines the neighborhood around business cycle turning points for reliable patterns. To facilitate analysis, the aggregates (not deflated) were subjected to the logarithmic transformation and then "detrended." The result is essentially the percentage of deviation from a constant growth rate trend.[5]

Figure 2 depicts this measure of monetary fluctuations for M1 and M2 in the neighborhoods of business troughs and peaks and shows the results of the following calculations. For each turning point, the deviation from trend of the log of money at the month of the business peak or trough is subtracted from the deviation from trend in each of the months ranging from nine months before to nine months after the business turning point. These values are plotted against the number of months from the turning point. A flat line indicates a growth rate equal to trend. A rising line indicates faster-than-trend growth; a falling line, slower-than-trend growth.

M1 fell relative to trend during contractions until one or two months before business cycle troughs, after which money growth exceeded trend. The 1975 trough was an exception. Money growth in each case tapered off three or four months after the trough. The behavior of money in the vicinity of the 1970 and 1980 troughs looks similar to the typical pattern identified over cycles prior to the 1970's, but the behavior of money near the 1975 trough was unusual.

During expansions the narrow money measure typically grew rapidly until three to five months before the peak, followed by a decline in growth until a month before the peak. Money growth slightly exceeded trend in the three months around two of the three peaks before dropping sharply. This pattern carries an important warning: one should not expect M1 growth to decline in the immediate vicinity of a peak. A peak can occur while money growth temporarily accelerates, as indeed occurred at all three cycle crests in the 1970's. The behavior of M1 growth around the three peaks roughly conforms to the typical pre-1970's pattern, except possibly for the sharp recovery in money growth beginning shortly after the 1981 peak. Also, the monetary contraction starting three months before the 1981 peak was unusually rapid.

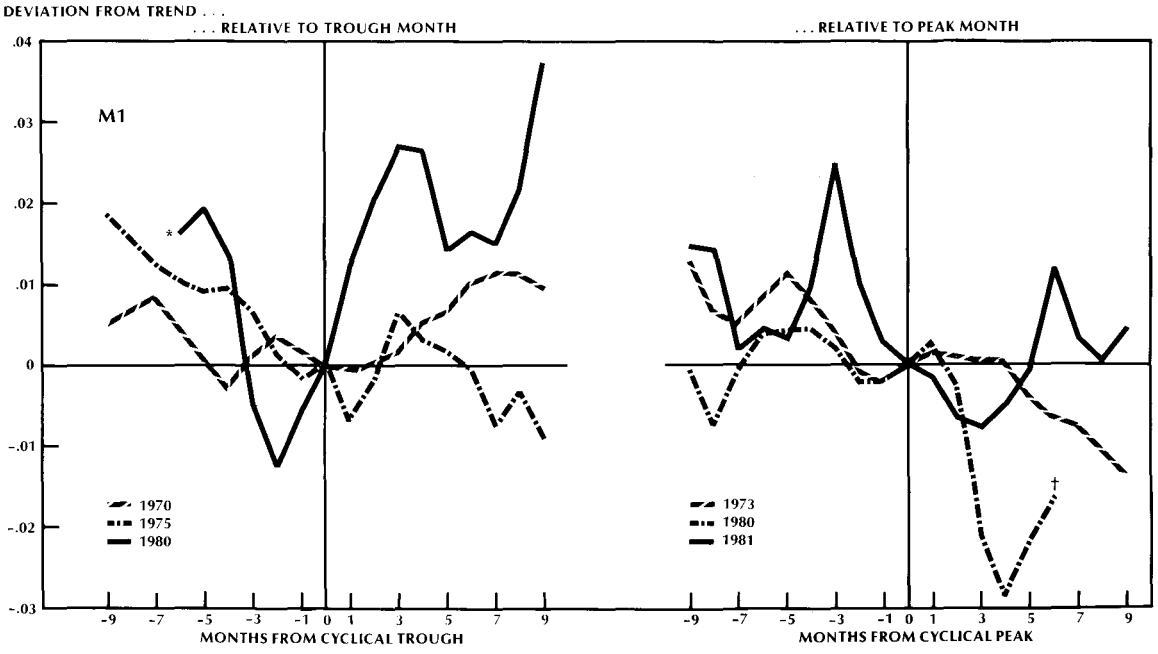
The behavior of M2 appeared considerably more reliable than that of M1 around turning points. M2 growth was well below trend until two to four months prior to troughs. It then steadily outstripped trend growth except after the 1980 trough, which marked the beginning of a very short recovery. M2 generally began to grow slowly well in advance of peaks and, except for the above-trend growth in the first month of recession, continued its slow growth for a few months beyond the peak. The behavior of M3, not shown, was similar to that of M2—an unsurprising result because most assets in M3 are also contained in M2.

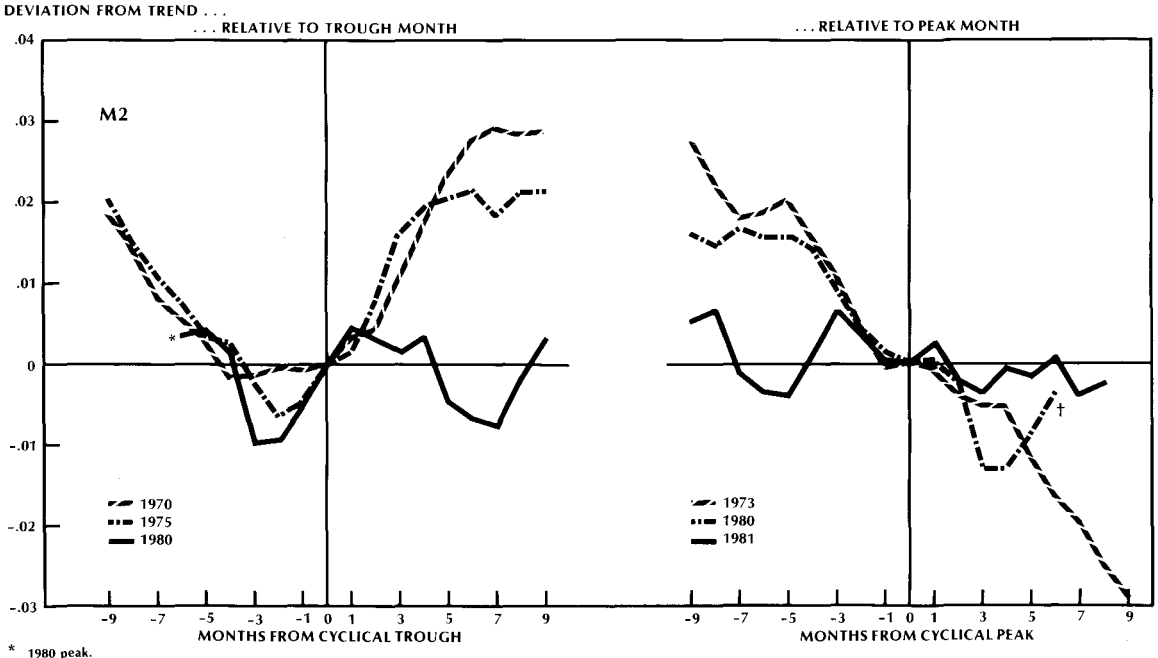
4. Deflated monetary aggregates actually combine information, in a particular way, from both money and prices. Deflating the money series goes far toward eliminating their long-term trends.

5. Elimination of trend in this fashion can generate spurious cyclical behavior. However, trend growth rates are established here merely for the purpose of providing a reasonable standard against which to judge money growth in the vicinity of peaks and troughs. Trend growth rates, at compound annual percentage rates, were 6.6 for M1, 10.1 for M2, and 11.1 for M3.

FIGURE 2

Behavior of M1 and M2 near Business Cycle Troughs and Peaks





* 1980 peak.
† 1980 trough.
SOURCE OF PRIMARY DATA: Board of Governors, Federal Reserve System.

The events of the 1970's, viewed from the business cycle approach, suggest that the larger aggregates can serve as useful leading indicators of economic activity. However, these same events cast some doubt on the reliability of M1.

Economic activity is statistically dependent on past M2 growth

The presence or absence of a relationship between pairs of time series—in this case, a money measure and economic activity—can be established by a statistical test of independence. If this relation is to prove useful to a forecaster, past and current observed changes in money must be correlated with future changes in business activity. Such correlations are termed "cross correlations." The cross correlation between two series y and m at lag j, denoted $\rho_{ym}(j)$, is simply the correlation between y_t and m_{t-j}.

Although direct examination of the cross correlations between changes in the monetary aggregates and subsequent changes in a business index might appear useful, this procedure is not generally valid. Large but spurious cross correlations can occur between two independent series as a result of autocorrelation in each.[6] Consequently, a prior step is required to eliminate autocorrelation in each series before cross correlations are estimated. Such autocorrelation can be eliminated by fitting an autoregressive-moving average (ARMA) model to each of the two series and estimating the residuals, alternatively referred to as "innovations."[7] The residuals can then be cross-correlated and tested for independence. ARMA models fitted for changes in the log of the index of four roughly coincident indicators (y) and the log of the alternative money measures (m) are reported in the accompanying box.[8]

Figure 3 displays the cross correlogram—the cross correlations for leads from money to real activity of 1 to 12 months ($1 \leqslant j \leqslant 12$) and lags from 1 to 12 months ($-12 \leqslant j \leqslant -1$)—between residuals of the coincident indicator index equation and those of the three alternative money measures. Statistically significant cross correlations at ($j > 0$) imply that changes in the money measure foreshadowed movements in the coincident index j months later. On the other hand, the magnitude of cross correlations at ($j < 0$) suggests the degree to which the coincident index foreshadowed future changes in the monetary aggregate. These latter cross correlations are displayed here because they are of interest in other contexts. The cross correlation at ($j = 0$) measures the contemporaneous relation.

Since M1 is published weekly with a two-week lag, it may, in principle, be used to predict the current month's activity. The reporting lag for M2 is longer, so its figures are released after the coincident indicator has been revealed. Thus, only in the case of M1 would a significant contemporaneous dependence manifest predictive usefulness.

M1 and the coincident index were directly dependent at ($j = -1$) and ($j = +1$), suggesting that each foreshadows the other with a one-month lead. The two series are essentially independent within the same month. For positive ranges of j, significance levels for cross correlations suggest that M1 is a poor indicator of future movements in the coincident index. However, movements in the coincident index significantly foreshadow money growth.

As an auxiliary set of tests, cross correlations of innovations within ranges of j, from l_1 to l_2, are examined for significance by forming:

$$S = n \sum_{j=l_1}^{l_2} r_{ym}^2(j),$$

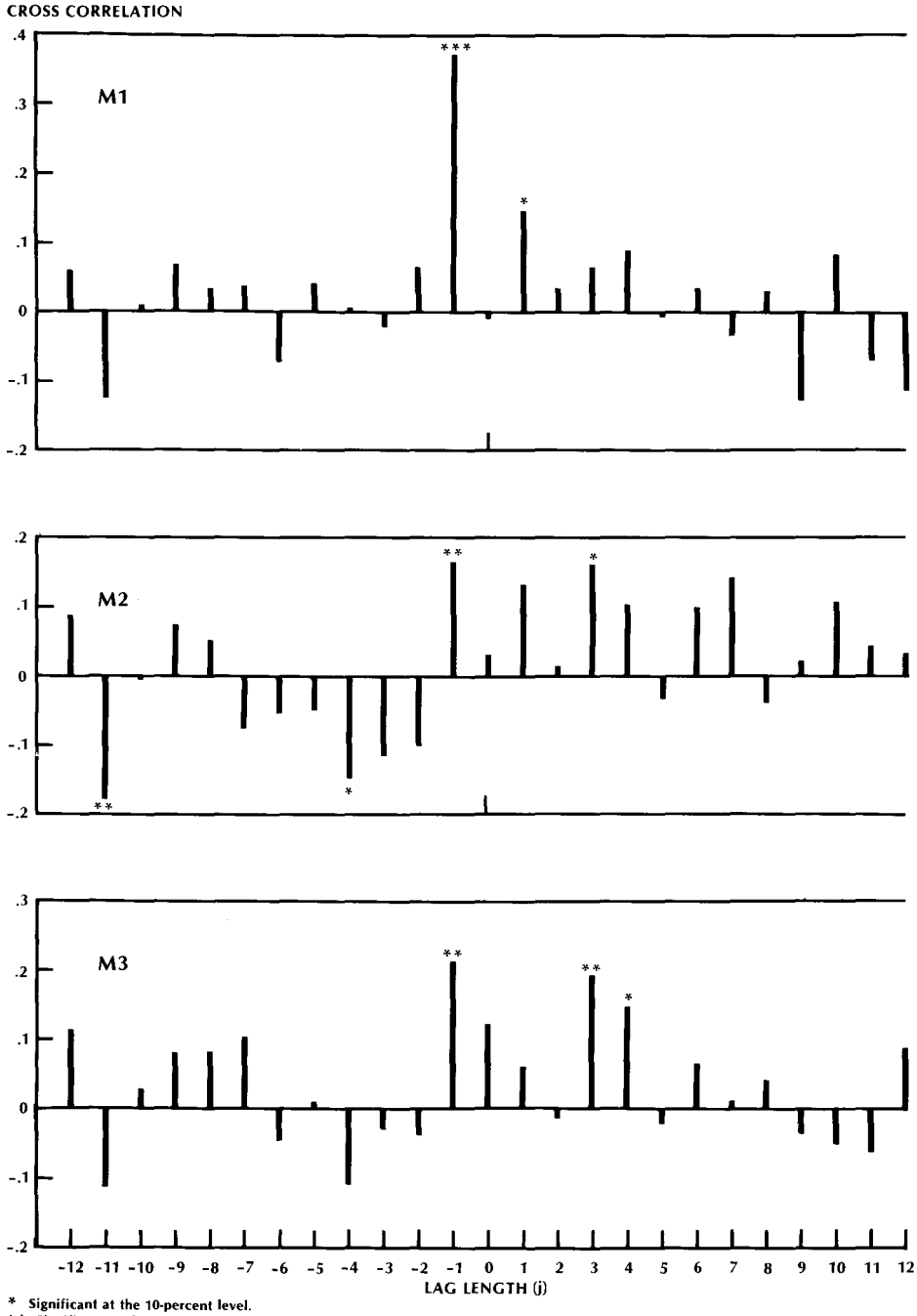
6. This problem is elucidated in Gwilym M. Jenkins and Donald G. Watts, *Spectral Analysis and Its Applications* (San Francisco: Holden-Day, 1968), especially pp. 336-38. As a special case, autocorrelation at seasonal lags—which are often found even in seasonally adjusted data—can lead to spurious cross correlations, particularly at the seasonal lag. This problem can be resolved by fitting the more complex seasonal ARIMA (autoregressive integrated moving average) models. Seasonal autoregression in the seasonally adjusted series at hand was small and insignificant, allowing the use of simpler and more transparent ARIMA models.

7. Strictly speaking, autoregressive integrated moving average models are employed here, in that first differences (changes) in the series are modeled as autoregressive-moving average equations.

8. The Commerce Department's index of roughly coincident indicators reflects movements in (1) the number of employees on nonagricultural payrolls, (2) industrial production, (3) personal income, less transfer payments, in 1972 dollars, and (4) manufacturing and trade sales, in 1972 dollars. During the period of study, the dating of business peaks and troughs (as designated by the National Bureau of Economic Research) coincided exactly with peaks and troughs in the index.

FIGURE 3

Cross Correlograms for Money Measure and Coincident Index Residuals



* Significant at the 10-percent level.
** Significant at the 5-percent level.
*** Significant at the 1-percent level.

ARMA Equations for Real Activity and Money Measures

(1) $y = \Delta\ln$(index of roughly coincident indicators).
ARMA(1,4):

$$y_t = .00138 + .28\, y_{t-1} + a_t + .17\, a_{t-1} + .18\, a_{t-2} + .18\, a_{t-3} + .17\, a_{t-4}.$$

Standard error of equation = .00743.

	Chi-square test
M	Significance
12	.94
24	.68

(2) $m = \Delta\ln(M1)$.
ARMA(0,4):

$$m_t = .00529 + a_t + .21\, a_{t-1} - .17\, a_{t-2} - .04\, a_{t-3} - .27\, a_{t-4}.$$

Standard error of equation = .00458.

	Chi-square test
M	Significance
12	.81
24	.56

(3) $m = \Delta\ln(M2)$.
ARMA(2,2):

$$m_t = .00200 + .39\, m_{t-1} + .35\, m_{t-2} + a_t + .16\, a_{t-1} - .38\, a_{t-2}.$$

Standard error of equation = .00296.

	Chi-square test
M	Significance
12	.34
24	.47

(4) $m = \Delta\ln(M3)$.
ARMA(0,7):

$$m_t = .00875 + a_t + .40\, a_{t-1} + .16\, a_{t-2} + .29\, a_{t-3} + .24\, a_{t-4} + .20\, a_{t-5} + .19\, a_{t-6} - .15\, a_{t-7}.$$

Standard error of equation = .00251.

	Chi-square test
M	Significance
12	.41
24	.47

The methods of selecting and estimating ARMA (autoregressive-moving average) models are described in George E. P. Box and Gwilym M. Jenkins, *Time Series Analysis: Forecasting and Control*, rev. ed. (San Francisco: Holden-Day, 1976).

The criteria used here in the selection among alternative models were that the number of parameters be small and that the residuals (a_t) not be autocorrelated; this last property is essential for the tests of dependence between y and m. Autocorrelation in the residuals was tested for using the statistic:

$$Q = n \sum_{k=1}^{M} r_k^2(a_t),$$

where $r_k(a_t)$ is the correlation between a_t and a_{t-k}. If the residuals are not autocorrelated, Q takes approximately a chi-square distribution with $(M - p - q)$ degrees of freedom, where p and q are the number of autoregressive parameters and moving average parameters, respectively. Significance levels of the Q statistic for M equal to 12 and 24 are reported below the equation to which they relate. These significance levels are well above classic critical values, such as .1. The distribution theory underlying the test is expounded in G. E. P. Box and David A. Pierce, "Distribution of Residual Autocorrelations in Autoregressive-Integrated Moving Average Time Series Models," *Journal of the American Statistical Association* 65 (December 1970):1509-26.

Table 2
CHI-SQUARE STATISTICS FOR INDEPENDENCE TESTS

Lag range l_1	l_2	M1	M2	M3
0	0	0.0	0.1	2.1
0	3	4.0	—	—
0	6	5.3	—	—
0	12	11.5	—	—
1	1	—	2.5	0.6
1	3	—	6.4*	6.1
1	6	—	9.6	9.9
1	12	—	15.0	12.2
-3	-1	20.5***	7.3*	6.9*
-6	-1	21.5***	11.2*	8.9
-12	-1	25.3***	18.8*	16.1
-1	1	23.0***	6.6*	9.2**
-3	3	24.5***	13.8*	15.1**
-6	6	26.8**	21.0*	20.8*
-12	12	36.8*	34.0	30.4

* Significant at the 10-percent level.
** Significant at the 5-percent level.
*** Significant at the 1-percent level.

where n is the sample size and $r_{ym}(j)$ is the sample cross correlation between innovations in y and m at lag j. S, reported in Table 2 for selected lag ranges, is approximately distributed as a chi-square with $(l_2 - l_1 + 1)$ degrees of freedom if y and m are independent.[9]

Although none of the sets of correlations for positive ranges of j are highly significant by conventional standards, M2 and M3 gave evidence of being more suitable indicators. M2 was most strongly related to subsequent months' values of the coincident index. The only leading relationships significant at less than 10 percent were the correlations between the residuals of the index and residuals of M2 one to three months earlier. Overall, the pattern of cross correlations reveals that accelerated growth in the two larger aggregates foreshadowed acceleration in the growth of economic activity with a three-month lead time.

The independence tests in this section yield the qualitative conclusion that the larger aggregates could aid economic forecasting. In the next section are reports of tests, from a somewhat different method, that quantify the potential improvement in forecast accuracy.

Broader aggregates are the most informative

A linear forecasting equation can take the form:

$$\hat{y}_t = a + \sum_{i=1}^{k} b_i y_{t-i} + \sum_{i=0}^{k} c_i m_{t-i},$$

where $\hat{y}$ is the predicted value of y and m is the growth rate of one of the three monetary aggregates. The subscripts denote the time of the observation. The index i represents the lag, expressed in months. The values of a, b_i, and c_i can be estimated by the ordinary least squares regression procedure. The equation constitutes an explicit formula, or recipe, for predicting y for a given month from information on previous values of y and m. If the monetary aggregate used is M1, then m_t is included in the equation. Otherwise, the monetary variables range from m_{t-1} to m_{t-k}.

The issue at hand is whether the use of known values of m can increase the accuracy of forecasts of y. If so, then m can be used to reduce the magnitude of typical forecasting errors. This hypothesis can be tested directly by estimating the above equation, both with and without the money terms. If the standard error (a gauge of the typical error) of the regression equation is lower when these terms are included, it is concluded that m can be used to improve forecasts of y.[10] Furthermore, the proportional reduction in the standard error is an empirical measure of the information gained from including the money measure in the forecasting scheme. Only if the information gain is sufficient to justify additional costs should an indicator be incor-

9. The distribution theory is found in Larry D. Haugh, "Checking the Independence of Two Covariance-Stationary Time Series: A Univariate Residual Cross-Correlation Approach," *Journal of the American Statistical Association* 71 (June 1976):378-85.

10. The hypothesis referred to, formally designated "Granger causality," is described in C. W. J. Granger and Paul Newbold, *Forecasting Economic Time Series* (New York: Academic Press, 1977), pp. 224-26. A causal interpretation is not hereby intended. A slight variant of the test is used in assessing the predictive usefulness of M1, since current as well as past values enter into the regression.

Table 3
RESULTS OF COMPARING STANDARD ERRORS OF FORECAST EQUATIONS AND NAIVE PROJECTION

	Forecast equation regressors							
		Lagged y plus lagged						
	Lagged y only	M1	M2	M3	M1 and M2	M2 and M3	M1 and M3	M1, M2, and M3
Lag length	Reduction in standard error relative to standard error of naive projection (Percent)							
0	—	0.2	—	—	—	—	—	—
1 month ...	14.5	15.2	16.3	15.3	16.0	16.0	15.3	15.7
3 months ...	14.6	15.1	18.6	17.6	17.6	18.8	17.1	17.8
6 months ...	14.2	14.3	17.5	16.4	17.5	18.0	16.2	18.3
9 months ...	13.7	15.6	19.4	19.2	19.8	21.7	18.1	23.3

porated into forecasts.

The forecasting equations were estimated with the three money growth measures for m and lag lengths of zero, one month, and three, six, and nine months. The lag length is the number of months of past data that the forecaster uses. In most practical situations, a forecasting scheme that has greater data requirements (larger k) would not be chosen over one with fewer data requirements unless there is sufficient gain in information.

The simplest equation uses no past information ($k = 0$):

$$\hat{y}_t = a + c_0 m_t,$$

where m is the growth rate of M1. If M1 is removed, it is simply the "naive" projection:

$$\hat{y}_t = a = \bar{y}_t;$$

the predicted value of y is its mean value. The standard error of this latter equation is equal to the standard deviation of y, .008922, or a little less than 0.9 percent. Including the money term results in a better-fitting equation, even though penalizing the standard error for the loss of one degree of freedom through the estimation of the additional parameter. Using the estimated value of c_0, .19, the equation has a standard error of .008908, a reduction of only 0.2 percent from the forecast that ignored m_t. Because the improvement is so small, the conclusion is that current M1 values alone contain very little information about current economic activity.

Table 3 summarizes results for alternative specifications, showing the reduction in standard error for each equation relative to that of the naive projection.[11] From these, some interesting conclusions can be made.

A forecaster could significantly improve accuracy by collecting recent values of y. Just using the last month's value of y reduces the standard error by 14.5 percent. The addition of the current and most recent prior value of M1 growth brings only a modestly greater reduction, down to 15.2 percent. Extending the set of information to include nine lagged values of y and M1 results in only slightly improved forecasting accuracy.

M2 and M3 each provided more information about probable movements in the coincident index than did M1. One fairly simple equation, with M2 and a lag length of 3, would have served well:

$$\hat{y}_t = \underset{(.002)}{-.007} + \underset{(.085)}{.387}\, y_{t-1} + \underset{(.095)}{.018}\, y_{t-2} + \underset{(.088)}{.083}\, y_{t-3}$$
$$+ \underset{(.218)}{.462}\, m_{t-1} - \underset{(.246)}{.124}\, m_{t-2} + \underset{(.221)}{.629}\, m_{t-3},$$

where $m_t = \Delta \ln(M2_t)$ and standard errors are given in parentheses below the parameter estimates to

11. Serial correlation of disturbances in equations with lagged y values can bias results and is difficult to test. However, run tests on signs of residuals, Durbin-Watson statistics (ranging from 1.90 to 2.08), and first-order autocorrelation estimates (ranging from −.07 to +.01) did not suggest problems that would invalidate conclusions.

which they relate. This equation has a standard error 18.6 percent less than the naive projection. Only a small gain in forecasting accuracy is achieved by lengthening the lag beyond three months.

A model that included all three aggregates with nine lagged values performed best, reducing the standard error relative to that of the naive forecast by 23.3 percent. Compared with the standard errors of the equations using past *y* alone, the standard error of this equation is roughly one-tenth lower. This might be regarded as an upper bound on the information available from the aggregates within the context of the linear forecasting model.[12]

The evidence from linear forecasting equations suggests that forecasters can, at very low cost, gain accuracy in predicting economic activity by focusing on the M2 growth rates for a few earlier months. But the improvement obtained from adding any single monetary aggregate to the forecast scheme is not high.

Conclusions

The extent to which the results reported above will prove useful for practical applications in the 1980's depends on the validity of a number of assumptions. The coincident index is not the only measure of overall real economic activity, but it has been assumed to be appropriate for an important segment of the business community. In addition, the individual data points of both the coincident indicators and monetary aggregates have undergone revision since they were first released. The analysis assumes that the relationships between the originally reported series do not differ significantly from the relationships between the revised series.

A more serious problem is the changing composition of the monetary aggregates, particularly M2. This aggregate once consisted almost entirely of deposits with fixed interest rates. Thus, when market interest rates rose, funds flowed out of M2 to other assets. Over the 1970's, however, most of the growth in M2 occurred in components paying yields that rise and fall with market interest rates. This change is likely to have made M2 less sensitive to changes in interest rates, but whether it has had a similar effect on the relationship between interest rates and economic activity is harder to assess. In any case, the relation between the aggregates and the economy is likely to change over time, and the relevance of the results of this article depends on the change not being overly large.

Subject to these caveats, the analysis permits the following conclusions. First, M2 can be usefully employed to improve forecasts of a measure of the business cycle. M3 is about equally useful, but M1 alone is not. Heavy reliance on weekly M1 announcements appears especially unjustified. Second, a comparison between results of the business cycle method and statistical forecasting suggests that the former approach can lead to misleading conclusions. In particular, M1 appeared to be of at least some usefulness because it tends to lead the economy; yet statistical tests uncovered insignificant information content.

12. Forecasting based on disaggregated monetary data (currency, demand deposits, and so on) most likely could achieve considerable improvements in accuracy. P. A. Tinsley, P. A. Spindt, and M. E. Friar ("Indicator and Filter Attributes of Monetary Aggregates: A Nit-picking Case for Disaggregation," *Journal of Econometrics* 14 [September 1980]:61-91) found that the aggregation of monetary assets conceals much, or even most, of the available information. Many forecasters would find component-by-component analysis uneconomically time-consuming, however.

Sources of Depressed Earnings Along the Texas-Mexico Border

*By Alberto E. Davila**

The Texas-Mexico border region has typically been characterized as having depressed wages relative to wages in nonborder regions. The Public Use Sample of the 1970 Census shows that residents of Texas border cities had annual earnings that were 30 percent lower than earnings of residents of nonborder cities in the Southwest. Furthermore, earnings of border residents in blue-collar employment were 35 percent below earnings of their nonborder counterparts. These statistics appear to contradict economic theory, which implies that over the long run, wages along the Mexican border should be as high as wages for similar workers in other parts of the Southwest.

Three economic forces should maintain approximate equality of wages in any two regions under a competitive market system.[1] First, lower wages should lead to lower production costs and, thus, lower prices for firms in a region. These lower prices, in turn, should induce consumers to demand more goods from the lower-price region, prompting firms in that region to increase production and employment. This would put upward pressure on wages in the region. The reduced demand in the higher-price region would bid wages down for the labor there. Second, in attempting to maximize profits, firms would migrate to the lower-wage region to reduce costs. This would further increase the demand for labor in the lower-wage region and decrease the demand in the higher-wage region. The third effect would work on the supply side of the market. Workers would have an incentive to migrate to the higher-wage region. The increase in supply to the higher-wage region, coupled with the decrease in supply to the lower-wage region, would also narrow the wage differential.

What makes the behavior of wages along the border of special interest is that illegal immigration from Mexico supposedly provides an elastic supply of labor to the area. This supply allegedly prevents any increase in wages in border cities (relative to the nonborder cities), resulting in a differential that

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1. For a more detailed discussion of regional wage equalities, see Don Bellante and Mark Jackson, *Labor Economics: Choice in Labor Markets* (New York: McGraw-Hill Book Company, 1979), pp. 156-61, and Michael Bradfield, "Necessary and Sufficient Conditions to Explain Equilibrium Regional Wage Differentials," *Journal of Regional Science* 16 (August 1976):247-55.

is permanent. The low average earnings of border residents appear to support this logic.

But before accepting illegal Mexican labor as the cause of depressed border wages, two points should be considered. First, the implicit assumption that the border region receives the bulk of illegal aliens may not be realistic. The probability that illegal aliens will cross the border and migrate to industrial centers, such as Houston or even Chicago, is quite high. In these cities, job opportunities are more plentiful, and detection of illegal entry is more unlikely.

Second, other factors may be responsible for the lower earnings along the border. Border residents possess different socioeconomic characteristics (characteristics such as educational and skill levels), and the border region has a lower cost of living than in interior regions and a higher concentration of Mexican-Americans, who typically earn lower wages. Controlling for these factors properly should decrease or eliminate the income differential cited above.[2]

This article gives support to the second explanation. The major sources of differences in incomes of heads of households living in the border region and those living elsewhere in the Southwest are found to be differences in cost of living, concentrations of Mexican-Americans, occupational distributions, and time spent working in a year. The results presented also imply that economic forces—for example, capital and labor mobility—are working efficiently between the border region and interior regions (since similar labor seems to be receiving similar wages in both) and that any effects of illegal entry are not confined to the border alone. Policy actions, if any, should therefore turn attention to regional differences in such underlying characteristics as the education and training of workers.

Characteristics of the border cities

The data used in this analysis are from the 5-percent county group sample in the Public Use Samples of Basic Records from the 1970 Census. The Census samples contain the annual earnings and a variety of socioeconomic characteristics of a large number of individuals. The information can be used to construct control variables for a multiple regression analysis of the determination of earnings.

The sample analyzed consists of household heads in 19 "cities" in Texas, Arizona, Colorado, and New Mexico.[3] The cities all have high concentrations of Mexican-Americans and have likely absorbed a significant amount of illegal Mexican immigration. The sample was restricted to residents of these four states to avoid having to control for regional differences in wage structures.[4]

The cities within 20 miles of the Mexican border—Brownsville, El Paso, and Laredo, Texas—are defined as border cities. They are modest in size compared with some other cities in the four states, such as Houston and Dallas, which generally have higher wages. Houston and Dallas also have lower unemployment rates and higher living costs.[5] To

2. Barton Smith and Robert Newman addressed this question and found that controlling for these factors narrowed the differential considerably, but even after their adjustments, earnings were significantly lower in border cities ("Depressed Wages Along the U.S.-Mexico Border: An Empirical Analysis," *Economic Inquiry* 15 [January 1977]:51-66).

3. The Census data do not have a measure of cities as such. Consequently, the analysis here draws upon population statistics that are available by "county group," which may be a standard metropolitan statistical area (SMSA), a combination of SMSAs or counties, or a single county. The term "cities" in this article refers to these units, with the name of only the dominant city being used to identify the county group.

4. Many California cities have large percentages of Mexican-Americans but also have higher wage structures than the cities in this study.

5. The unemployment rates for Brownsville, El Paso, and Laredo averaged 6.2 percent in 1970, compared with 3.0 percent for Dallas and Houston. For the sample used here, the cost-of-living index averaged 87.19 for cities with population less than 200,000, compared with 100.75 for cities with population over 500,000 (the U.S. average was 100.00). Except for the cost-of-living estimate for Brownsville—obtained from Smith and Newman, "Depressed Wages Along the U.S.-Mexico Border," p. 54—these figures are based on data from Ben-Chieh Liu, *Quality of Life Indicators in U.S. Metropolitan Areas, 1970: A Comprehensive Assessment*, prepared for the Washington Environmental Research Center, U.S. Environmental Protection Agency (Washington, D.C.: Government Printing Office, 1975), pp. 231-81 passim.

The importance of comparing real, rather than nominal, earnings has been documented elsewhere. For example, see Philip R. P. Coelho and Moheb A. Ghali, "The End of the North-South Wage Differential," *American Economic Review* 61 (December 1971):932-37, and Don Bellante, "The North-South Differential and the Migration of Heterogeneous Labor," *American Economic Review* 69 (March 1979):166-75. These studies found that persistent geographic wage differentials are partly explained by regional differences in cost of living.

Table 1
DISTRIBUTION OF SAMPLE USED IN ANALYSIS OF DETERMINANTS OF BORDER-INTERIOR EARNINGS

Area[1]	Heads of households: Number	Heads of households: Percent of sample
Texas		
Houston	457	19.3
Dallas	370	15.6
Fort Worth	178	7.5
San Antonio	178	7.5
Odessa	78	3.3
Galveston	76	3.2
EL PASO[2]	71	3.0
Austin	69	2.9
Beaumont	69	2.9
San Angelo	57	2.4
Corpus Christi	50	2.1
Lubbock	47	2.0
BROWNSVILLE[2]	45	1.9
LAREDO[2]	43	1.8
Arizona		
Phoenix	211	8.9
Tucson	66	2.8
Colorado		
Denver	138	5.8
Pueblo	95	4.0
New Mexico		
Albuquerque	74	3.1
19 "cities"	2,372	100.0

1. County group, identified by name of dominant city in group.
2. Border city.
SOURCE OF PRIMARY DATA:
Public Use Sample from the 1970 Census.

reduce the possibility that estimated differences in earnings of border and interior residents are due to differences in the sizes of their respective cities, the set of nonborder cities covered here contains several communities of modest size (Table 1).[6]

Differences in the characteristics of the workers themselves also contribute to the lower average earnings found along the border (Table 2). The interior cities have higher concentrations of workers in white-collar occupations (professionals, managers, and sales and clerical workers) and, more important, higher concentrations of workers in the highly skilled subgroups of the white-collar and blue-collar occupations. Furthermore, the residents of nonborder cities have, on average, completed approximately three more years of schooling than border residents. These facts suggest that to some extent, greater skill and productivity account for the higher earnings of the nonborder labor force.

Differences in racial composition in the two areas reinforce the effect of differences in skill mentioned above. Blacks and Mexican-Americans typically earn less than whites, even after identifiable differences in skill and education are taken into account. The lower wages may reflect discrimination, the effect of illegal immigration (particularly for Mexican-Americans), or systematic differences in tastes for nonpecuniary aspects of jobs. The border cities have slightly lower concentrations of blacks (2 percent versus 9 percent) but much higher proportions of Mexican-Americans (50 percent versus 7 percent).

Determinants of earnings for the full sample . . .

The foregoing discussion indicates that border and nonborder cities in the four states differ significantly in their costs of living, unemployment, and population characteristics. The differences go far in explaining why average annual earnings are much lower in the border cities. The analysis described below estimates the effect of these factors on the border-nonborder earnings differential.

Multiple regression analysis has been used to estimate the earnings differential that remains after

6. This is the major departure from the study by Smith and Newman. They included one nonborder city, Houston, Texas. The inclusion of only one nonborder city, together with the size differential between this city and the border cities in their study (Brownsville, Corpus Christi, and Laredo), may have biased their results.

Table 2
CHARACTERISTICS OF HEADS OF HOUSEHOLDS IN 19 SELECTED CITIES

	Heads of households in 3 border cities					Heads of households in 16 interior cities				
	All	Mexican-American	Non-Mexican-American	White-collar	Blue-collar	All	Mexican-American	Non-Mexican-American	White-collar	Blue-collar
Average age	43	45	41	44	44	42	38	42	41	43
Average years of schooling	11	8	13	14	9	14	10	14	16	12
Percent in high-skill occupations[1]										
White-collar workers	19	13	27	60	—	29	12	31	66	—
Blue-collar workers	24	26	22	—	47	32	46	31	—	71
Percent in low-skill occupations[2]										
White-collar workers	13	14	12	40	—	15	9	15	34	—
Blue-collar workers	42	48	41	—	53	24	33	23	—	29
Percent working at least 50 weeks in 1969	69	65	73	83	59	76	74	76	80	72

1. Includes professional workers and managers for white-collar occupations and craftsmen and transport equipment operatives for blue-collar occupations.
2. Includes sales and clerical workers for white-collar occupations and laborers for blue-collar occupations.
NOTE: Percentages may not add to 100 because of rounding.
SOURCE OF PRIMARY DATA: Public Use Sample from the 1970 Census.

accounting for differences in cost of living, weeks worked, and socioeconomic characteristics. The models express the natural logarithm of real annual earnings (nominal earnings deflated by the consumer price index) as functions of, first, weeks worked and, then, weeks worked, experience, schooling, sex, marital status, race, occupation, and industry of employment. (See the Appendix for details on the regressions.)

Each equation also includes a "border residence" variable, which is equal to 1 when the individual lives in a city within 20 miles of the border and zero when he does not. The coefficient of this variable, b, can be used to estimate the percentage differential between border and nonborder earnings after adjusting for the other variables included in the equation. The expression for the estimated differential is:

$$[1 - \exp(b)] \times 100.$$

This formula was used to calculate the third and fifth rows of figures in Table 3.

In nominal terms, before any adjustments, the average earnings of border workers are 30 percent lower than those for nonborder workers. However, when each worker's nominal earnings are divided by the cost-of-living index for the appropriate city, the average earnings differential falls to 23 percent. When account is taken of differences between the two groups in working time in a year, the differential falls to 19 percent. This figure is an estimate of the differential in real weekly earnings, and it indicates that lower cost of living and higher unemployment account for about one-third of the border-nonborder difference in nominal annual earnings.

After controlling for socioeconomic characteristics, real earnings of border workers are, on average, approximately equal to earnings of nonborder workers. The major contributor to the gap in average real weekly earnings is the difference in concentrations of Mexican-Americans in the border and nonborder regions. This accounts for approximately 12 percentage points of the lower border earnings. However, if the differential is adjusted to take into account the difference in concentrations of blacks in the two regions, the net racial composition effect falls to 10 percent.

The next major contributor is the occupational

Table 3
DIFFERENTIALS BETWEEN BORDER AND NONBORDER EARNINGS, 1969

	Heads of households in 19 selected cities				
	All	Mexican-American	Non-Mexican-American	White-collar	Blue-collar
	Earnings of interior residents less earnings of border residents as percent of earnings of interior residents				
Before adjustment	29.7	30.8	11.5	14.8	35.4
After adjustment for differences					
In cost of living	22.9	22.6	3.3	5.8	29.3
In cost of living and weeks worked[1]	18.8	11.0	-.2	7.1	23.0
	(3.5)	(1.3)	†	(.7)	(3.0)
In cost of living, weeks worked, and socioeconomic characteristics[1]	.4	3.2	-4.6	-6.0	6.0
	(.1)	(.4)	(-.7)	(-.7)	(.8)
Number in sample	2,372	251	2,121	1,028	1,344

1. Equal to $[1 - \exp(b)] \times 100$, where b is the coefficient of the border residence dummy variable in the regression of real annual earnings on the dummy variable and the indicated control variables. Figures in parentheses are t statistics for the b's.
† Absolute value less than .05.
SOURCES OF PRIMARY DATA: Liu, *Quality of Life Indicators in U.S. Metropolitan Areas.*
Public Use Sample from the 1970 Census.
Smith and Newman, "Depressed Wages Along the U.S.-Mexico Border."

distribution in the two regions. This accounts for approximately 8 percentage points of the differential. The other principal source is education, accounting for roughly 2 percentage points of the earnings gap.

. . . and for racial and occupational groups

In general, the results here indicate that the lower average earnings along the border can be explained by the area's lower cost of living, higher unemployment rate, higher concentrations of Mexican-Americans and workers in low-skill occupations, and lower average education. This suggests that illegal immigration has not had a larger effect on border earnings than on nonborder earnings. To subject this hypothesis to a stronger test, additional analysis was conducted using a procedure similar to that outlined above, with the sample split into two racial groups—Mexican-Americans and non-Mexican-Americans. In addition, the sample was analyzed on the basis of two occupational groups—white-collar workers and blue-collar workers.

The average unadjusted earnings differentials for Mexican-Americans and non-Mexican-Americans are consistent with the hypothesis that Mexican-Americans are more affected by illegal entry. The border-nonborder differential for Mexican-Americans is larger than the comparable differential for their non-Mexican-American counterparts. However, as was the case earlier, these figures are misleading. On average, border Mexican-Americans have fewer years of schooling than nonborder Mexican-Americans, work fewer weeks a year (which accounts for 13 percent of the difference in earnings), and are mostly concentrated in laborer occupations. The corresponding differences for non-Mexican-Americans are much smaller.

After controlling for these differences and others, using the multiple regression model, the differentials for these groups fall to −4.6 percent for non-Mexican-Americans (non-Mexican-Americans have higher earnings along the border) and to 3.2 percent for Mexican-Americans. The t statistics for the regression coefficients are very small, however, indicating the differentials are not significantly different from zero.

A very similar story emerges when comparing

blue-collar workers and white-collar workers. The blue-collar group has a large average weekly earnings differential relative to the white-collar group. This, again, would seem to support the hypothesis that illegal aliens are depressing wages along the border since they compete mostly with blue-collar workers for jobs. But after adjustment for differences in workers' characteristics, the earnings differential declines sharply and becomes statistically insignificant.

The sources of the difference in earnings for the blue-collar workers and white-collar workers are the same as those responsible for the differential between Mexican-Americans and non-Mexican-Americans: educational and occupational differences between the border and nonborder regions. For white-collar workers the differences in the characteristics of border and nonborder residents are very small. This similarity leads to insignificant differences in real weekly earnings, both before and after adjustment for socioeconomic characteristics.

Conclusions

Labor and capital mobility seems to be operating efficiently between the border and the interior since similar workers are getting the same earnings in the two regions. More important, given lower educational levels and a lower-skill occupational distribution along the border, policy actions designed to help the border region should foster human capital investment. Such investment would help the border residents in at least two major ways. First, their earnings would increase, on average, because firms would be willing to pay more for more productive workers. Second, nonborder capital-intensive firms would be attracted to the border region because they would have a high-skill labor pool from which to recruit. This, in turn, would alter the skewed occupational distribution along the border.

The study here did not test the hypothesis that illegal immigration depresses wages in the Southwest. The lack of data on the number of illegal aliens prevents such a test. The results do indicate, however, that if illegal immigration of Mexicans does reduce wages, the effect is not confined to the border.

Appendix

Description of Variables in the Earnings Model

The dependent variable is an annual earnings measure that includes only wages, salary, commissions, bonuses, or tips from all jobs. The sample is limited to heads of households in an effort to restrict the analysis to individuals likely to have a strong attachment to the labor force.

The border residence variable is defined in the article. The schooling variable and work experience variable (age less years of schooling less 5) capture any differences in human capital investment. Individuals with more human capital tend, on average, to earn more than those with less human capital. The "married" variable controls for the lower annual earnings generally found for individuals who are not married. Females, Mexican-Americans, and blacks are all identified in the model with appropriate dummy variables to account for possible discrimination effects.

"Full time" is a dummy variable depending on whether the individual worked more than 34 hours a week (=1). "Weeks worked" is entered as a set of dummy variables because the number of weeks the individual worked is recorded as a range, such as 27 to 39. If the exact number had been provided, annual earnings divided by weeks worked could have been used to construct the dependent variable. (The deleted group is 48 to 49 weeks worked in a year.) Future

research should test if the border residence coefficient is affected by the assumption that weeks worked and hours worked are exogenous variables.

Occupation and industry dummies control for any earnings differentials that may arise from working in a particular occupation or industry. This was based on two-digit occupation and industry codes. (The deleted group for the set of occupation variables is laborers, except farm. For the industry variables the deleted group is public administration.)

The accompanying table reports the regression coefficients for the full sample. The regressions for the subgroups show similar results.

RESULTS OF REGRESSING SOCIOECONOMIC CHARACTERISTICS OF THE FULL SAMPLE ON REAL ANNUAL EARNINGS

Variable	Coefficient	*t* statistic
Border residence (*b*)	-.004	-.08
Work experience	.04	12.69
Work experience squared	-.001	-12.93
Years of schooling		
Less than 7	-.07	-.90
7 to 8	-.04	-.75
9 to 11	-.02	-.54
13 to 16	.08	2.08
17	.26	3.39
More than 17	.24	3.57
Female	-.23	-4.15
Married	.20	4.49
Mexican-American	-.32	-7.24
Black	-.28	-5.98
Weeks worked		
13 or less	-1.60	-17.39
14 to 26	-1.00	-11.72
27 to 39	-.57	-7.41
40 to 47	-.08	-1.11
50 to 52	.06	.98
Full time	.19	4.82
Occupation		
Professional	.43	7.91
Manager, administrator	.42	7.67
Sales worker	.19	2.81
Clerical worker	.13	2.17
Craftsman	.19	3.76
Operative	.05	.76
Transport operative	-.01	-.14
Farmer, farm manager	-.36	-3.69
Service worker	-.12	-2.08
Private household worker	-.49	-3.78
Industry group		
Agriculture	-.70	-2.57
Mining	.08	.99
Construction	.01	.26
Manufacturing	.05	1.08
Transportation	.003	.05
Wholesale trade	-.01	-.20
Retail trade	-.04	-.74
Finance	.04	.63
Professional services	-.08	-1.38
Other services	-.11	-1.87
Regression intercept	3.47	40.00

Number in sample = 2,372; R^2 = .54.

The *Economic Review* is published by the Federal Reserve Bank of Dallas and will be issued five times in 1982 (March, May, July, September, and November). This publication is sent to the mailing list without charge, and additional copies of most issues are available from the Publications Department, Federal Reserve Bank of Dallas, Station K, Dallas, Texas 75222. Articles may be reprinted on the condition that the source is credited.