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The High-Yield Spread as a Predictor of Real Economic Activity: Evidence of a Financial Accelerator for the United States

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Previous studies find that the interest rate term spread predicts real U.S. economic activity. We show that this relationship breaks down for the 1990s and suggest that its earlier success was due to high and volatile inflation. We find, however, that the high-yield spread (HYS) between "junk bond" and government bond yields predicts real activity during the 1990s—especially high levels of the HYS. We also find that the HYS works through both the demand and the supply side of the economy. We interpret our findings as supportive of a financial accelerator mechanism. [JEL E33, E44]

The slope of nominal yield curve, or the term spread, was shown by studies published in the late 1980s and early 1990s to have significant predictive content for future real economic activity, both in the United States and in Europe.[1] Following the early work by Stock and Watson (1989) and Estrella and Hardouvelis (1991),[2] however, confidence in the predictive power of the term spread waned a little when it failed to predict the 1990–91 U.S. recession (see, for example, Dotsey, 1998). Nevertheless, further work by, among others, Estrella and Mishkin (1997) and Plosser and Rouwenhorst (1994) seemed to establish that its power as a leading indicator of real economic activity had not evaporated. This somewhat mixed evidence on the forecasting performance of the term spread remains in the literature.

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[1]See, for example, Stock and Watson (1989), Harvey (1989), Chen (1991), Estrella and Hardouvelis (1991), Hu (1993), Caporale (1994), Peel and Taylor (1998), and Bernard and Gerlach (1998).

[2]See also Laurent (1988).

Dotsey (1998, p. 50), for example, in a paper that is generally supportive of the view that the term spread does indeed contain predictive information, notes that "that conclusion must be tempered, however, by the observation that over more recent periods the spread has not been as informative as it has been in the past."

Gertler and Lown (1999), drawing on the theory of the financial accelerator (see, for example, Bernanke and Gertler, 1995; Bernanke, Gertler, and Gilchrist, 1999, and the references cited therein), argue that an alternative financial variable should also have predictive power for real economic activity—this is the premium required on less than investment-grade corporate bonds (also referred to as "high-yield" or "junk" bonds) over government debt or AAA-rated corporate bonds. Gertler and Lown (1999) provide some empirical support for this view based on correlation and impulse-response analysis, using data on the high-yield spread and a measure of the U.S. output gap.

We seek in this paper to contribute to this literature in a number of ways. First, we examine the robustness of the term spread as a predictor of economic activity by estimating long-horizon regressions covering broadly three periods—the 1960s, the 1970s and 1980s, and the 1990s. In brief, we find that the term spread does not predict real economic activity well for the most recent period, although it does perform well in this capacity for the 1970s and 1980s. Interestingly, however, we find that the predictive content of the term spread appears to be unique to the 1970s and 1980s, in that we also find it to be only weakly present in the data for the 1960s.

We then move on to examine the predictive content of the high-yield spread. We believe this analysis to be the first using the long-horizon regression, which has been the standard tool for judging the predictive ability of the term spread. We find that the high-yield spread has a high predictive content. In addition, we find evidence of some nonlinearity, in that abnormally high levels of the high-yield spread have significant additional short-term predictive power. Also, despite the low power of out-of-sample tests of forecast accuracy (Inoue and Kilian, 2002), we find that out-of-sample forecasts of movements in economic activity based on the high-yield spread are significantly superior to those produced using the term spread during the 1990s.

Finally, we break down our measure of real economic activity—real industrial production—into temporary and permanent components, using a variant of an econometric technique developed by Blanchard and Quah (1989). After estimating the long-horizon regressions with output purged of, respectively, its permanent (or "supply") and temporary (or "demand") components, we find that the high-yield spread retains its predictive ability. The results suggest that the high-yield spread works through both, which we interpret as further evidence in support of a financial accelerator mechanism for the United States.

Although the predictive content of the high-yield spread is of general interest, we were led to this investigation because of our finding in previous research that the high-yield spread is an important variable in the modeling of capital flows to emerging markets. It has been conventional wisdom, at least since a well-known paper by Calvo, Leiderman, and Reinhart (1996), that U.S. monetary policy through its influence on short-term interest rates has a significant influence on capital flows to developing economies. Recent events raise a question mark over this stylized fact, however: while U.S. interest rates have fallen sharply, capital flows have at best remained stable. In previous research, we have proxied the influence of conditions in international capital markets by the U.S. high-yield spread rather than by U.S. interest rates. In particular, we find that a rise in the high-yield spread is associated with reduced supply of capital to emerging markets and the inclusion of this spread eliminates the influence of interest rates (Mody and Taylor, 2002a). A rise in the high-yield spread is also associated with increased regional vulnerability as observed in heightened exchange market pressure (Mody and Taylor, 2002b). Thus, movements in the U.S. high-yield spread clearly have an important bearing on emerging market access to international capital markets. In Mody and Taylor (2002a), we speculated that an international financial accelerator mechanism may be at work: high-yield spreads predict higher default rates and hence slower economic activity, which dampens access to credit, further reducing economic activity, and so on (see, for example, Bernanke and Gertler, 1995). Thus, the question we pose in this paper is whether a rise in high-yield spreads does in fact signal slower growth in the U.S., since establishing such a link would provide a firmer basis for understanding the implications of developments in the "North" for access to capital and vulnerability to currency crises in the "South."

I. Predicting Real Economic Activity: Theoretical Background

The Term Spread as a Predictor of Real Activity

Although several studies have found the term spread to contain information with respect to future economic activity, the theoretical basis for this relationship has remained unclear, as noted, for example, by Plosser and Rouwenhorst (1994) and Dotsey (1998). Thus, Estrella and Hardouvelis (1991), while documenting the predictive ability of the term spread, also cautioned that the relationship could easily wane.

The slope of the yield curve may be influenced by factors such as expected real interest rates, current and expected inflation, and risk or term premiums. A starting point for the link between the term spread and real economic activity could therefore be the theoretical relationship between real interest rates and macroeconomic activity—for example—through consumption and investment (see Taylor, 1999, for a survey). One can use, for example, a simple optimizing model of consumption to derive a theoretical model of the link between future consumption and the real term structure as follows. Consider a representative agent whose real consumption in period t is C_t, whose instantaneous utility function is $U(.)$, and whose subjective rate of time preference is ρ. If the j-period real interest rate is $i_t^{(j)}$, then, making the usual assumptions such as additive separability of preferences, we can derive from the first-order conditions for the agent's optimal consumption plan Euler equations of the form:

$$U'(C_t) = (1 + i_t^{(1)})(1 + \rho)^{-1} E_t U'(C_{t+1}) \tag{1}$$

$$U'(C_t) = (1 + i_t^{(2)})(1 + \rho)^{-2} E_t U'(C_{t+2}), \tag{2}$$

where $U'(.)$ denotes the first derivative of the utility function and hence marginal utility, and E_t denotes the mathematical expectation operator conditional on information at time t. The intuition is standard: if the agent is optimizing, then it is impossible to improve the plan by, say, reducing consumption slightly today [at a cost of $-U'(C_t)$], investing for j periods at the real interest rate $i_t^{(j)}$, and increasing consumption in period j, yielding an expected gain, in period-t present-value terms, of $[(1+i_t^{(j)})(1+\rho)^{-j}E_tU'(C_{t+j})]$—the cost just offsets the expected gain. From (1) and (2) we can, however, derive a close approximation:

$$\left(i_t^{(2)}-i_t^{(1)}\right)=\left(1+\rho\right)\left[\frac{E_tU'\left(C_{t+1}\right)}{E_tU'\left(C_{t+2}\right)}\right]-1. \tag{3}$$

Equation (3) thus describes a very simple possibility for how movements in the *real* yield curve may affect future economic activity. An increase in the slope of the real term structure will induce optimizing agents to take advantage of the better yield available at longer maturities by reducing consumption in the short term and increasing consumption in the long term. With diminishing marginal utility, a rise in $(i_t^{(2)}-i_t^{(1)})$ requires a reduction in C_{t+1} and an increase in C_{t+2}. Insofar as movements in the nominal term spread move with the real term spread, therefore, and insofar as increased consumption demand raises economic activity, this framework predicts that rises in the nominal term spread will indeed be associated with increases in future economic activity.

Note, however, that this analysis is based on a consideration of Euler equations rather than proper reduced forms: these are conditions that must hold *at the margin*, rather than being reduced-form equations. Moreover, the issue becomes complicated when the move is made from considering the behavior of the representative agent to considering the behavior of the economy in aggregate. In fact, the implication of a large empirical literature on consumption is that the statistical link between real interest rates and aggregate consumption is extremely tenuous (Deaton, 1992; Taylor, 1999), suggesting that it is unlikely that the nominal term spread, by acting as a proxy for the real term spread, is predicting future shifts in consumption demand.

A huge amount of empirical work on aggregate investment also concludes that the statistical link between real interest rates and investment demand is weak (Chirinko, 1993; Taylor, 1999), moreover, suggesting that searching for a theoretical link between the term spread and investment is also likely to be fruitless.

Alternatively, we might explore the avenue that the term spread reflects expected future inflation. However, the long-term interest rates typically used in this connection are quite long horizon—of the order of 10 years or more. Given that the term spread appears to have predictive content for at most a few years, it therefore seems unlikely that this forward-looking element plays a large role in this respect. With respect to term or risk premiums, empirical work has typically found no evidence of strong and statistically stable models (see, for example, Taylor, 1992).

There seem to be two other remaining avenues through which the term spread may predict future real activity. First, insofar as a general monetary easing will be reflected in a fall in short-term interest rates and hence a steepening of the yield curve, the term spread will be positively correlated with future movements in real activity brought about by the expansionary policy.

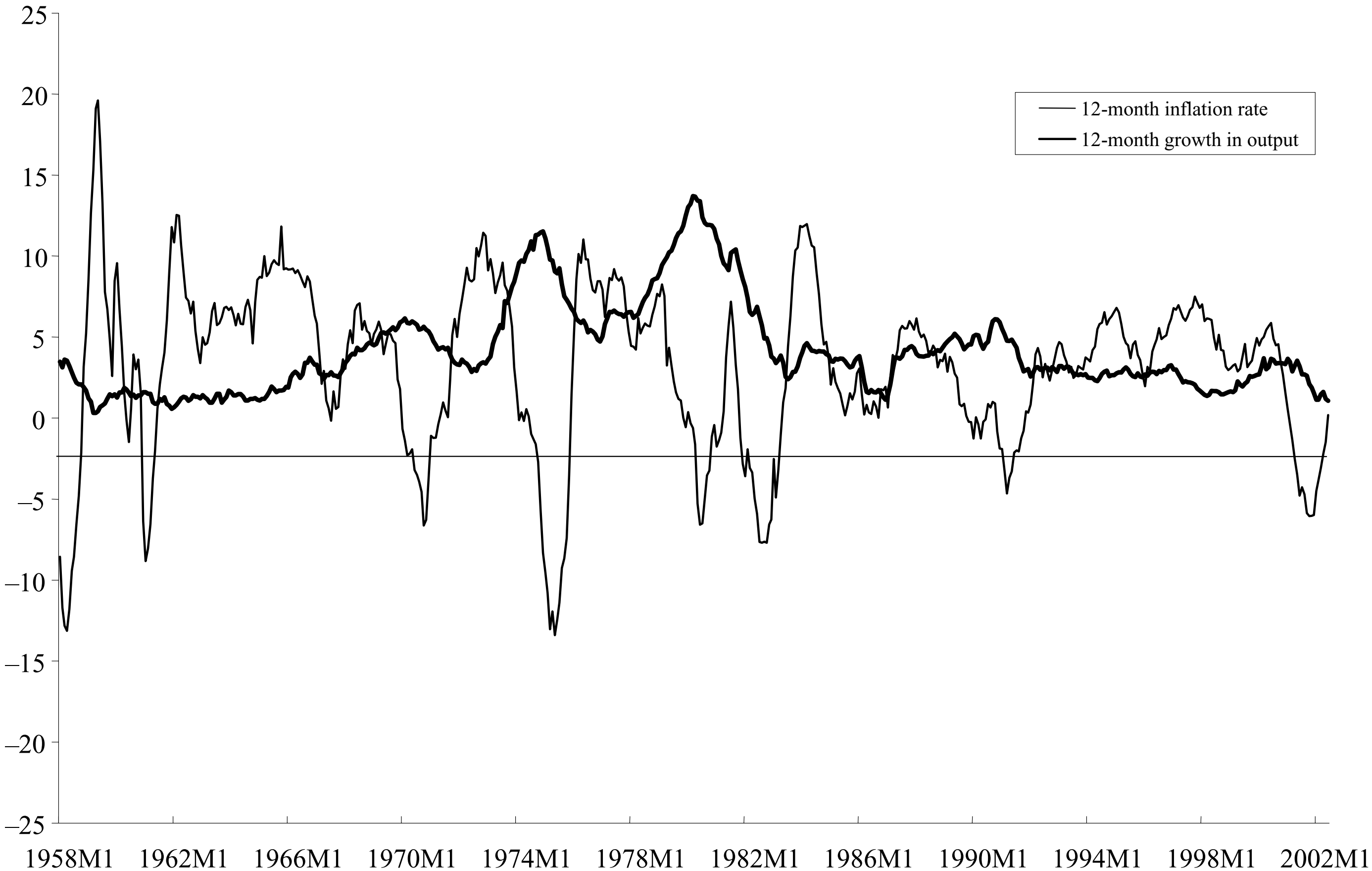
The second possibility is that the term spread also reflects movements in the *current* rate of inflation. If a rise in current inflation leads to a rise in short-term interest rates—and, hence, a flattening of the yield curve—and if inflation and real activity are negatively correlated, a fall in the term spread will predict slower future real activity. The proposition that high inflation is likely to be associated with a weakening of economic activity is supported by recourse to standard economic theory. In a simple aggregate supply–aggregate demand framework, for example, reductions in real output brought about by shifts in aggregate supply will be accompanied by a rise in prices and inflation as the economy moves along the aggregate demand schedule. If we introduce nominal wage inertia and a long-run vertical supply curve into such a framework, then aggregate demand shifts may also lead to negative correlation between inflation and growth since, while the short-run effect of a positive demand shock will be to raise output, prices will initially be largely unaffected because of nominal inertia. If the supply curve is vertical in the long run, moreover, then after a few periods the initial rise in output will begin to decline, just as the rise in prices is beginning to feed through, so that inflation and the change in output will tend to correlate negatively. In Appendix I, we set out a formal macroeconomic model with long-run monetary neutrality and nominal wage inertia induced through wage contracting, in which we show that the overall covariance between inflation and output growth may be negative.[3]

If, further, we allow for the negative effects on economic activity from inflationary uncertainty and other distortions induced by an environment of high and volatile inflation, then a negative correlation between inflation and growth seems even more likely—at least in a period of high inflation.

In Figure 1 we have graphed the 12-month consumer price index inflation rate and the 12-month percentage growth in real industrial production for the United States. over the period 1958M1–2001M12 (see Section II for data sources). Two aspects of the graph are particularly striking. First, the rate of inflation is higher and more volatile during the 1970s and 1980s than it was during either the 1960s or the 1990s. Second, there appears to be stronger evidence of negative correlation between inflation and the rate of growth of industrial production during the 1970s and 1980s. In addition, as argued above, while demand shocks may induce, in certain circumstances, negative correlation between output growth and inflation, supply shocks will unambiguously do so, and this effect appears to be particularly marked following the first and second oil shocks of 1974 and 1979. In contrast, the behavior of inflation during the 1990s appears to have much more in common with that of the 1960s, in that it is generally much lower, less volatile, and apparently less negatively correlated with output growth. In light of our discussion of the possible underlying causes of the link between the term spread and future real activity, therefore, this suggests testing for the strength of the link during the 1960s, as well as during the 1990s, to see if the link is in fact significantly weaker during these two periods.

[3]Fama (1981) argues that the fact that real stock price returns and inflation tend to be negatively correlated may be because inflation and (current and expected) real output may be negatively correlated.

Figure 1. U.S. Inflation and Output Growth, 1958–2001



The High-Yield Spread as a Predictor of Real Activity

The theoretical underpinning of the high-yield spread as a predictor of real economic activity primarily relates to the theory of the financial accelerator (see, for example, Bernanke and Gertler, 1995; Bernanke, Gertler, and Gilchrist 1999; and the references therein). While the details of these models differ, their central features are reasonably uniform and their key elements may be set out informally as follows.

There is some friction present in the financial market, such as asymmetric information or costs of contract enforcement, which, for a wide class of industrial and commercial businesses, introduces a wedge between the cost of external funds and the opportunity cost of internal funds—the "premium for external funds." This premium is an endogenous variable that depends inversely on the balance sheet strength of the borrower, since the balance sheet is the key signal through which the creditworthiness of the firm is evaluated. However, balance sheet strength is itself a positive function of aggregate real economic activity, so that borrowers' financial positions are procyclical and hence movements in the premium for external funds are countercyclical. Thus, as real activity expands, the premium on external funds declines, which, in turn, leads to an amplification of borrower spending, which further accelerates the expansion of real activity. This is the basic mechanism of the financial accelerator.

A problem in testing the theory of the financial accelerator empirically in the past has, however, been the lack of any reliable data on a key central variable in the theory—the premium on external funds. This is because firms that are subject to important financial constraints of this kind have typically relied on commercial bank loans as the chief source of external finance, and time series of relevant bank borrowing rates are not available. Moreover, as Gertler and Lown (1999) point out, even if they were, the fact that bank loans typically contain important nonprice terms would render these series very imperfect and noisy signals of the premium on external funds.

Since the mid-1980s, however, the U.S. market for below-investment-grade debt, sometimes referred to as high-yield bonds or, less euphemistically, "junk bonds," has developed enormously. Gertler and Lown (1999) note that firms raising funds in the high-yield bond market are likely to be precisely those that face the type of market frictions that the theory of the financial accelerator describes. Moreover, since the opportunity cost of internal funding for firms is likely to be close to the "safe" rate of interest such as that on government or AAA rated debt, the spread between high-yield bonds and government debt or AAA rated debt is likely to be a good indicator of the premium on external finance.

If the theory of the financial accelerator works in practice, therefore, one would expect the high-yield spread to be a countercyclical predictor of future real activity.

II. Data

Monthly data for the United States for the period 1964M1–2001M12 were obtained on real industrial production, the consumer price index, the three-month Treasury bill rate, and the ten-year government bond yield from the International Monetary

Fund's *International Financial Statistics* database. A monthly series on the high-yield spread was constructed as follows. First, we obtained data from the Merrill Lynch Global Bond Indices database, an index (in annualized yield terms) of the yields on corporate bonds publicly issued in the U.S. domestic market with a year or more to maturity that were rated BBB3 or lower. We then subtracted the ten-year government bond yield from this to construct the spread. Because the market for below-investment-grade debt only developed during the mid-1980s, a reliable series for the high-yield spread could be constructed only for the period of the 1990s.[4]

III. Long-Horizon Regressions

The dependent variable in the basic long-horizon regressions is the annualized cumulative percentage change in real industrial production:

$$\nabla_k y_{t+k} \equiv \frac{1200}{k}\left(y_{t+k} - y_t\right), \tag{4}$$

where k denotes the forecasting horizon in quarters and y_t is the logarithm of an index of real industrial production at time t. The k-period change in the logarithm of industrial output is multiplied by $(1200/k)$ to ensure that the percentage growth rate is expressed in annualized terms, as the interest rates are. The slope of the nominal yield curve is measured by the difference between the yield on ten-year U.S. government bonds (R_t) and the three-month U.S. Treasury bill rate (r_t), while the high-yield spread is measured as the difference between the "junk bond" yield (Q_t) and the ten-year government bond yield (R_t).

The basic regression equations are therefore of the form:

$$\nabla_k y_{t+k} = \alpha_k + \beta_k\left(R_t - r_t\right) + \eta_{t+k}, \tag{5}$$

for the term spread regressions, and

$$\nabla_k y_{t+k} = \gamma_k + \delta_k\left(Q_t - R_t\right) + \varepsilon_{t+k}, \tag{6}$$

for the high-yield spread regressions, where η_{t+k} and ε_{t+k} are the forecast errors.

[4]Note that, since the index of yields on below-investment-grade corporate debt is constructed using a range of maturities, while we subtract the ten-year government bond yield to obtain a measure of the high-yield spread, there is a possibility that our measure of the high-yield spread may contain some term structure effects. We would argue that this is not important for our analysis, however, on the following grounds. First, if term structure effects were important in our high-yield spread measure, then we should expect the predictive content of the two series to be similar whereas—as we show below—they behave quite differently. Second, the correlation between the two series is in fact very low: over the period 1991M1–2001M12 the correlation coefficient is –0.11. We also experimented using high-yield spread measures constructed using government bond yields of different maturities and found that this made little difference to the results—which is not surprising given the very high correlation of these alternative measures of the high-yield spread and the measure used in this paper: using daily data from the end of 1987 until the beginning of 2003, we found that the correlation between the high-yield spreads using ten-year and two-year government bond yields was 0.93, while the correlation between the high-yield spreads using ten-year and three-year government bond yields was 0.95.

As is well known, even under the assumption of rational expectations, the fact that the sampling interval is smaller than the forecasting horizon generates a moving average forecast error of order one less than the number of sampling periods in the forecast horizon, because of common "news" items generating successive forecast errors. Hence, the forecast errors may be assumed to have a moving average representation of order $k-1$. This was allowed for by using an appropriate method-of-moments correction to the estimated covariance matrix (Hansen, 1982). As is also well known, however, tests for the significance of long-horizon parameters may also suffer from considerable size distortion in small samples. Accordingly, we constructed empirical marginal significance levels for the asymptotic *t*-ratios using bootstrapping techniques that allow for the small-sample empirical distribution of the test statistics to be constructed under the null hypothesis that the term spread or the high-yield spread does not predict economic activity. A brief description of this bootstrapping algorithm is given in Appendix II.[5]

Term Spread Regressions

The results of estimating equation (5) for forecast horizons up to 24 months ahead are given in Tables 1, 2, and 3 for various sample periods.

In Table 1, we report the long-horizon regressions for the 1970s and 1980s—i.e., for the sample period 1970M1–1990M12. These results are consistent with those reported in the literature for similar sample periods: the slope coefficient is strongly significantly different from zero, with *t*-ratios in every case of the order of around four and empirical marginal significance levels of zero to two decimal places.

In Table 2, we report results for the same regressions applied to data for the mid- to late 1960s—i.e., 1964M1–1970M12. Although the term spread does have some predictive power for real activity during this period, the slope coefficients are significantly different from zero at the 5 percent level only for horizons ranging from six to nine months. The value of the *t*-ratios, even for the significant estimated coefficients, is also much lower than for the 1970s and 1980s, ranging between 2.1 and 2.9.

Table 3 shows the results of estimating the long-horizon term spread regressions for the most recent period, 1991M1–2001M12. The estimated slope coefficients are in every case insignificantly different from zero at the 5 percent level. The goodness of fit of the long-horizon regressions has also fallen dramatically at all horizons, relative to the corresponding levels for the 1970s and 1980s.

Overall, therefore, the strong predictive content of the term spread with respect to future real economic activity seems to be largely confined to the period

[5]We also tested for the possibility of simultaneity in the long-horizon regressions, since it is feasible that shocks to current output (which enters the *k*-period change) may also affect the term spread or the high-yield spread through, for example, a policy Taylor rule or because of an immediate effect of an output shock on the premium for external funds. To test for this we used Hausman's (1978) specification test, which tests for differences between OLS and instrumental variable estimators (since only the latter are consistent when there is simultaneity), using three lags of each of the change in output, the term spread, and the high-yield spread as instruments. In no case was there evidence of simultaneity at the 5 percent level.

Table 1. Term Spread Predictions of Industrial Production Growth, 1971M1–1990M12

Forecast Horizon k	β_k	R^2	s.e. (percent)
1	2.038 (4.080) [0.00]	0.071	10.433
2	2.255 (3.566) [0.00]	0.120	8.610
3	2.392 (3.625) [0.00]	0.165	7.612
4	2.449 (3.734) [0.00]	0.200	6.931
5	2.438 (3.833) [0.00]	0.223	6.435
6	2.409 (3.870) [0.00]	0.243	6.005
7	2.395 (3.954) [0.00]	0.269	5.586
8	2.391 (3.938) [0.00]	0.294	5.243
9	2.370 (3.868) [0.00]	0.316	4.931
12	2.349 (3.928) [0.00]	0.384	4.223
18	2.102 (3.864) [0.00]	0.445	3.353
24	1.632 (4.218) [0.00]	0.375	3.029

Notes: Estimation is by ordinary least squares, with a method-of-moments correction to the estimated co-variance matrix. k is the forecast horizon in months, R^2 denotes the coefficient in determination, and s.e. denotes the standard error of the regression. Figures in parentheses below coefficient estimates are asymptotic t-ratios and those in square brackets are the bootstrapped empirical marginal significance levels to two decimal places. An intercept term was also included in the regressions.

Table 2. Term Spread Predictions of Industrial Production Growth, 1964M1–1970M12

Forecast Horizon k	β_k	R^2	s.e. (percent)
1	1.366 (0.428) [0.80]	0.003	9.790
2	1.798 (0.536) [0.71]	0.010	7.272
3	2.703 (0.709) [0.58]	0.028	6.263
4	3.934 (1.027) [0.37]	0.068	5.652
5	5.059 (1.470) [0.17]	0.119	5.245
6	6.018 (2.127) [0.04]	0.182	4.812
7	6.898 (2.912) [0.01]	0.252	4.403
8	7.513 (2.893) [0.01]	0.310	4.125
9	8.070 (2.414) [0.02]	0.372	3.821
12	7.424 (1.996) [0.06]	0.365	3.593
18	5.303 (1.947) [0.06]	0.284	2.980
24	3.400 (1.985) [0.06]	0.175	2.614

Notes: Estimation is by ordinary least squares, with a method-of-moments correction to the estimated covariance matrix. k is the forecast horizon in months, R^2 denotes the coefficient in determination, and s.e. denotes the standard error of the regression. Figures in parentheses below coefficient estimates are asymptotic t-ratios and those in square brackets are the bootstrapped empirical marginal significance levels to two decimal places. An intercept term was also included in the regressions.

Table 3. Term Spread Predictions of Industrial Production Growth, 1991M1–2001M12

Forecast Horizon k	β_k	R^2	s.e. (percent)
1	0.880 (1.981) [0.06]	0.025	6.082
2	1.015 (2.031) [0.06]	0.052	4.812
3	1.085 (1.888) [0.08]	0.069	4.423
4	1.116 (1.729) [0.11]	0.079	4.212
5	1.129 (1.595) [0.32]	0.090	3.980
6	1.164 (1.520) [0.16]	0.104	3.789
7	1.216 (1.497) [0.17]	0.124	3.610
8	1.269 (1.479) [0.17]	0.145	3.438
9	1.275 (1.450) [0.18]	0.158	3.285
12	1.174 (1.416) [0.30]	0.155	3.021
18	0.870 (1.538) [0.16]	0.122	2.484
24	0.908 (1.775) [0.11]	0.170	2.148

Notes: Estimation is by ordinary least squares, with a method-of-moments correction to the estimated covariance matrix. k is the forecast horizon in months, R^2 denotes the coefficient in determination, and s.e. denotes the standard error of the regression. Figures in parentheses below coefficient estimates are asymptotic t-ratios and those in square brackets are the bootstrapped empirical marginal significance levels to two decimal places. An intercept term was also included in the regressions.

of the 1970s and 1980s. For the 1960s, the relationship appears to be much weakened, while for the 1990s the predictive power of the term spread appears to have virtually disappeared.

High-Yield Spread Regressions

Given that the market for below-investment-grade debt only developed in the United States in the mid-1980s, lack of availability of data on the high-yield spread forced us to consider only the most recent of the three sample periods, i.e., 1991M1–2001M12. The resulting long-horizon regressions are reported in Table 4.

The sign of the estimated slope coefficient is negative in every case: a larger spread predicts a slowdown, exactly as suggested by the theory of the financial accelerator. The predictive content of the high-yield spread is, moreover, quite striking. In every case, the estimated slope coefficient is strongly significantly different from zero, with an empirical marginal significance level of virtually zero in every case, with *t*-ratios ranging in absolute value from around three to around nine. The goodness of fit, as measured by the coefficient of determination, is in nearly every case very much higher than the corresponding R^2 for the term spread regressions, even during the "heyday" of the term spread during the 1970s and 1980s, the two exceptions being at the 18- and 24-month horizons.

Finally, since the theory of the financial accelerator suggests the possibility of nonlinear interactions between financial variables and real activity, we examined whether "unusual" levels of high-yield spreads convey additional information on real activity. Our proxy for "unusual" levels is a spread that is more than 1.5 standard deviations above the sample mean. To test for this, we adjusted the long-horizon regression (6) to:

$$\nabla_k y_{t+k} = \gamma_k + \delta_k (Q_t - R_t) + \theta_k I_t (Q_t - R_t) \varepsilon_{t+k}, \tag{7}$$

where I_t is a dummy variable that takes the value unity if the high-yield spread is more than 1.5 standard deviations above its mean over the sample period. The results of estimating this equation are shown in Table 5 and reveal that such abnormally high spreads do indeed predict an additional slowing down in growth at horizons of one to three months. It should be noted, however, that most of the abnormally large observations of the high-yield spread fall in the last year or so of the data sample. This was why we did not run the long-horizon regressions for horizons greater than 12 months.

IV. Out-of-Sample Predictions

All of the tests of predictability that we have so far employed are *in-sample* tests in that they employ all of the data sample to estimate the long-horizon parameters. This contrasts with out-of-sample forecasting methods that typically either use a fixed post-estimation sample of data over which to forecast or else employ recursive or rolling (fixed window) regressions to forecast over a moving post-estimation sample. Typically, in macroeconomics and finance, researchers find it much easier

Table 4. High-Yield Spread Predictions of Industrial Production Growth, 1991M1–2001M12

Forecast Horizon k	δ_k	R^2	s.e. (percent)
1	–2.064 (–8.744) [0.00]	0.318	5.088
2	–1.985 (–7.120) [0.00]	0.471	3.597
3	–1.942 (–5.488) [0.00]	0.524	3.162
4	–1.869 (–4.427) [0.00]	0.522	4.374
5	–1.775 (–3.950) [0.00]	0.518	2.899
6	–1.685 (–3.620) [0.00]	0.499	2.834
7	–1.603 (–3.368) [0.00]	0.482	2.776
8	–1.544 (–3.212) [0.00]	0.478	2.687
9	–1.492 (–3.105) [0.00]	0.473	2.600
12	–1.345 (–3.097) [0.001]	0.436	2.470
18	–0.852 (–3.859) [0.00]	0.285	2.089
24	–0.682 (–7.258) [0.00]	0.297	1.642

Notes: Estimation is by ordinary least squares, with a method-of-moments correction to the estimated covariance matrix. k is the forecast horizon in months, R^2 denotes the coefficient in determination, and s.e. denotes the standard error of the regression. Figures in parentheses below coefficient estimates are asymptotic t-ratios and those in square brackets are the bootstrapped empirical marginal significance levels to two decimal places. An intercept term was also included in the regressions.

Table 5. Threshold Effects in High Yield Spread Predictions of Industrial Production, 1991M1–2001M12

Forecast Horizon k	δ_k	θ_k	R^2	s.e. (percent)
1	–1.312 (–2.635) [0.00]	–0.608 (–2.144) [0.03]	0.334	5.024
2	–1.186 (–2.483) [0.01]	–0.630 (–2.430) [0.01]	0.481	3.480
3	–1.198 (–2.699) [0.00]	–0.516 (–2.121) [0.03]	0.494	3.043
4	–1.251 (–2.685) [0.00]	–0.385 (–1.657) [0.09]	0.468	2.903
5	–1.265 (–2.621) [0.00]	–0.307 (–1.193) [0.23]	0.466	2.720
6	–1.312 (–2.720) [0.00]	–0.239 (–0.751) [0.45]	0.466	2.608
7	–1.342 (–2.671) [0.00]	–0.172 (–0.514) [0.60]	0.456	2.546
8	–1.222 (–2.150) [0.03]	–0.237 (–0.650) [0.51]	0.460	2.450
9	–1.230 (–2.007) [0.04]	–0.211 (–0.683) [0.49]	0.455	2.380
12	–1.217 (–1.750) [0.07]	–0.044 (–0.223) [0.82]	0.364	2.357

Notes: Estimation is by ordinary least squares, with a method-of-moments correction to the estimated covariance matrix. k is the forecast horizon in months, R^2 denotes the coefficient in determination, and s.e. denotes the standard error of the regression. Figures in parentheses below coefficient estimates are asymptotic t-ratios and those in square brackets are the bootstrapped empirical marginal significance levels to two decimal places. An intercept term was also included in the regressions.

to reject the null hypothesis of no predictability using in-sample tests than they do with out-of-sample tests. This stylized fact appears to have generated a widely accepted belief that in-sample tests are biased in favor of detecting spurious predictability. In fact, as noted in a recent paper by Inoue and Kilian (2002), "This perception has led to a tendency to discount significant evidence in favor of predictability based on in-sample tests, if this evidence cannot be supported by out-of-sample tests."

Inoue and Kilian go on, however, to challenge this view, through a formal analysis of the size and power characteristics of in-sample and out-of-sample tests of predictability. They demonstrate, inter alia, that although in-sample and out-of-sample tests are asymptotically equally reliable under standard assumptions,[6] in-sample tests may have much greater power to reject a false null hypothesis of no predictability in small samples. Indeed, these authors show that out-of-sample tests may have less than 50 percent of the power of in-sample tests, thus providing an alternative explanation of the observed tendency of in-sample tests to reject the null of no predictability more often than out-of-sample tests.

It is clear, however, that the striking findings of Inoue and Kilian should not be taken as an excuse not to conduct out-of-sample tests but, rather, should be taken into account when interpreting the findings of in-sample and out-of-sample tests of forecast failure. In particular, and especially in cases such as the present analysis where there is not an issue of data mining, the low power of out-of-sample tests means that their failure to reject a null hypothesis of no predictability (or of equal predictive ability of two alternative methods) does not necessarily imply that in-sample evidence of predictability is spurious. On the other hand, if the null hypothesis of no predictability or of equal forecasting ability of methods can be rejected at standard significance levels using out-of-sample tests, then, given their low power, this should be taken as very strong corroborating evidence of the in-sample findings.

Accordingly, we proceeded to construct out-of-sample tests to compare the ability of movements in the high-yield spread to predict economic activity over the 1990s with that of movements in the term spread.

We did this in two ways. In our first investigation of relative out-of-sample predictive ability, we used a fixed post-estimation sample of three years, 1999M1–2001M12, to construct a "portmanteau" test of the equality of the predictive ability of the term spread and the high-yield spread. We used data over the sample period 1991M1–1998M12 to estimate the long-horizon equations (5) and (6) for $k = 1, 2, \dots 36$. We then obtained two sets of 36 forecast errors over the post-estimation sample, based alternately on the high-yield spread or the term spread in 1998M12, as

$$\zeta_k^{(1)} = \nabla_k y_{1998M12+k} - \hat{\alpha}_k - \hat{\beta}_k \left(R_{1998M12} - r_{1998M12} \right),\ k = 1, 2, \dots 36 \tag{8}$$

for the term spread, and

[6]That is, under the null of no predictability, and provided that no data mining has taken place, and in the absence of unmodeled structural change. The authors also show that both in-sample and out-of-sample tests are susceptible to size distortions arising from data mining.

$$\zeta_k^{(2)} = \nabla_k y_{1998M12+k} - \hat{\gamma}_k - \hat{\delta}_k\left(Q_{1998M12} - R_{1998M12}\right),\ k = 1,2,...36 \tag{9}$$

for the high-yield spread, where hats over the parameters denote that they were estimated using data for the period 1991M1–1998M12. We then used these errors to construct measures of the mean square error and mean absolute error over the 36 months, and in turn used these to construct a test for equal predictive ability based on the Diebold-Mariano (1995) test statistic for equality of forecast accuracy. The Diebold-Mariano statistic is defined as

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi\hat{f}(0)}{N}}}, \tag{10}$$

where $\bar{d}$ is an average over N forecast periods of a general loss differential function d_k such as the difference in squared forecast errors ($d_k = [\zeta_k^{(1)}]^2 – [\zeta_k^{(2)}]^2$) or, in absolute errors ($d_k = |\zeta_k^{(1)}| - |\zeta_k^{(2)}|$), i.e.,

$$\bar{d} = \frac{1}{N}\sum_{k=1}^{N} d_k$$

for $N = 36$ in the present application, and $\hat{f}(0)$ is a consistent estimate of the spectral density of the loss differential function at frequency zero.[7] Under certain regularity conditions, DM will be distributed as standard normal under the null hypothesis of equal forecast accuracy.[8]

Our second set of tests involved assessing the relative predictive ability of the high-yield spread and the term spread by comparing the forecast accuracy of the multi-step-ahead predictions of the long-horizon models (5) and (6) using recursive estimation over the period 1999M1–2001M12 (with initial estimates using data for 1991M1–1998M12) for the same values of k as used in our long-horizon in-sample exercises, i.e., k = 1–12, 18, 24. For the long-horizon regression model of horizon k, this generates a sequence of 36 k-step-ahead forecast errors of the form

$$\zeta_\tau^{(k,1)} = \nabla_k y_{1998M12+\tau} - \hat{\alpha}(\tau-1)_k - \hat{\beta}(\tau-1)_k\left(R_{1998M12+\tau-k} - r_{1998M12+\tau-k}\right),\ \tau = 1,...36 \tag{11}$$

for the term spread, and

$$\zeta_\tau^{(k,2)} = \nabla_k y_{1998M12+\tau} - \hat{\gamma}(\tau-1)_k - \hat{\delta}(\tau-1)_k\left(Q_{1998M12+\tau-k} - R_{1998M12+\tau-k}\right),\ \tau = 1,...36 \tag{12}$$

[7] A consistent estimate of the spectral density at frequency zero was obtained using the method of Newey and West (1987), with the truncation lag selected using the Andrews (1991) AR(1) rule.

[8] It is well known that problems may arise in using the *DM* statistic in small samples (see e.g., West, 1996; West and McCracken, 1998; McCracken, 2000; Clarida and others, 2002; and Kilian and Taylor, 2003). In the present application, particularly in the construction of our “portmanteau” test statistic where we are dealing with various multi-step-ahead forecasts, the asymptotic distribution of the *DM* statistic is unknown so that the marginal significance levels we report for this statistic should be treated with caution.

for the high-yield spread, where $\widehat{\lambda}(\tau{-}1)_k$ denotes the estimated value of the long-horizon parameter λ_k using data for the period 1991M1 to 1998M12 + τ – 1, for $\lambda = \alpha, \beta, \gamma, \delta$. We then again used the Diebold-Mariano statistic (10) to test for equality of the forecast accuracy of the models for each value of k, based on the difference in squared errors or in absolute errors ($d_\tau^k = [\zeta_\tau^{(k,1)}]^2 - [\zeta_\tau^{(k,2)}]^2$ or $d_\tau^k = |\zeta_\tau^{(k,1)}| - |\zeta_\tau^{(k,2)}|$ and

$$\bar{d} = \frac{1}{N} \sum_{\tau=1}^{N} d_\tau^k$$

for the k-horizon model one-step-ahead forecasts).

The results of the out-of-sample portmanteau test of equality of forecast accuracy of the high-yield spread and term spread models are given in Table 6 and show that the high-yield spread regressions easily and significantly dominate the term spread regressions in terms of out-of-sample forecast accuracy. This result is echoed, moreover, in the k-step-ahead forecast results for each of the individual long-horizon regressions, as shown in Table 7: the high-yield spread model forecasts are in every case superior in terms of either mean square error or mean absolute error, and strongly significantly so in every case except for the $k = 1$ and $k = 2$ regression models, based on mean square error.

Given our earlier remarks concerning the relatively low power of out-of-sample forecast tests, this is indeed a strong vindication of the superiority of the high-yield spread as a predictor of economic activity over the 1990s relative to the term spread.

V. Supply and Demand Innovations in Real Output

Given the apparent importance of the high-yield spread as a predictor of real economic activity during the last decade or so, we carried out some further investigations as to whether the spread is able to predict the cumulative growth in output when it is stripped of, alternately, its demand-side and supply-side components or, to be precise, its temporary and permanent components.

Permanent and temporary output movements may be variously interpreted according to the underlying theoretical framework employed. In the traditional aggregate demand–aggregate supply (ADAS) model with a long-run vertical supply curve, for example, aggregate demand disturbances result in a temporary rise

Table 6. Portmanteau Tests of Equality of Out-of-Sample Forecast Accuracy over the Period 1999M1–2001M12

	Forecasts Based on High-Yield Spread	Forecasts Based on Term Spread	Diebold-Mariano Statistic
Mean square error	4.06	18.65	–4.94 (0.00)
Mean absolute error	1.94	4.25	–6.21 (0.00)

Notes: See Section IV on the construction of these statistics. Figures in parentheses are marginal significance levels to two decimal places.

Table 7. Out-of-Sample Tests of Equality of Forecast Accuracy over the Period 1999M1–2001M12, *k*-Step-Ahead Forecasts

Long-Horizon Regression Model, k	Mean Square Error from Forecasts Based on High-Yield Spread	Mean Square Error from Forecasts Based on Term Spread	Diebold-Mariano Statistic Based on Mean Square Error	Mean Absolute Error from Forecasts Based on High-Yield Spread	Mean Absolute Error from Forecasts Based on Term Spread	Diebold-Mariano Statistic Based on Mean Absolute Error
1	30.95	36.47	–1.20	3.72	4.63	–2.37
			(0.23)			(0.02)
2	13.70	18.69	–1.59	2.59	3.69	2.70
			(0.11)			(0.01)
3	8.96	13.56	–2.02	2.28	3.19	–2.28
			(0.04)			(0.02)
4	7.02	11.66	–2.52	2.15	3.04	–2.40
			(0.01)			(0.02)
5	10.31	10.31	–2.96	1.89	2.91	–3.14
			(0.00)			(0.00)
6	5.33	10.30	–3.39	1.87	2.92	–3.43
			(0.00)			(0.00)
7	4.86	10.04	–3.84	1.84	2.91	–3.74
			(0.00)			(0.00)
8	4.51	10.40	–4.67	1.79	2.96	–4.64
			(0.00)			(0.00)
9	3.98	10.16	–5.30	1.69	2.95	–5.28
			(0.00)			(0.00)
12	2.84	10.54	–6.76	1.41	3.01	–8.04
			(0.00)			(0.00)
18	1.84	10.73	–9.55	1.06	3.07	–20.38
			(0.00)			(0.00)
24	1.98	9.49	–9.20	1.15	2.89	–23.27
			(0.00)			(0.00)

Notes: See Section IV on the construction of these statistics. Figures in parentheses are marginal significance levels to two decimal places.

in output, while aggregate supply disturbances permanently affect the level of aggregate output.

Blanchard and Quah (1989) use an ADAS framework in their analysis and associate aggregate supply shocks with permanent shocks and aggregate demand shocks with temporary shocks. In this paper we shall follow their taxonomy. While it is possible that demand disturbances may have permanent effects on the real side of the economy, we concur with Blanchard and Quah that shocks having a permanent effect on output are likely to be due mostly, if not wholly, to supply-side factors, while those having only a temporary effect are likely to be due mostly, if not wholly, to demand-side factors. If the permanent long-run effects of demand disturbances are small relative to the long-run permanent effects of supply disturbances, then the Blanchard-Quah taxonomy is a useful organizing principle for empirical purposes. Readers rejecting this taxonomy, however, may simply reinterpret our analysis as investigating whether nominal spreads affect the permanent or the temporary components of real output movements.

Given this taxonomy of permanent and temporary shocks to output, supply and demand shocks to real economic activity can be identified by imposing appropriate restrictions on the Wold representation of time series for real and nominal macroeconomic variables. In particular, consider the Wold representation for annualized percentage changes in the logarithm of output and the logarithm of prices:

$$\begin{bmatrix} \nabla_1 y_t \\ \nabla_1 p_t \end{bmatrix} = \sum_{j=1}^{\infty} L^j \begin{bmatrix} \phi_{11j} & \phi_{12j} \\ \phi_{21j} & \phi_{22j} \end{bmatrix} \begin{bmatrix} \varsigma_{1t} \\ \varsigma_{2t} \end{bmatrix}, \tag{13}$$

where the ϕ_{imj} are the parameters of the multivariate moving average representation and ς_{1t} and ς_{2t} are white-noise innovations. We can identify ς_{1t} and ς_{2t} as demand and supply innovations in the following way. Write $\varsigma_t = (\varsigma_{1t} \varsigma_{2t})'$, and denote the bivariate vector of innovations recovered from the vector autoregressive representation for $(\nabla_1 y_t \; \nabla_1 p_t)'$ as υ_t. Since the vector autoregressive (VAR) representation is simply an inversion of the Wold representation (13), υ_t will in general be a linear function of ς_t, $\upsilon_t = \mathbf{A} \varsigma_t$, say, where $\mathbf{A}$ is a 2×2 matrix of constants. To recover the underlying demand and supply innovations from the VAR residuals then requires that the four elements of $\mathbf{A}$ be identified, which requires four identifying restrictions. Three restrictions can be obtained by normalizing the variances of ς_{1t} and ς_{2t} to unity and setting their covariances to zero. (See Blanchard and Quah, 1989, for a defense of these restrictions.)

The fourth, crucial identifying restriction, which effectively identifies ς_{1t} as the demand innovation (or temporary output innovation), is the requirement that ς_{1t} have no long-run effect on the (log-) *level* of real output, although it may affect the long-run price level. The latter restriction on the Wold representation (13) may be written:

$$\sum_{j=1}^{\infty} \phi_{11j} = 0. \tag{14}$$

These four restrictions are then sufficient to recover the underlying temporary and permanent innovations to output, which, as we discussed above, may be interpreted as underlying demand and supply innovations, respectively.[9]

Having identified the supply and demand innovations, we can then partition the moving average representation for real industrial output into counterfactual series, corresponding to the path that would have obtained in the absence of demand innovations and the path that would have obtained in the absence of supply innovations over the estimation period. We can then utilize these counterfactual series in tests of the predictive power of the high-yield spread.

We applied this method to the monthly series in the logarithm of industrial production and the consumer price index for the whole sample period, 1964M1–2001M12. Preliminary unit root (Augmented Dickey–Fuller) tests on the data (not reported) showed the change in the logarithm of real industrial output and the change in the logarithm of the consumer price index to be stationary processes. There was also no evidence of cointegration between industrial production and prices. This implies that output growth and inflation can be modeled as a bivariate moving average representation, which can be inverted to a pure autoregression not involving error correction terms. We therefore proceeded to estimate a vector autoregressive representation for the vector time series $(\nabla_1 y_t \nabla_1 p_t)'$. The order of the VAR was chosen by sequentially excluding the highest lags of both series, starting from a twelfth-order VAR and testing the exclusion restrictions on the system using a likelihood ratio test. This process was stopped when the exclusion restrictions were jointly significant at the 5 percent level. This led to a choice of lag depth of six. The residuals from the estimated equations were judged to be approximately white noise, using either individual Ljung–Box statistics or Hosking's multivariate portmanteau statistic. In fact, this choice of lag depth coincided with the lag depth chosen by minimizing the Akaike Information Criterion.

In Figure 2 we have graphed the impulse response functions for the log-levels of output and prices in response to the identified supply and demand innovations. By construction, the long-run impact of demand shocks on real output is zero, but the shape of each of the impulse response functions in each case accords with simple economic priors in that a positive demand shock raises both output (in the short run) and prices (in both the short run and the long run), while a positive supply shock raises output and depresses prices (in both the short run and the long run).[10]

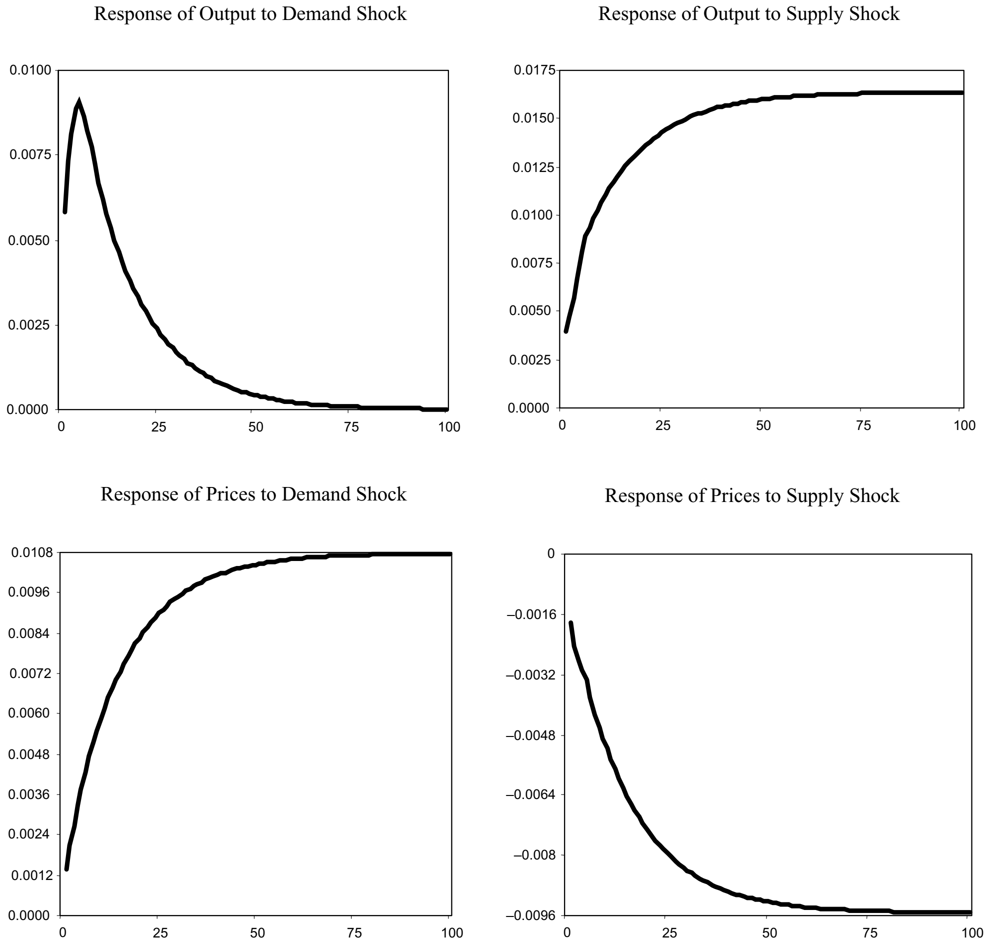
VI. Counterfactual Analysis

We then used the Blanchard-Quah estimation results to break down the series for U.S. real industrial production into counterfactual series, corresponding to the

[9]For further details of the decomposition, see Blanchard and Quah (1989), Bayoumi and Taylor (1995), or Taylor (2003). Taylor (2003) discusses recursive restrictions of this type in the general multivariate case.

[10]Taylor (2003) notes that, in general, there will be multiple solutions to recursive restrictions of the type suggested by Blanchard and Quah (1989) and that informal or qualitative identifying restrictions of this kind are necessary in order to achieve full identification.

Figure 2. Impulse Responses



path that would have obtained in the absence of demand innovations in the moving average representation and the path that would have obtained in the absence of supply innovations. Effectively, this involves using the estimated VAR to recover the moving average representation (13) and then calculating a counterfactual series for y_t by alternately holding the identified supply and demand shocks constant at zero over the sample period. We then used this series in estimates of the long-horizon regression using the high-yield spread, the results of which are given in Tables 8 and 9.

The results are interesting and supportive of the financial accelerator theory. We should expect the financial accelerator process to operate through both the supply and the demand sides of the economy. In particular, a positive supply, or productivity, shock that leads to a permanent change in output will increase the collateral value of the future stream of output. The reduced premium for external funds will, therefore, be associated with future output growth. The results strongly confirm this relationship. When the industrial output series is purged of "demand disturbances," leaving the supply or permanent shocks in, the predictive ability of the high-yield spread remains strong at all horizons (Table 8). Temporary demand shocks can also generate an accelerator. Indeed, following a permanent shock, induced investment demand can generate additional cyclical effects. Interestingly, the high-yield spread does indeed significantly predict the "demand-driven" component of industrial production (Table 9).

VII. Conclusion

Why did the term spread become a much weaker predictor of economic activity in the 1990s? Gertler and Lown (1999) suggest that changes in U.S. monetary policy may have had something to do with this. In particular, a more robust defense of inflation starting in the mid-to late 1980s may have changed private sector expectations with respect to future inflation. While the shift in monetary policy may have been influential, it is relevant that the predictive ability of the term spread was also weaker prior to 1970.

The period during which the term spread was informative with respect to real activity—the 1970s and 1980s—was the period of the two oil shocks and was characterized by high inflation (and possibly, therefore, greater inflation uncertainty) and volatile growth. We should expect in such a period that the negative covariance between current inflation and real activity would be most pronounced. A rise in current inflation, associated with a rise in short-term rates, would lead to a flattening of the term spread and lower real activity. However, in periods when inflation is low—and more predictable—these effects may be weaker.

In contrast, the financial accelerator creates a more robust foundation for the high-yield spread as a predictor of future real macroeconomic activity. That relationship is based on financial frictions that amplify the business cycle. While such frictions, in particular asymmetric information, may decline over time, that seems unlikely to occur in the immediate future. The robustness of this relationship is also suggested by the finding that the high-yield spread captures both the supply-side (or permanent) shocks and the demand-side (temporary) shocks.

Table 8. High-Yield Spread Predictions of Industrial Production Growth with Industrial Production Purged of Demand-Side Disturbances, 1991M1–2001M12

Forecast Horizon k	δ_k	R^2	s.e. (percent)
1	–0.392 (–2.366) [0.01]	0.070	2.173
2	–0.474 (–1.923) [0.04]	0.126	1.956
3	–0.571 (–1.799) [0.05]	0.182	1.935
4	–0.637 (–1.851) [0.04]	0.222	1.924
5	–0.687 (–2.026) [0.03]	0.254	1.864
6	–0.714 (–2.142) [0.02]	0.271	1.811
7	–0.721 (–2.213) [0.02]	0.277	1.782
8	–0.730 (–2.293) [0.02]	0.285	1.767
9	–0.731 (–2.400) [0.01]	0.294	1.732
12	–0.730 (–2.700) [0.01]	0.311	1.672
18	–0.679 (–3.966) [0.00]	0.314	1.567
24	–0.592 (–2.330) [0.02]	0.229	1.700

Notes: Estimation is by ordinary least squares, with a method-of-moments correction to the estimated covariance matrix. The series for industrial production has been purged of demand-side disturbances using the Blanchard-Quah method described in the text. k is the forecast horizon in months, R^2 denotes the coefficient in determination, and s.e. denotes the standard error of the regression. Figures in parentheses below coefficient estimates are asymptotic t-ratios and those in square brackets are the bootstrapped empirical marginal significance levels to two decimal places. An intercept term was also included in the regressions.

Table 9. High-Yield Spread Predictions of Industrial Production Growth with Industrial Production Purged of Supply-Side Disturbances, 1991M1–2001M12

Forecast Horizon k	δ_k	R^2	s.e. (percent)
1	–1.785 (–6.189) [0.00]	0.212	5.255
2	–1.684 (–5.009) [0.00]	0.337	3.701
3	–1.622 (–4.141) [0.00]	0.398	3.186
4	–1.534 (–3.620) [0.00]	0.411	2.960
5	–1.407 (–3.282) [0.00]	0.387	2.800
6	–1.292 (–3.155) [0.00]	0.356	2.685
7	–1.168 (–3.167) [0.00]	0.323	2.589
8	–1.078 (–3.171) [0.00]	0.310	2.461
9	–0.998 (–3.183) [0.00]	0.302	2.320
12	–0.858 (–2.994) [0.01]	0.284	2.094
18	–0.635 (–2.758) [0.02]	0.221	1.862
24	–0.482 (–1.904) [0.06]	0.142	1.856

Notes: Estimation is by ordinary least squares, with a method-of-moments correction to the estimated covariance matrix. The series for industrial production has been purged of supply-side disturbances using the Blanchard-Quah method described in the text. k is the forecast horizon in months, R^2 denotes the coefficient in determination, and s.e. denotes the standard error of the regression. Figures in parentheses below coefficient estimates are asymptotic t-ratios and those in square brackets are the bootstrapped empirical marginal significance levels to two decimal places. An intercept term was also included in the regressions.

APPENDIX I

The Negative Covariation of Inflation and Output Growth in a Model with Nominal Wage Inertia and Long-Run Monetary Neutrality

Consider the following simple, log-linear macroeconomic model, which displays long-run monetary neutrality and short-run nominal wage inertia induced through a wage formation equation in which wages are set in a two-period overlapping contracts framework:

$$y_t = m_t - p_t \tag{A1}$$

$$y_t = n_t + \theta_t \tag{A2}$$

$$p_t = w_t - \theta_t \tag{A3}$$

$$w_t = w \mid \{E_{t-2}n_t = n^*\} \tag{A4}$$

Equation (A1) represents the aggregate demand side of the economy as a function of real balances. The production function (A2) relates output to the level of employment, n_t, and productivity, θ_t. The price level is shown in (A3) to be a function of the nominal wage and productivity, while in (A4) the nominal wage contract is set two periods in advance at the level expected to generate full-employment level, n^*. The model is closed by assuming that money and productivity are determined by the evolution of demand and supply shocks, e_{dt} and e_{st}, respectively, as follows:

$$m_t = m_{t-1} + e_{dt} \tag{A5}$$

$$\theta_t = \theta_{t-1} + e_{st} \tag{A6}$$

Assume that the covariance of e_{dt} and e_{st} is zero and that the supply and demand shocks have constant variances.

Solving the model for inflation and output growth as a function of the exogenous demand and supply disturbances yields:

$$\nabla_1 p_t = e_{dt-2} - e_{st} \tag{A7}$$

$$\nabla_1 y_t = e_{dt} - e_{dt-2} + e_{st}, \tag{A8}$$

where ∇_1 denotes the first-difference operator. Note that only supply shocks have a permanent effect on output, while both supply and demand shocks can affect long-run prices. Using (A7) and (A8), the covariance of growth and inflation is easily seen to be negative:

$$Cov(\nabla_1 p_t, \Delta_1 y_t) = -[Var(e_{dt}) + Var(e_{st})] < 0. \tag{A9}$$

APPENDIX II

A Bootstrap Algorithm for the Long-Horizon Tests

We discuss only the algorithm for the standard long-horizon regression involving the term spread. The algorithms for the other long-horizon regressions are identical except for a change of variable or the addition of an extra regressor. The algorithm consists of four steps:

1. Estimate the long-horizon regression

$$\nabla_k y_{t+k} = \alpha_k + \beta_k (R_t - r_t) + \eta_{t+k}$$

for k = 1, 2, 3, 4, 5, 6, 7, 8, 9, 12, 18, 24 by OLS, and in each case construct the test statistic for the null hypothesis H_0: $\beta_k = 0$ as the ratio of the estimated value of β_k to its estimated standard error (the latter constructed using a method-of-moments correction to allow for moving average serial correlation up to order $k - 1$); call this test statistic τ.

2. Since $\Delta y_t = y_t - y_{t-1}$ and $(R_t - r_t)$ are each assumed to be stationary, $I(0)$ processes, by Wold's theorem they will have an invertible joint vector moving average representation, which can be approximated by a vector autoregressive representation of sufficiently high order, say p:[11]:

$$\Delta y_t = \phi_1 + \sum_{i=1}^{p} \kappa_i \Delta y_{t-i} + \sum_{i=1}^{p} \lambda_i \left(R_{t-i} - r_{t-i}\right) + u_{1t},$$

$$\Delta\left(R_t - r_t\right) = \phi_2 + \sum_{i=1}^{p} \mu_i \Delta y_{t-i} + \sum_{i=1}^{p} \nu_i \left(R_{t-i} - r_{t-i}\right) + u_{2t}.$$

Under the null hypothesis that economic activity is unpredictable, however, we have $\kappa_i = \lambda_i = 0$ for all i. This VAR model is therefore estimated by generalized least squares with these exclusion restrictions imposed and with the lag order p chosen using the Akaike information criterion.

3. Based on the fitted model from step 2, a sequence of pseudo observations $\{\Delta y_t^*\}$ and $\{(R_t - r_t)^*\}$ is generated of the same length as the original data series from realizations of the bootstrap data generating process:

$$\Delta y_t = \hat{\phi}_1 + u_{1t}^*,$$

$$\Delta\left(R_t - r_t\right)^* = \hat{\phi}_2 + \sum_{i=1}^{p} \hat{\mu}_i \Delta y_{t-i}^* + \sum_{i=1}^{p} \hat{\nu}_i \left(R_{t-i} - r_{t-i}\right)^* + u_{2t}^*,$$

where the coefficients are the corresponding estimated parameters from step 2, and the vector pseudo innovation $(u_{1t}^*, u_{2t}^*)'$ is drawn with replacement from the set of residuals generated in step 2. The process is initialized by setting $\Delta y_{t-i}^* = (R_{t-i} - r_{t-i})^* = 0$ for $I = p-1, ..., 1$ and the first 500 transients are discarded. This step is repeated 2,000 times.

4. For each of the 2,000 bootstrap replications in step 3, construct the pseudo annualized cumulative percentage change in real industrial production as:

$$\nabla_k y_{t+k}^* = \frac{1200}{k} \sum_{j=1}^{k} \Delta y_{t+j}^*$$

and estimate the long-horizon regression

[11]Note that there is no issue of cointegration in the present application, which would involve using a vector equilibrium correction model rather than a VAR as the data-generating process—see Kilian (2000).

$$\nabla_k y^*_{t+k} = \alpha^*_k + \beta^*_k (R_t - r_t)^* + \eta^*_{t+k}$$

for k = 1, 2, 3, 4, 5, 6, 7, 8, 9, 12, 18, 24. For each replication construct the test statistic for the null hypothesis $H_0{:}\beta^*_k = 0$ as the ratio of the estimated value of β^*_k to its estimated standard error (the latter again constructed using a method-of-moments correction to allow for moving average serial correlation up to order $k - 1$); call the test statistic for the i-th replication τ^*_i.

5. Use the empirical distribution of the 2,000 replications of the sequence of bootstrap test statistic $\{\tau^*_i\}$ to determine the marginal significance level of τ.

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