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THE EFFECT OF MONETARY POLICY ON CREDIT SPREADS

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Abstract

We analyze the effect of monetary policy on yield spreads between corporate bonds with different credit ratings over the business cycle. We use futures contracts to distinguish between expected and unexpected changes in the Fed funds target rate and several indicators to distinguish between different phases of the business cycle. In line with the predictions of imperfect capital market theories, we find that yields on corporate bonds with low credit ratings widen (narrow) with respect to those with high credit ratings following an unexpected increase (decrease) in the Fed funds target rate during recession periods. Several tests suggest that our results are robust to outliers, potential endogeneity problems, empirical specification, control variables, countercyclical risk premium in futures, and alternative definitions of credit spreads and economic conditions.

JEL Classification: E44, E51, E52, G18

I. Introduction

Imperfect capital market theories (e.g., Bernanke and Gertler 1989; Kiyotaki and Moore 1997) predict that the effect of a monetary policy shock on rates in financial markets does not only depend on asset-specific characteristics but also on macroeconomic conditions. In all these models, whether based on the balance sheet or the bank lending channel, variables related to a firm's level of financial distress play an important role in determining the sensitivity of its financial assets to monetary policy shocks. Specifically, these models predict that rates on financial assets of firms with higher financial distress would be more sensitive to a monetary policy shock, especially during periods of economic slowdown, than those with lower financial distress.

Considering the importance of these models, it is not surprising to find a large literature analyzing the reaction of equity returns and Treasury bond yields to monetary policy shocks. Among others, Rigobon and Sack (2004) and Bernanke and Kuttner (2005) analyze the reaction of equity returns to monetary policy shocks. Several articles including but not limited to Kuttner (2001), Rigobon and Sack (2004), and Faust et al.

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(2007) analyze the relation between monetary policy and Treasury bond yields. In line with imperfect capital market theories, most of these studies find that monetary policy shocks have an important effect on returns in financial markets. However, there are only a small number of articles analyzing the effect of monetary policy on corporate bond yields. Kim, Ni, and Ratti (1998) and Beckworth, Moon, and Toles (2010) find that yield spreads between Moody's Baa- and Aaa-rated bond indices react significantly to monetary policy shocks.

In this article, we test the cross-sectional and time-series implications of imperfect capital market theories using yield spreads on bonds with different credit ratings. Our hypothesis can be summarized as follows: yields on corporate bonds of firms with lower credit ratings will be more sensitive to monetary policy shocks, and this differential effect will be more pronounced during periods of economic slowdown. Specifically, we analyze the effect of unexpected monthly changes in the Fed funds target rate on monthly changes in credit spreads between Moody's Baa- and Aaa-, Aa-, and A-rated bond indices. In line with the predictions of imperfect capital market theories, we find yields on Moody's Baa index to be more sensitive to monetary policy shocks in recessions compared to yields on Moody's indices with higher credit ratings. In other words, credit spreads widen (narrow) following an unexpected monetary policy tightening (easing) during periods of economic slowdown. For example, the credit spread between Moody's Baa- and Aaa-rated bond indices increases by 2.8 basis points per month following a 10 basis point (approximately 1 standard deviation) unexpected monthly increase in the Fed funds target rate during periods of recessions as defined by the National Bureau of Economic Research (NBER). We also uncover several asymmetries in the effect of unexpected changes on credit spreads. For example, unexpected increases and decreases have significantly different marginal effects on credit spreads during economic slowdowns. Furthermore, unexpected changes in monetary policy have different effects on credit spreads depending on whether the Fed decides to keep its target rate constant or not during economic slowdowns.

Our choice of variables as proxies for credit spreads, monetary policy, and its expectation is motivated by previous studies. We use yields on bond indices rather than individual bonds as a proxy for credit spreads because we need a long sample that covers several business cycles, which is not possible with limited data on individual bonds.[1] Following Bernanke and Blinder (1992), we use the target rate as an indicator of monetary policy. Our choice to use futures to distinguish between expected and unexpected changes in monetary policy is motivated by Kuttner (2001), who shows that futures contracts provide a good measure of monetary policy expectations. However, our article differs from these previous studies in several ways. First, to measure monetary policy shocks, we use futures on the Fed funds rate rather than a vector autoregression (VAR) approach. More important, we distinguish between different phases of the business cycle and analyze the time-varying effect of monetary policy on yield spreads over the business cycle.

[1]Moody's bond indices are available for our entire sample period between 1989 and 2008, which covers three recessions (1990–1991, 2001, and 2007–2008). On the other hand, most databases on individual bonds, such as Mergent and Trace, are only available starting in the mid-1990s. Hence, ignoring the 2007–2008 recession, these data sets cover a period of only one relatively short-lived recession.

We then focus on several issues related to our empirical framework. First, we provide empirical evidence that our results are robust to using alternative definitions of credit spreads and business cycle indicators (BCI). To this extent, we use yield spreads between Moody's Baa- and Aa- and A-rated bond indices as alternative definitions of credit spreads. We also distinguish between ex post and real-time measures of economic conditions depending on their availability in real time. Second, following Bernanke and Kuttner (2005), we analyze the robustness of our results to outliers and find that our results continue to hold when we remove these potential outliers from our sample. Third, following Piazzesi and Swanson (2008), we use futures contracts adjusted for the risk premium as a measure of monetary policy expectations in our empirical framework. We show that the effect of monetary policy shocks on credit spreads are not due to a countercyclical risk premium. Fourth, we show that our results are not due to possible endogeneity of unexpected changes in the Fed funds target rate or BCI. Following Bernanke and Kuttner, we analyze the reaction of unexpected changes in the Fed funds target rate and credit spreads to macroeconomic news and find that credit spreads and the Fed do not react jointly and contemporaneously to new economic information. We also provide further empirical evidence on the effect of monetary policy shocks on credit spreads over the business cycle in a two-stage least squares (TSLS) framework. Finally, we estimate an exponential generalized autoregressive conditional heteroskedacity (GARCH) specification and include variables discussed in Collin-Dufresne, Goldstein, and Martin (2001) as controls. Our results suggest that the effect of monetary policy shocks on credit spreads is robust to using an alternative empirical specification with time-varying volatility and to including control variables.

II. Theoretical Background

In this section, we first discuss the literature on imperfect capital market theories. We then present our hypothesis based on the cross-sectional and time-series implications of these theoretical models.

The classic textbook models assume that different sources of financing can be treated equally and that capital structure and information asymmetry are irrelevant. Based on these and other similar assumptions, which might not hold in reality, these "money view" models predict that all rates in financial markets would change in a similar fashion following monetary policy shocks. Hence, yield spreads between bonds with different characteristics are not expected to react to monetary policy shocks.

Bernanke and Blinder (1988) are among the first to question the assumptions underlying the money view models. They develop a model of monetary policy transmission based on asymmetric information and capital structure differences between borrowers and lenders. These "credit view" models distinguish between different sources of financing and financial securities such as bank loans, bonds, and equity. These models show that an increase in the open market interest rate decreases not only the demand but also the supply of credit. Hence, in contrast to models based on the money view, those based on the credit view predict that rates on different financial securities will react differently to monetary policy shocks. These models also predict that the effect of monetary policy on rates in financial markets depends on macroeconomic conditions with a stronger effect during periods of economic slowdown. The models based on the credit view can be classified in two main groups with respect to the transmission channel: balance sheet and bank lending channels. The balance sheet channel focuses on the informational asymmetry between borrowers and lenders whereas the bank lending channel focuses mostly on lending activities of banks and bank-dependent borrowers.

Models based on the balance sheet channel (e.g., Bernanke and Gertler 1989; Kiyotaki and Moore 1997) assume there is an informational asymmetry between borrowers and lenders. Borrowers generally know their financial situations and the profitability of their projects better than lenders. Because of this informational asymmetry, borrowers' assets serve not only as means of production but also as collateral for external financing. An unexpected monetary policy tightening not only increases firm's cost of debt but also decreases cash flows from its assets because of weakened aggregate demand. This, in turn, weakens its balance sheet or net worth. This effect would be even more pronounced during periods of economic slowdown when the aggregate demand and balance sheets of firms are already weak. On the other hand, the models of Bernanke and Blinder (1992) and Kashyap, Stein, and Wilcox (1993) based on the bank lending channel assume that banks' lending activities are negatively affected following a worsening of their balance sheets because of an unexpected monetary policy tightening. Hence, they are either unable or unwilling to lend as much as before. Hence, firms that are more bank dependent than others would be more sensitive to a monetary policy shock because of the change in banks' supply of credit. This effect would be more pronounced during periods of economic slowdown when banks' supply of credit is already low due to their weak balance sheets.

Whether it is the balance sheet or the bank lending channel, a firm's level of financial distress plays an important role in determining the sensitivity of its financial assets to monetary policy shocks. Firms that have higher levels of financial distress tend to be more bank dependent or have weaker balance sheets. Hence, one would expect financially distressed firms to be more sensitive to monetary policy shocks, especially during periods of economic slowdown. Using credit ratings as a proxy for financial distress and corporate bonds as financial securities of interest, our hypothesis based on the cross-sectional and time-series implications of imperfect capital market theories can be summarized as follows: yield spreads between corporate bonds of firms with low and high credit ratings widen (narrow) following an unexpected monetary policy tightening (easing) and the effect of a monetary policy shock on yield spreads is stronger in recessions compared to expansions.

III. Data

In this section, we describe the data sets used in our empirical analysis. We first present different measures of economic conditions. We then discuss how we extract expected and unexpected changes in the Fed funds target rate using data on futures contracts. Finally, we describe our data set on credit spreads.

Business Cycle Indicators

We use four measures of economic conditions, which we call BCI. We classify these four BCI as either ex post or real-time depending on whether they would have been available to market participants in real time. We use two ex post and two real-time BCI. The first ex post measure is a dummy variable that equals 1 in a given month if the economy is in a recession as defined by the NBER, and 0 otherwise. The second ex post measure is the monthly (log) growth rate of industrial production based on the vintage of May 15, 2009. These two data sets are available to us from the websites of the NBER and the Federal Reserve Bank of Philadelphia. These two measures are considered ex post because they would not have been available to market participants in real time. For the first ex post measure, we observe a significant delay between NBER announcements and the effective start or end of a recession. For the second ex post measure, we use revised rather than real-time data. Like many other macroeconomic variables, the data on industrial production get revised to reflect more accurate estimates as additional information arrives. However, market participants would not have had access to these revised data in real time when forming their expectations of a recession. Hence, to avoid a look-ahead bias, we also use BCI based on the information set that the market participants would have had in real time.

For the first real-time measure, we estimate the following Markov regime-switching model for the growth rate of industrial production using real-time data vintages:

$$\Delta \ln(IP_t) = \alpha_{S_t} + \omega_{S_t} \in_t, \tag{1}$$

where $\in_t$ is independent and identically distributed normal random variable with zero mean and unit variance. αS_t and ωS_t are the mean and standard deviation of the growth rate of industrial production as functions of the state variable, S_t. We assume that the state variable follows a two-state Markov chain. We consider the state in which the growth rate of industrial production is lower as the recession state. Hence, as our first real-time measure ($Prob_{1,t}$), we use the filtered probability[2] of the recession state for the last observation in each vintage of real-time data. Our approach to use real-time data can be summarized as follows using the first month in our sample, May 1989, as an example. First, note that initial data on industrial production for a given month are released by the Federal Reserve Board generally toward the middle of the following month. For example, data for industrial production in April 1989 were only available to market participants on May 15, 1989. Furthermore, data for industrial production in previous months might also get revised in May 1989 as new data are released. Hence, to obtain the real-time probability of recession in May 1989, we estimate the Markov regime-switching model in equation (1) using data on industrial production between January 1950 and April 1989 as it would have been available on May 15, 1989. Then, the real-time probability of recession in May 1989 is the filtered probability of the recession state for April

[2]We estimate the Markov regime-switching model in equation (1) separately for each vintage of data on industrial production. Because we keep the probability of the recession state only for the last observation in each vintage, the filtered and smoothed probabilities are equal.

1989.[3] We continue in this fashion using an expanding window of observations to obtain our first real-time measure of economic conditions.[4] For example, the real-time probability of recession in June 1989 is based on the data for industrial production between January 1950 and May 1989 as it would have been available on June 15, 1989.

Our approach to obtain real-time recession probabilities is based on a single indicator of economic activity, industrial production. One can also consider estimating real-time probabilities of recession based on several indicators of economic activity including but not limited to industrial production. Such an approach is implemented by Chauvet and Piger (2008) using a dynamic four-factor Markov switching model for changes in industrial production, personal income, manufacturing, and employees on nonfarm payrolls. The real-time probabilities of recession based on Chauvet and Piger's approach are available to us from Jeremy Piger's website at the University of Oregon (http://pages.uoregon.edu/jpiger/us_recession_probs.htm). We use these probabilities as our second real-time measure of economic conditions ($Prob_{2,t}$).

Figure I presents the two real-time probabilities of recession ($Prob_{1,t}$ and $Prob_{2,t}$) as well as the NBER recession periods and the growth rate of industrial production. It is easy to see that the two real-time recession probabilities are similar. However, as expected, the recession probabilities based on four indicators of economic activity are much smoother than those based only on industrial production. Not surprisingly, both recession probabilities increase and approach one during NBER recession periods whereas they are close to zero during NBER expansion periods. Although not presented, all indicators except the growth rate of industrial production are positively but not perfectly correlated. The negative correlation between the growth rate of industrial production and other BCI is due to the fact that a positive growth rate of industrial production indicates improving economic conditions and a lower probability of recession.

Unexpected Changes in the Federal Funds Target Rate

In this article, we use the Fed funds target rate as an indicator of monetary policy rather than other measures such as monetary base. Our choice is motivated by Bernanke and Blinder (1992) who argue that the Fed funds target rate is a good indicator of monetary policy. Furthermore, one can obtain a measure of unexpected changes in the target rate based on futures data rather than a statistical approach. As discussed in Kuttner (2001), there are several advantages of using futures market data over statistical approaches such as lack of generated regressors problem or need for model selection. However, several complications also arise due to the nature of futures contracts. First, the payoffs from futures contracts depend on the average of daily effective rates in the expiration

[3]One can also consider forming one-month-ahead forecasts of real-time recession probabilities based on the estimated transition probabilities and the filtered probability of the last observation. We use these forecasted probabilities as an alternative business cycle indicator in our empirical specifications. Our results do not change significantly and are available upon request.

[4]We also considered real-time recession probabilities based on a rolling window of real-time observations. Our results based on a rolling window of observations are qualitatively and quantitatively similar to those based on an expanding window of observations and are available upon request. We also considered rolling and expanding windows with fewer observations and our results do not change significantly.

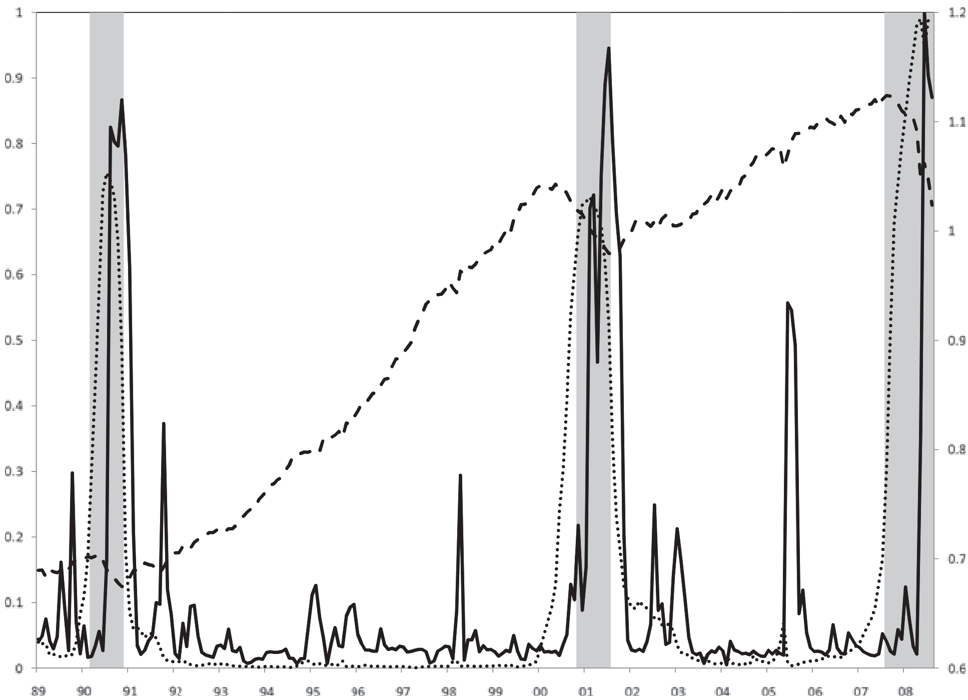

FIGURE I. Business Cycle Indicator. This figure plots the time series of real-time recession probabilities ($Prob_{1,t}$ and $Prob_{2,t}$), the industrial production index (IP_t) and National Bureau of Economic Research (NBER) recession periods ($NBER_t$) between May 1989 and December 2008. The solid line represents the real-time recession probability based on a two-state Markov regime switching model for the real-time growth rate of the industrial production index ($Prob_{1,t}$). The dotted line represents the real-time recession probability from Chauvet and Piger (2008) available at http://pages.uoregon.edu/jpiger/us_recession_probs.htm ($Prob_{2,t}$). The dashed line represents the industrial production index (IP_t) divided by 100 and is measured on the right axis. The shaded regions are the NBER recession periods ($NBER_t$).

month rather than the target rate on a specific day. Second, these futures contracts might reflect a risk premium and provide biased expectations of monetary policy as discussed in Piazzesi and Swanson (2008). For the latter, we defer the discussion to later in the article where we analyze the robustness of our empirical results to using risk-adjusted measures of unexpected changes in the Fed funds target rate. For the first issue, we refer the reader to Kuttner who argues that the difference between effective and target rates is not crucial when calculating monthly expectations of monetary policy. Furthermore, he suggests several approaches to undo the effect of time-averaging in futures contracts. In this article, we follow Kuttner and define the unexpected change in the Fed funds target rate in month t as the difference between the average realized Fed funds target rate in month t and the target rate predicted by the Fed funds futures on the last day of the previous month:

$$U_t = \frac{1}{D_t}\sum_{d=1}^{D_t} i_{t,d}^{tar} - f_{t-1,D_{t-1}}^{1}, \tag{2}$$

where $i_{t,d}^{tar}$ is the Fed funds target rate on day d of month t and D_t is the number of total calendar days in month t. The target rate implied by the price of the one-month Fed funds rate futures on the last day (D_{t-1}) of previous month (t–1) is denoted $f_{t-1,D_{t-1}}^{1}$. The expected change in the Fed funds rate in month t is the difference between the implied target rate from the futures price and the actual rate in month t is the difference between the implied target rate from the futures price and the actual Fed funds rate on the last day of month t–1:

$$E_t = f_{t-1,D_{t-1}}^{1} - i_{t-1,D_{t-1}}^{tar}. \tag{3}$$

The sum of the unexpected and expected changes in the Fed funds target rate is not the actual change but rather the difference between the average Fed funds target rate in month t and the implied target rate on the last day of month t–1. The actual change in month t, A_t, is the difference between the Fed funds target rates on the last day of month t and t–1:

$$A_t = i_{t,D_t}^{tar} - i_{t-1,D_{t-1}}^{tar}. \tag{4}$$

Several notes on how to interpret unexpected changes in the Fed funds target rate are in order. One observes a positive (negative) unexpected change in the target rate under one of the following four possible scenarios: (1) the Fed increases the target rate more (less) than expected, (2) the Fed increases (decreases) the target rate when either a rate cut (increase) or a constant rate was expected, (3) the Fed decreases the target rate less (more) than expected, or (4) the Fed keeps the target rate unchanged when a rate cut (increase) was expected. In other words, an unexpected change in the target rate is related not only to the sign and magnitude of the actual change but also to its timing as under scenarios 2 and 4. Hence, one can still observe positive (negative) surprises even when the actual change is negative (positive) as it is generally the case in recessions (expansions).

For the rest of the article, we focus on the effect of unexpected changes in the Fed funds target rate on credit spreads except when we analyze the risk premium in futures contracts based on the effective, rather than target, rate. There are several reasons we focus on unexpected changes rather than actual or expected changes in monetary policy. First, the expected component of actual changes in the Fed funds target rate must have already been incorporated in credit spreads. More important, expected and actual changes in the Fed funds target rate could suffer from an endogeneity problem.

Figure II presents expected, unexpected, and actual changes in the Fed funds target rate. As it is well known, the Fed decreases the target rate during recessions relatively rapidly and increases it during expansions at a slower pace. In fact, there is no recession period during which the Fed increases the target rate. However, for reasons discussed above, we still observe positive unexpected changes in recessions and negative changes in expansions. Although not presented, summary statistics suggest that unexpected changes

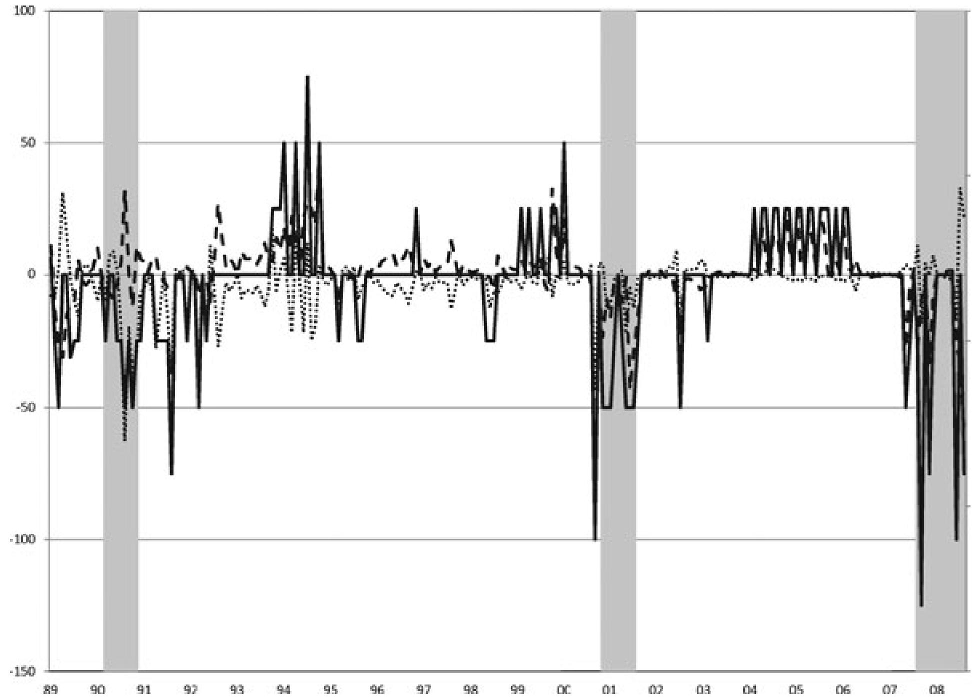

FIGURE II. Expected, Unexpected, and Actual Changes in the Fed Funds Target Rate. This figure plots the time series of expected (dashed line), unexpected (dotted line), and actual (solid line) changes in the Fed funds target rate in basis points between May 1989 and December 2008. The actual changes in the Fed funds target rate are from the Federal Reserve Bank of New York. The expected and unexpected changes are based on the Fed funds futures contracts traded on the Chicago Board of Trade. The shaded regions are the National Bureau of Economic Research recession periods ($NBER_t$).

in the Fed funds target rate are negative, on average, both in expansions and recessions with a higher standard deviation in recessions. In other words, the market participants overpredict actual changes in the Fed funds target rate both in expansions and recessions. As we discuss later, this overprediction might reflect the positive risk premium that the investors demand for holding futures contracts. Like many other financial variables, the higher standard deviation in recessions might reflect the higher uncertainty of investors in recessions.

Credit Spreads

Monthly average yields on Moody's seasoned Baa-, A-, Aa-, and Aaa-rated bonds, for the sample period between May 1989 and December 2008, are available to us from the Global Financial Data. Credit spreads are defined as the difference between the yield on Baa-rated bonds and the yields on A-, Aa-, and- Aaa-rated bonds, respectively. In this article, we choose to use bond indices to capture credit spreads rather than individual bonds for several reasons. First, Moody's bond indices are one of the most used measures of aggregate credit market conditions. In addition to the aforementioned articles, David (2008), Davies (2008), and Bevan and Garzarelli (2000) also use Moody's bond indices

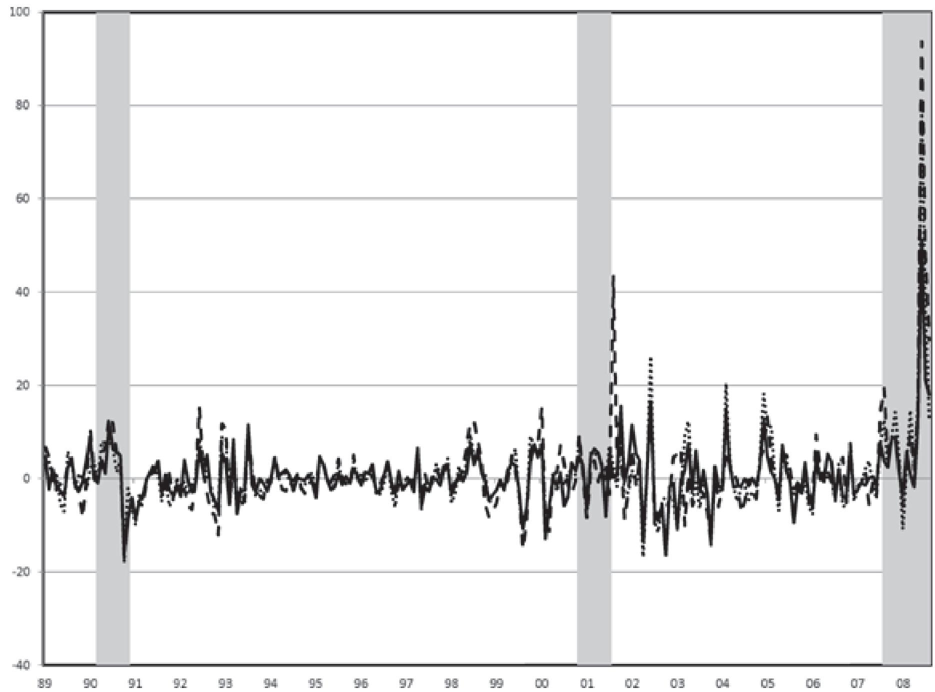

FIGURE III. Credit Spreads. This figure plots the time series of monthly changes in credit spreads in basis points between May 1989 and December 2008. The dashed, dotted, and solid lines correspond to credit spreads between Baa-rated bonds and Aaa-, Aa-, and A-rated bonds, respectively. The shaded regions are the National Bureau of Economic Research recession periods ($NBER_t$).

as proxies for aggregate credit spreads. Second, Moody's bond indices are available for a much longer sample period than most databases on individual bonds, such as Mergent and Trace. Because we focus on the effect of unexpected changes in monetary policy on credit spreads over the business cycle, a sample period that includes at least several recessions is absolutely necessary for our analysis. Finally, we believe that bond indices are more suitable than individual bonds to analyze the effect of a systematic factor such as monetary policy. In this article, we use changes in credit spreads rather than levels of credit spreads. Avramov, Jostova, and Philipov (2007) argue that changes in credit spreads capture important aspects of fixed-income markets and the difference between levels and changes is similar to the difference between equity prices and returns. Furthermore, our preliminary analysis (not presented) suggests that credit spread levels might not be stationary. However, our results based on augmented Dickey–Fuller tests suggest that changes in credit spreads are stationary.

Figure III presents monthly changes in credit spreads between May 1989 and December 2008. This figure suggests that three definitions of changes in credit spreads are closely related. Furthermore, although there seems to be a relation between monthly changes in credit spreads and NBER recession periods, credit spreads seem to have their own cycle with periods of relative calm and periods of high volatility. Summary statistics, not presented, suggest that credit spreads widen during recessions at a fast pace whereas they narrow at a relatively slower pace during expansions. Furthermore, credit spreads tend to be more volatile in recessions compared to expansions. These effects are more pronounced for the spread between Baa- and Aaa-rated bonds than other definitions of the credit spread. These results are broadly consistent with those in Fama and French (1989). They find that credit spreads widen when economic conditions deteriorate.

Here, we discuss the composition of the bond indices used in this article and then argue how index construction could impact our empirical results. Our discussion for the composition of the Moody's Corporate Bond Indices follow from Bhanot (2005) and the information available on Bloomberg. The Moody's Long-Term Corporate Bond Indices are generally composed of 75 to 100 individual bonds issued by large nonfinancial corporations. Individual bonds must have an outstanding value over $100 million, an initial maturity as close to 30 years as possible, and a liquid secondary market. A bond is dropped from the index if it is susceptible to redemption, if the remaining life falls below 20 years, or if the rating changes.

We believe that the Moody's approach of constructing bond indices should not significantly affect our empirical results. First, according to the definition on Bloomberg, Moody's regularly updates the composition of the index to reflect changes in bond and firm characteristics such as maturity, exercise of call and conversion options, or liquidity problems. Second, Bhanot (2005) also writes referring to the Moody's Long-Term Corporate Bond Indices: "Bonds comprising an index are often 'refreshed' in order to maintain constant credit quality. In other words, the yield change from one period to another does not measure the change in the same set of bonds but rather the change in the average yield on two sequential sets of bonds that share the same credit rating" (p. 4). This suggests that a measure of credit spreads based on the Moody's indices mostly reflects the spread due to credit rating rather than other factors. Finally, we use yield spreads between Moody's indices as a measure of credit spreads rather than using yields on a Treasury security as a benchmark. As long as Moody's updates the constituents of different indices on a similar schedule (which is our understanding), this should also mitigate some of the potential problems associated with index construction.

Another issue that might affect our empirical results is related to rating practices. Most rating agencies use a through-the-cycle approach to assign ratings to individual bonds. In contrast to a point-in-time approach, which assigns ratings based on short-term estimates of default risk, through-the-cycle ratings tend to be long-term estimates that control for any cyclical behavior in default risk. Through-the-cycle ratings tend to respond to permanent changes in default risk and might not reflect short-term changes in default risk. In other words, ratings based on a through-the-cycle approach might lag any recent changes in default risk. For example, a bond with a rating of Baa might continue to have a Baa rating even if there was a recent change in the firm's default risk. This in turn implies that an index of, say, Baa-rated bonds might not provide a pure measure of default risk associated with a credit rating of Baa. To see this, consider the individual bonds in the Baa-rated index in a recession, a period during which default risk increases for most firms in the economy. Because of this possible delay in rating changes, one might find in the index some bonds that actually have higher default risks than a correctly rated bond with a Baa rating. This might in turn affect our results on the effect of unexpected changes in monetary policy on credit spreads in recessions. However, we believe this effect to be relatively small for the following reasons. First, this possible delay in rating changes presents a similar problem for all indices with different rating categories. The fact that we are using the yield difference between two bond indices rather than using a Treasury security should decrease, but not necessarily eliminate, the effect of this problem on our results.[5] More important, Bangia et al. (2002) present empirical evidence that the percentage of bonds in an index for which the delay in rating changes presents a problem is relatively small. Specifically, Bangia et al. analyze quarterly and annual rating migration matrices of individual bonds between 1981 and 1998. They find that less than 5% (15%) of bonds with a Standard & Poor's rating of BBB or higher (which roughly corresponds to Moody's Baa rating or higher) migrates to another rating category within a quarter (year). This provides an order of magnitude for the problem of delay in rating changes. For example, in the worst-case scenario where there is a one-year delay in updating ratings, this would present a problem at most for 15% of the bonds. We believe this is a relatively small proportion of bonds and should not affect our results significantly.

IV. The Effect of Monetary Policy on Credit Spreads over the Business Cycle

In this section, we analyze the effect of unexpected changes in the Fed funds target rate on monthly changes in credit spreads over the business cycle. We first present and discuss our empirical results. We then analyze the robustness of our results using risk-adjusted measures of unexpected changes in monetary policy.

Empirical Results

In this section, we present our empirical results on the effect of unexpected changes in the Fed funds target rate on credit spreads over the business cycle. To this extent, we estimate the following empirical specification via ordinary least squares with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors:[6]

$$\Delta Spread_t = \beta_0 + \beta_1 U_t + \beta_2 BCI_t + \beta_3 (U_t \times BCI_t) + \varepsilon_t, \tag{5}$$

where BCI_t is one of the four BCI in month t. The interaction term allows us to analyze the marginal effect of unexpected changes in the Fed funds target rate on credit spreads during periods of economic slowdown. Before discussing our results, we should first note that the NBER recession dummy variable and the two real-time measures are similar in the sense that a higher number represents either a recession or a higher probability of

[5]This is because credit spreads, in general, widen during recessions. The yield spread between, say, Baa- and Aaa-rated bonds in recessions might be even higher than it should be if there were no delays in rating changes. Hence, the approach of using yield spread between bond indices instead of using a Treasury security does not eliminate problems associated with delays in rating changes.

[6]The HAC standard errors are based on the Newey–West approach with lag length and bandwidth chosen automatically. We also prewhiten with a lag length chosen automatically based on the Hannan–Quinn information criteria.

TABLE 1. The Effect of Unexpected Changes in the Fed Funds Rate on Credit Spreads over the Business Cycle.

Variable	$\Delta(Baa_t - Aaa_t)$	$\Delta(Baa_t - Aa_t)$	$\Delta(Baa_t - A_t)$
Panel A. Business Cycle Indicator: NBER			
Constant	0.0034	−0.2131	−0.2034
U_t	0.0237	0.0072	−0.0319
$NBER_t$	10.4747***	9.3611***	6.0195***
$U_t \times NBER_t$	0.2764***	0.2272***	0.1879***
Adjusted R^2	12.47%	13.50%	8.96%
Panel B. Business Cycle Indicator: Industrial Production			
Constant	1.4510**	1.0866**	0.7016*
U_t	0.0371	0.0235	−0.0117
$\Delta ln(IP_t)$	−2.9468***	−2.2114***	−2.0166***
$U_t \times \Delta ln(IP_t)$	−0.3952	−0.2781**	−0.2245**
Adjusted R^2	12.06%	8.23%	9.28%
Panel C. Business Cycle Indicator: Real-Time Recession Probabilities I			
Constant	−0.8108	−0.3533	−0.3371
U_t	0.0264	0.0347	−0.0269
$Prob_{1,t}$	20.4633**	12.9534*	8.6403
$U_t \times Prob_{1,t}$	0.4323***	0.2362**	0.2415***
Adjusted R^2	17.34%	9.27%	6.53%
Panel D. Business Cycle Indicator: Real-Time Recession Probabilities II			
Constant	−0.6799	−0.6302*	−0.5248*
U_t	0.0278	0.0267	−0.0170
$Prob_{2,t}$	16.2494***	13.1601***	8.9020***
$U_t \times Prob_{2,t}$	0.2958***	0.1901**	0.1671**
Adjusted R^2	17.26%	15.38%	11.28%

Note: This table presents the effect of unexpected changes in the Fed funds target rate on changes in credit spreads over the business cycle. U_t is the unexpected change in the Fed funds rate in month t. Panel A presents results based on the NBER recession dummy variable ($NBER_t$), which equals 1 if the economy is in a recession in month t as defined by the NBER, and 0 otherwise. Panel B presents results based on the (log) growth rate of industrial production ($\Delta \ln IP_t$). Panel C presents results based on the real-time recession probabilities from the estimation of equation (1). Panel D presents results based on the real-time recession probabilities from Chauvet and Piger (2008). The coefficients are estimated via OLS with HAC standard errors.
***Significant at the 1% level.
**Significant at the 5% level
*Significant at the 10% level.

recession. On the other hand, the interpretation of our results based on the growth rate of industrial production is slightly different in the sense that a positive number represents economic growth and a negative number represents economic slowdown.

Table 1 presents empirical results using ex post and real-time measures of business conditions. The results are similar whether we use ex post or real-time measures of business conditions and can be summarized as follows. First, significant coefficient estimates of BCI indicate that credit spreads widen, on average, during periods of economic slowdown. More important, unexpected changes in the Fed funds target rate have a positive and significant effect on credit spreads during periods of economic slowdown although the overall effect is insignificant. This is more pronounced for the credit spread between Baa- and Aaa-rated bonds than the two other definitions of credit spread. These results are significant not only statistically but also economically: consider the empirical specification with the NBER recession dummy variable for which the economic interpretation of the coefficient estimates is the easiest. A 10 basis point (approximately 1 standard deviation) unexpected increase in the Fed funds target rate results in an additional increase of 2.8 basis points in the credit spread between Baa- and Aaa-rated bonds during NBER recessions.

Our results suggest that credit spreads increase (decrease) significantly following unexpected monetary policy tightening (easing) during periods of economic slowdown. In other words, firms with low credit ratings are more sensitive to unexpected changes in monetary policy during recessions. These results provide statistically significant evidence in line with our hypothesis based on imperfect capital market theories.

Discussion

Our article is related to a large empirical literature on the implications of imperfect capital market theories but is closest in spirit to Gertler and Gilchrist (1994). They test the implications of imperfect capital market theories using firm size as a proxy for capital market access, sales, and inventories as measures of firm performance, and gross national product growth as a measure of business conditions. In line with the predictions of imperfect capital market theories, they find that sales and inventories of small manufacturing firms exhibit sharper declines following a monetary policy tightening in bad times. They also show that the effect of monetary policy is significantly different for small firms between periods of economic growth and slowdown, but not for large firms.

Our article is also related to a relatively smaller literature on the relation between credit spreads and monetary policy. Kim, Ni, and Ratti (1998) analyze the effect of monetary policy over monetary easing and tightening periods. They use several measures of monetary policy including Romer dates, the Boschen and Mills index, and the first difference in the Fed funds target rate, and they find that increases in the Fed funds target rate significantly raise the yield on Baa bonds absolutely and relative to the yield on Aaa bonds. They argue that the asymmetric effect of monetary policy might be due to the credit channel of monetary policy. Avramov, Jostova, and Philipov (2007) attempt to explain credit spreads in corporate bonds using a structural model. As part of an additional robustness test for their results, they include a dummy variable for expansionary and contractionary monetary policy to control for the effect of marketwide liquidity on changes in credit spreads. They find that the dummy variable for monetary policy is significant only for high-grade bonds and expansionary (contractionary) policy decreases (increases) credit spreads. Recently, Beckworth, Moon, and Toles (2010) analyze the effect of monetary policy shocks on credit spreads. Using money supply as an indicator of monetary policy in a VAR framework, they find that an unexpected increase in the money supply results in a decrease in the spreads between Moody's Baa and Aaa bond yields. As mentioned in the introduction, our article differs from the previous studies in several ways. First, these studies do not use futures data on the Fed funds target rate to distinguish between expected and unexpected changes in monetary policy. Furthermore, they do not distinguish between different phases of the business cycle.

Asymmetries

Our baseline study suggests that unexpected changes in monetary policy have an asymmetric effect on credit spreads depending on the state of the economy. In addition to asymmetries with respect to economic conditions, unexpected changes in monetary policy might also have asymmetric effects on credit spreads with respect to other factors. In this section, we analyze two such asymmetries with respect to the sign of the unexpected change and the timing of the policy action.

We first analyze possible asymmetries due to the sign of the unexpected change in the Fed funds target rate. Specifically, we distinguish between unexpected increases and decreases and analyze their effects on credit spreads separately. To do so, we estimate the following empirical specification via OLS with HAC standard errors:

$$\Delta Spread_t = \beta_0 + \beta_1 BCI_t + \beta_2(U_t \times D_t) + \beta_3(U_t \times (1 - D_t)) + \beta_4(U_t \times BCI_t \times D_t) + \beta_5(U_t \times BCI_t \times (1 - D_t)) + \varepsilon_t, \tag{6}$$

where D_t is a binary variable that equals 1 if the unexpected change in the Fed funds target rate is positive, and 0 otherwise. Before discussing our results, one should recall the possible scenarios that would result in an unexpected increase in the target rate during recessions. Given that the Fed does not generally increase the target rate during recessions, one would observe an unexpected increase in the target rate if the Fed decreases the target rate less than expected or the Fed keeps the target rate unchanged when a rate cut was expected. These two scenarios would both be considered signals for worsening credit market conditions especially in recessions. Our results reported in Table 2 suggest that only unexpected increases in the target rate in recessions have a significant effect on credit spreads. Specifically, credit spreads widen following unexpected increases in the target rate in recessions. These results also suggest that the significant effect of unexpected changes on credit spreads in recessions from our baseline study is mainly due to unexpected increases rather than a decrease in the target rate during recessions. Results based on Wald statistics (not presented in Table 2) suggest that unexpected increases and decreases do not have significantly different overall effects on credit spreads whereas their marginal effects in recessions are significantly different from each other.

We now turn our attention to possible asymmetries due to the timing of policy actions. Bernanke and Kuttner (2005) argue that a decision by the Fed to delay a policy action by one meeting might surprise market participants although they might have a clear idea about its direction and magnitude. In other words, some of the unexpected changes during periods when the Fed decides to keep the rate constant might due to surprises related to the timing of policy actions rather than their direction or magnitude. This in turn suggests treating differently the periods when the Fed decides to keep its target rate constant, which we refer as asymmetries due to timing. To this end, we estimate the empirical specification in equation (6) where, this time, D_t is defined to capture such asymmetries. Specifically, D_t is a binary variable that equals 1 if the Fed decides to

TABLE 2. Asymmetric Effect of Unexpected Changes in the Fed Funds Rate on Credit Spreads.

Variable	$\Delta(Baa_t - Aaa_t)$	$\Delta(Baa_t - Aa_t)$	$\Delta(Baa_t - A_t)$
Panel A. Business Cycle Indicator: NBER			
Constant	0.1125	−0.2368	−0.2004
$NBER_t$	4.7933**	6.6295***	4.0470***
$U_t \times (U_t > 0)$	−0.0252	0.0179	−0.0333
$U_t \times (U_t <= 0)$	0.0375	0.0042	−0.0315
$U_t \times NBER_t \times (U_t > 0)$	1.1825***	0.6404***	0.4922***
$U_t \times NBER_t \times (U_t <= 0)$	−0.0399	0.0806	0.0805
Adjusted R^2	17.55%	14.75%	9.9%
Panel B. Business Cycle Indicator: Industrial Production			
Constant	0.2492	0.2238	0.1938
$\Delta \ln(IP_t)$	−1.9135***	−2.0725***	−1.7140***
$U_t \times (U_t > 0)$	0.4311***	0.3311***	0.1602**
$U_t \times (U_t <= 0)$	−0.0727	−0.0649	−0.0602
$U_t \times \Delta\ln(IP_t) \times (U_t > 0)$	−0.4735***	−0.2261***	−0.2336***
$U_t \times \Delta\ln(IP_t) \times (U_t \leq 0)$	−0.3114	−0.2960	−0.2064
Adjusted R^2	15.09%	9.96%	9.99%
Panel C. Business Cycle Indicator: Real-Time Recession Probabilities I			
Constant	−0.6240	−0.2326	−0.1765
$Prob_{1,t}$	14.0892	8.1002	4.9121
$U_t \times (U_t > 0)$	0.0735	0.0795	−0.0209
$U_t \times (U_t <= 0)$	0.0289	0.0338	−0.0187
$U_t \times Prob_{1,t} \times (U_t > 0)$	1.0909***	0.7308***	0.6430***
$U_t \times Prob_{1,t} \times (U_t \leq 0)$	0.1343	0.0116	0.0619
Adjusted R^2	19.58%	10.94%	7.99%
Panel D. Business Cycle Indicator: Real-Time Recession Probabilities II			
Constant	−0.2387	−0.4116	−0.2815
$Prob_{2,t}$	9.8656**	9.6006***	6.1310***
$U_t \times (U_t > 0)$	−0.0239	0.0098	−0.0621
$U_t \times (U_t <= 0)$	0.0943	0.0790*	0.0189
$U_t \times Prob_{2,t} \times (U_t > 0)$	1.1050***	0.6327***	0.5348***
$U_t \times Prob_{2,t} \times (U_t <= 0)$	−0.1506	−0.0554	−0.0330
Adjusted R^2	20.88%	16.56%	12.42%

Note: This table presents the asymmetric effect of unexpected changes in the Fed funds target rate on changes in credit spreads over the business cycle. U_t is the unexpected change in the Fed funds rate in month t. Panel A presents results based on the NBER recession dummy variable ($NBER_t$), which equals 1 if the economy is in a recession in month t as defined by the NBER, and 0 otherwise. Panel B presents results based on the (log) growth rate of industrial production ($\Delta\ln IP_t$). Panel C presents results based on the real-time recession probabilities from the estimation of equation (1). Panel D presents results based on the real-time recession probabilities from Chauvet and Piger (2008). The coefficients are estimated via OLS with HAC standard errors.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

change its target rate, and 0 if the Fed decides to keep it constant. Our results presented in Table 3 suggest that unexpected changes have a significant effect on credit spreads in recessions only when the Fed decides to keep the target rate constant. In other words, our results suggest that the significant effect of unexpected changes on credit spreads is mainly related to the timing of policy actions. Given that market participants generally expect the Fed to decrease the target rate during recessions, one would observe a positive unexpected change when the Fed decides to keep the target rate constant. Thus, one would expect credit spreads to widen following a timing-related surprise in recessions. Hence, one would expect a significant and positive coefficient estimate on the unexpected change when the Fed decides to keep the target rate constant in recessions, that is, $U_t \times BCI_t \times (1 - D_t)$, as in Table 3. Based on Wald statistics (not presented in Table 3), there is no timing-related asymmetry in the overall effect whereas there is evidence of such an asymmetry in the marginal effect of unexpected changes on credit spreads in recessions. In other words, during period of economic slowdowns, unexpected changes in monetary policy have different effects on credit spreads depending on whether the Fed decides to keep its target rate constant.

V. Robustness Checks

Outlier Analysis and Subsample Stability

To analyze the effect of possible outliers on our empirical results, we consider three sets of outliers. In the first case (case (a) of Table 4), we follow Bernanke and Kuttner (2005) and compute influence statistics for each observation based on the squared scaled change in the coefficient vector due to removing that observation from the sample.[7] Specifically, for a given month t, we obtain coefficient estimates $(\hat{\beta}_t)$ of the specification in equation (5) by removing the observation for month t from our sample. The influence statistic for month t is then calculated as $\Delta\hat{\beta}' \ \hat{\Sigma} \ -1\Delta\hat{\beta}_t$ where $\hat{\Sigma} \ -1$ is the estimated covariance matrix of coefficients from the original regression based on the whole sample, and $\Delta\hat{\beta}_t = \hat{\beta}_t - \hat{\beta}$ is the change in the vector of coefficients due to removing the observation for month t. Following Bernanke and Kuttner, we consider any observation with an influence statistic greater than 0.3 to be an outlier. Figure IV presents the histogram of these influence statistics for the credit spread between Baa- and Aaa-rated bonds and alternative measures of economic conditions. The histograms of influence statistics for the two other definitions of credit spreads are similar and are omitted for the sake of brevity. The number of outliers changes with respect to the measure of credit spread and the business cycle indicator considered. However, there are two periods (October

[7]We also considered two alternative influence statistics: Cook's D-statistic (Cook 1977) and the covariance ratio statistic. Cook's D-statistic measures the effect of deleting an observation on the coefficient estimates whereas the covariance ratio statistic measures the influence of an observation on the variance–covariance matrix of the estimates. We consider any observation to be an outlier if the Cook's D-statistic is greater than $4/T$ or the covariance ratio statistic is outside the $1 \pm 3(k+1)/T$ interval, where $T = 236$ is the number of observations and $k = 4$ is the number of parameters estimated. These influence statistics identify more outliers than those based on the squared scaled change in the coefficient vector. However, our results remain similar.

TABLE 3. Asymmetric Effect of Unexpected Changes in the Fed Funds Rate on Credit Spreads.

Variable	$\Delta(Baa_t - Aaa_t)$	$\Delta(Baa_t - Aa_t)$	$\Delta(Baa_t - A_t)$
Panel A. Business Cycle Indicator: NBER			
Constant	0.0151	−0.1999	−0.2131
$NBER_t$	8.1630**	7.7007***	5.2629***
$U_t \times (A_t \neq 0)$	0.0093	−0.0090	−0.0201
$U_t \times NBER_t \times (A_t \neq 0)$	0.1455	0.1394	0.1277**
$U_t \times (A_t = 0)$	0.0460	0.0325	−0.0502
$U_t \times NBER_t \times (A_t = 0)$	1.0086***	0.7423***	0.4575***
Adjusted R^2	15.26%	15.33%	9.14%
Panel B. Business Cycle Indicator: Industrial Production			
Constant	1.2828***	0.9656**	0.6657*
$\Delta \ln(IP_t)$	−2.3514***	−1.7501***	−1.8346***
$U_t \times (A_t \neq 0)$	−0.0924	−0.0829	−0.0614
$U_t \times \Delta \ln(IP_t) \times (A_t \neq 0)$	−0.4295	0.4921*	−0.2585
$U_t \times (A_t = 0)$	0.3623***	0.2775***	0.0910
$U_t \times \Delta \ln(IP_t) \times (A_t = 0)$	−0.5569***	−0.3801***	−0.2353***
Adjusted R^2	16.06%	11.57%	9.79%
Panel C. Business Cycle Indicator: Real-Time Recession Probabilities I			
Constant	−0.6221	−0.1652	−0.2677
$Prob_{1,t}$	16.7405*	9.3592	7.0818
$U_t \times (A_t \neq 0)$	0.0491	0.0476	−0.0029
$U_t \times Prob_{1,t} \times (A_t \neq 0)$	0.2148	0.0387	0.1304
$U_t \times (A_t = 0)$	0.0017	0.0242	−0.0587
$U_t \times Prob_{1,t} \times (A_t = 0)$	1.2061***	0.9643**	0.5961**
Adjusted R^2	19.25%	11.87%	6.93%
Panel D. Business Cycle Indicator: Real-Time Recession Probabilities II			
Constant	−0.5923	0.5004*	−0.5236*
$Prob_{2,t}$	13.5726	11.0104***	8.0772***
$U_t \times (A_t \neq 0)$	0.0902	0.0780	0.0421
$U_t \times Prob_{2,t} \times (A_t \neq 0)$	0.0139	−0.0382	0.0153
$U_t \times (A_t = 0)$	−0.0041	−0.0004	−0.0751**
$U_t \times Prob_{2,t} \times (A_t = 0)$	1.0438***	0.7931***	0.4760***
Adjusted R^2	19.75%	17.57%	11.9%

Note: This table presents the asymmetric effect of unexpected changes in the Fed funds target rate on changes in credit spreads over the business cycle. U_t and A_t are the unexpected and the actual change in the Fed funds rate in month t, respectively. Panel A presents results based on the NBER recession dummy variable ($NBER_t$), which takes value of 1 if the economy is in a recession in month t as defined by the NBER, and 0 otherwise. Panel B presents results based on the (log) growth rate of industrial production ($\Delta \ln IP_t$). Panel C presents results based on the real-time recession probabilities from the estimation of equation (1). Panel D presents results based on the real-time recession probabilities from Chauvet and Piger (2008). The coefficients are estimated via OLS with HAC standard errors.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

TABLE 4. The Effect of Unexpected Changes in the Fed Funds Rate on Credit Spreads over the Business Cycle Excluding Outliers.

	Case (a)			Case (b)			Case (c)		
Variable	$\Delta(Baa_t - Aaa_t)$	$\Delta(Baa_t - Aa_t)$	$\Delta(Baa_t - A_t)$	$\Delta(Baa_t - Aaa_t)$	$\Delta(Baa_t - Aa_t)$	$\Delta(Baa_t - A_t)$	$\Delta(Baa_t - Aaa_t)$	$\Delta(Baa_t - Aa_t)$	$\Delta(Baa_t - A_t)$
Constant	0.0034	−0.2131	−0.2034	0.0034	−0.2131	−0.2034	0.0034	−0.2131	−0.2034
U_t	0.0237	0.0072	−0.0319	0.0237	0.0072	−0.0319	0.0237	0.0072	−0.0319
$NBER_t$	6.6305***	6.3300***	3.6589***	10.5027***	9.3846***	6.0134***	6.5265***	6.2840***	3.6519***
$U_t \times NBER_t$	0.3879***	0.2381***	0.0988	0.2742***	0.2254***	0.1883***	0.4193***	0.2520***	0.1055***
Obs.	232	232	230	235	235	235	231	231	229
Adjusted R^2	10.96%	11.06%	3.76%	12.47%	13.48%	8.92%	11.22%	11.06%	3.67%
Constant	1.2335**	0.7653	0.6624*	1.4397***	1.0760**	0.6940*	1.2236**	0.5144*	0.6568*
U_t	0.1081**	0.0649	0.0152	0.0401	0.0263	−0.0097	0.1129**	0.0710	0.0182
$\Delta \ln(IP_t)$	−3.0449***	−1.9716***	−2.2722***	−2.9263***	−2.1922***	−2.0029***	−3.0248***	−2.4172***	−2.2602***
$U_t \times \Delta \ln(IP_t)$	−0.2229***	−0.1040	−0.1215**	−0.3965*	−0.2793**	−0.2254**	−0.2262***	−0.1205	−0.1237**
Obs.	232	230	231	235	235	235	231	228	230
Adjusted R^2	11.55%	2.4%	7.89%	12.13%	8.3%	9.32%	11.71%	5.01%	7.91%
Constant	−0.1774	0.1503	0.0098	−0.8205	−0.3573	−0.3374	−0.0840	0.1565	0.0034
U_t	−0.0084	0.0214	−0.0238	0.0263	0.0346	−0.0269	−0.0241	0.0196	−0.0265
$Prob_{1,t}$	9.0722***	4.1359***	2.5668	20.6630**	9.6234*	8.6460	7.1670***	2.6896*	2.6706
$U_t \times Prob_{1,t}$	0.7197***	0.2159***	0.0546	0.4244***	0.2329**	0.2413***	0.9818***	0.2548***	0.0995
Obs.	229	232	229	235	235	235	227	231	228
Adjusted R^2	8.1%	0.88%	−0.57%	17.42%	9.27%	6.48%	8.96%	1.02%	−0.65%
Constant	−0.3798	−0.4385	−0.4009	−0.6821**	0.3285*	−0.5254*	−0.3767	−0.4385	−0.3988
U_t	−0.0001	0.0104	−0.0395	0.0277	0.0266	−0.0171	−0.0011	0.0104	−0.0402
$Prob_{2,t}$	9.7604***	9.0845***	6.0431***	16.3323***	13.2194***	8.9259***	9.6332***	9.0844***	5.9581***
$U_t \times Prob_{2,t}$	0.4999***	0.1694***	0.3038***	0.2903***	0.1862**	0.1656***	0.5287***	0.1694***	0.3230***
Obs.	232	232	232	235	235	235	231	231	231
Adjusted-R^2	12.81%	11.88%	7.27%	17.28%	15.38%	11.24%	12.94%	11.8%	7.31%

Note: This table presents the effect of unexpected changes in the Fed funds rate on changes in credit spreads over the business cycle based on data sets excluding outliers. U_t is the monthly unexpected change in the Fed funds rate. The coefficients are estimated via OLS with HAC standard errors. Case (a) presents coefficient estimates from samples excluding outliers based on influence statistics calculated with respect to the original sample including September 2001. Case (b) presents coefficient estimates based on the whole sample excluding only September 2001. Case (c) presents coefficient estimates from samples excluding September 2001 as well as other outliers based on influence statistics calculated with respect to the sample excluding September 2001.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

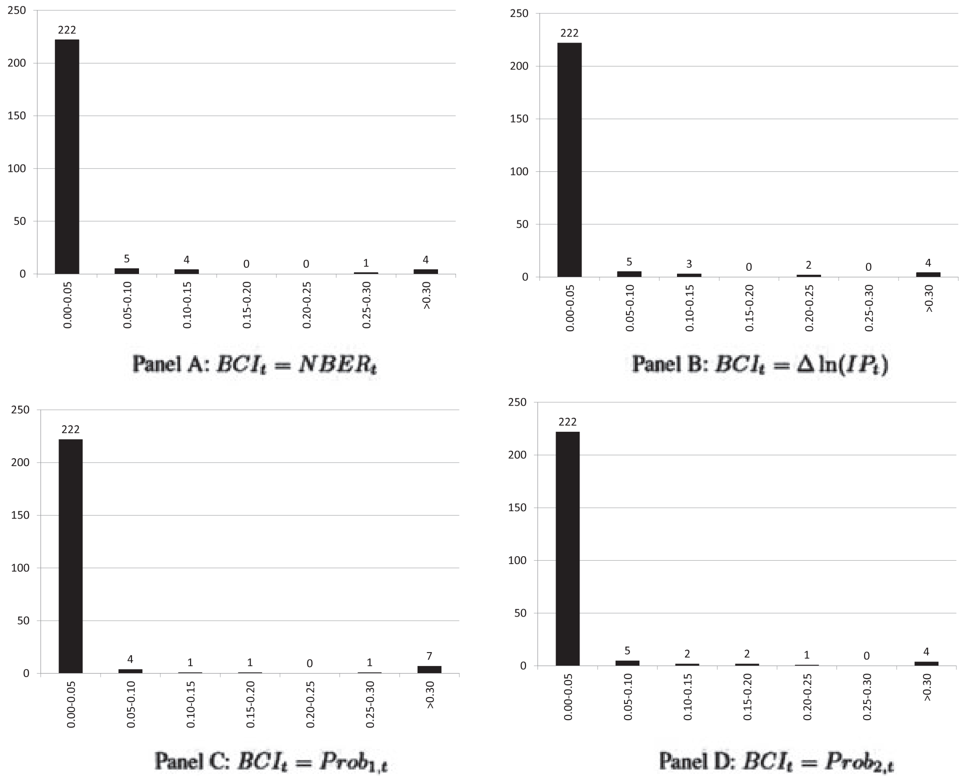

FIGURE IV. Histogram of Influence Statistics for $\Delta(Baa_t - Aaa_t)$. This figure presents the histogram of influence statistics from the estimation of equation (5) for $\Delta(Baa_t - Aaa_t)$. Different panels use different definitions for the business cycle indicator (BCI). Any observation with a statistic influence greater than 0.3 is considered an outlier.

and November 2008) identified as outliers independent of the measure of credit spread and the business cycle indicator considered. During these two periods that correspond to the midst of the 2007–2008 financial crisis, the credit spreads increased dramatically as can be seen from Figure III. For almost all definitions of credit spread and economic conditions, the two other periods identified as outliers are December 1990 and February 1991. Although the changes in credit spreads during these two months are relatively moderate, the Fed seemed to have surprised the markets as the unexpected changes in the target rate during these two months are among the biggest such changes in our sample. In the second case (case (b) of Table 4), following Bernanke and Kuttner, we also consider September 2001 as a stand-alone outlier due to the unprecedented events in that month following the September 11 terrorist attacks. Finally, in the third case (case (c) of Table 4), we identify another set of outliers based on influence statistics of each observation after having removed September 2001 from our data set. Table 4 presents the coefficient estimates of the empirical specification in equation (5) based on data sets excluding outliers corresponding to the three cases. Our results suggest that unexpected changes in the Fed funds target rate continue to have a significant and positive effect on credit spreads during economic slowdowns even when we control for possible outliers.

We now turn our attention to the robustness of our results to controlling for the period between the end of the 2001 recession and the beginning of the easing cycle toward the end of 2007. As can be seen from Figure II, the unexpected changes in the Fed funds rate are close to zero and their volatility is also relatively low during this period compared to other periods. This might be due to a change in the Fed's practice toward signaling its intentions well in advance of an actual policy change.[8] Given that this period is also mainly a period of expansion, it deserves special attention. If there were actually such a change in regime, one would expect unexpected changes not to have a significant effect on credit spreads during this period. To test this, we include as a control variable an interaction term between unexpected changes in the Fed funds rate and a binary variable that equals 1 for the period between December 2001 (the end of the 2001 recession) and either October 2007 (the last month before the beginning of the easing cycle in November 2007) or January 2006 (the last month of Greenspan's term as the Fed chairman).[9,10] For the sake of brevity, we choose not to present these results, which can be summarized as follows. First, unexpected changes in the Fed funds target rate continue to have a significant and positive effect on credit spreads during recessions. Second, in line with our expectations, the interaction term that captures the marginal effect of unexpected changes in the Fed funds target rate during this period of possible change in the Fed's practices does not seem to be significant at conventional levels.

Risk-Adjusted Measure of Monetary Policy Expectations

Piazzesi and Swanson (2008) argue that Fed funds futures are biased predictors of the Fed funds target rate. They show that the investors require a positive risk premium for holding Fed funds futures contracts. This risk premia on Fed funds futures with different maturities are countercyclical and can be predicted by macroeconomic and financial variables such as employment growth and corporate bond spreads. Specifically, they run a regression of excess returns on Fed funds futures with maturities ranging from one to six months on variables such as NBER recession dummy variable, employment growth, and corporate bond spreads. They find that these variables are good predictors of excess returns on Fed funds futures contracts with two months or more to maturity. Based on these results, they argue that one should adjust Fed funds futures contracts for risk premia when using them as measures of monetary policy expectations.

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[8] Another such change in the Fed's practices happened in February 1994. Before this date, the Fed signaled its intended target rate following Federal Open Market Committee meetings through open market operations instead of the current practice of officially announcing the target rate. This is arguably more important for the high-frequency (intraday or daily) effect of the Fed's decisions on financial markets rather than the low-frequency effect analyzed in this article.

[9] We consider January 2006 an alternative end to this period because this change in regime might have ended with Greenspan's departure from the Fed.

[10] We also considered other alternative definitions for this period including but not limited to January 2001–December 2007, January 2001–October 2007, and January 2001–January 2006. We also considered including an interaction term of unexpected changes, business cycle indicators, and the binary variable for this period. Of course, for some business cycle indicators (e.g., *NBER*) and some alternative definitions of this period (e.g., December 2001–October 2007), this interaction term is always equal to 0. Our results can be summarized as follows: neither of the interaction terms is significant for most of the specifications, and unexpected changes continue to have a significant effect on credit spreads during economic slowdowns.

In this section, we discuss the robustness of our results to adjusting the Fed funds futures contracts for the risk premium. To this extent, we first analyze the risk premium in the Fed funds futures contracts with one month to maturity. We then provide empirical evidence that the risk premium in one-month-ahead futures contracts is not countercyclical and, thus, cannot be possibly driving our results. Finally, we show that our results are robust to using risk-adjusted measures of monetary policy expectations.

To analyze whether there is a positive and countercyclical risk premium in one-month-ahead futures contracts, we estimate the empirical specifications considered in Piazzesi and Swanson (2008). Specifically, let rx_t denote the excess return on the one-month-ahead contract that matures in month t. Then, rx_t is defined as the difference between the rate implied by the one-month-ahead Fed funds future at the end of the preceding month ($f^1_{t-1,D_{t-1}}$) and the average realized effective Fed funds rate in that month,

$$rx_t = f^1_{t-1,D_{t-1}} - \frac{1}{D_t}\sum_{d=1}^{D_t} i^{eff}_{t,d}, \tag{7}$$

where $i^{eff}_{t,d}$ is the effective Fed funds rate on day d of month t. We consider a linear specification of the form $rx_t = \theta_0 + \theta_1 X_t + \nu t$ with different sets of right-hand-side variables. To analyze the average risk premium, we regress excess returns on just a constant. We then consider either the NBER recession dummy variable or lag employment growth as right-hand-side variables to analyze the countercyclicality of the risk premium. In the latter case, we also include the Fed funds futures rate $f^1_{t-1,D_{t-1}}$ as an additional right-hand-side variable following Piazzesi and Swanson. Our results can be summarized as follows. First, as in Piazzesi and Swanson, we find that the average excess return on Fed funds futures with one month to maturity has been significantly positive with an average of 3.21 basis points per month. The insignificant coefficient estimates on the NBER recession dummy variable and lag employment growth suggest that excess returns on one-month-ahead futures are not countercyclical. Our results are similar to those in Piazzesi and Swanson, who also find that these two variables are only significant for futures contracts with maturities longer than one month.

We next analyze the robustness of our results to adjusting the Fed funds futures for the positive risk premium when using them as measures of monetary policy expectations. To this extent, we consider three types of risk adjustments based on the three specifications discussed previously: (1) a constant risk premium adjustment, (2) a risk premium adjustment based on the empirical specification with NBER recession dummy variable, and (3) a risk premium adjustment based on the empirical specification with lag employment growth. Our approach of adjusting rates implied by Fed funds futures can be summarized as follows. Let $\hat{\theta}_0$ and $\hat{\theta}_1$ denote the coefficient estimates from the preceding regressions. Then, the risk-adjusted Fed funds futures rate ($f^{1,adj}_{t-1,D_{t-1}}$) and risk-adjusted measure of unexpected changes in the Fed funds rate target rate (U^{adj}_t) are given by

$$f^{1,adj}_{t-1,D_{t-1}} = f^1_{t-1,D_{t-1}} - [\hat{\theta}_0 + \hat{\theta}_1 X_t], \tag{8}$$

$$U_t^{adj} = \frac{1}{D_t} \sum_{d=1}^{D_t} i_{t,d}^{tar} - f_{t-1,D_{t-1}}^{1,adj}. \tag{9}$$

Our approach is similar to that of Piazzesi and Swanson (2008) but differs from it in several aspects. First, for the constant risk adjustment, we use 3.21 basis points per month (the average risk premium in our sample) instead of 1 basis point as used in Piazzesi and Swanson. Second, we consider a risk adjustment based on the empirical specification with the NBER recession dummy variable, which is not considered in Piazzesi and Swanson. Finally, for all risk adjustments, we use the coefficient estimates based on the whole sample instead of a rolling window of observations as in Piazzesi and Swanson. We are aware that a risk adjustment based on the whole sample would not have been available to market participants in real time. Our choice is caused by the limited number of recessions in our sample. Risk adjustment based on a rolling window of observations requires us to ignore the 1990–1991 recession. Furthermore, there would be estimation windows without any recession periods between 1991 and 2001 if we estimate a risk premium with a five-year rolling window of observations. Table 5 shows that our results on the effect of unexpected changes in the Fed funds target rate on the spread between Baa- and Aaa-rated bond indices continue to hold when we adjust for the risk premium in Fed funds futures contracts. Our results for other definitions of credit spreads are similar, and we choose not to present them here for the sake of brevity.

Endogeneity

The validity of our empirical results depends on the assumption that the error terms are orthogonal to the explanatory variables. In this section, we first discuss the possible endogeneity of unexpected changes in the Fed funds target rate in a similar fashion to Bernanke and Kuttner (2005) and provide some empirical evidence against it. We then analyze the endogeneity of BCI and discuss the robustness of our results in a TSLS framework. We choose to address the endogeneity of unexpected changes in the Fed funds target rate in a separate framework rather than in a TSLS framework because of the difficulty of finding valid instruments for this variable.

There are several reasons for which the assumption of exogeneity might be violated for unexpected changes in the Fed funds target rate. First, the Fed might be contemporaneously responding to credit spreads. Second, credit spreads and the Fed might be reacting jointly and contemporaneously to new economic information.

We start with the possibility of a contemporaneous response of monetary policy to credit spreads. Such responses of monetary policy are not a common practice for the Fed. However, one such response was observed during the recent financial crisis in 2007 and 2008 when the Fed decided to decrease the target rate following disruptions in financial markets. In his speech in January 2008, Mishkin (2008) mentioned the importance of monetary policy that takes into account variables indicating stress in financial markets in addition to variables of a simple Taylor rule (Taylor 1993). Among such variables indicating stress in financial markets are changes in the level and volatility of credit spreads. To this extent, McCulley and Toloui (2008) and Taylor (2008) propose modified

TABLE 5. The Effect of Risk-Adjusted Unexpected Changes in the Fed Funds Rate on Credit Spreads over the Business Cycle.

Variable	(1)	(2)	(3)
Panel A. Business Cycle Indicator: NBER			
Constant	−0.0727	−0.0487	−0.0577
U_t^{adj}	0.0237	0.0237	0.0384
$NBER$	9.6734***	7.7172***	8.6722*
$U_t \times NBER_t$	0.2643***	0.2643***	0.2785**
Adjusted R^2	11.94%	11.94%	12.67%
Panel B. Business Cycle Indicator: Industrial Production			
Constant	1.4354**	1.0599*	1.1618*
U_t^{adj}	0.0400	0.1086	0.0975
$\Delta \ln(IP_t)$	−1.9815***	−1.1979	−1.4189
$U_t \times \Delta \ln(IP_t)$	−0.4173	−0.3469***	−0.3583*
Adjusted R^2	11.30%	10.92%	11.13%
Panel C. Business Cycle Indicator: Real-Time Recession Probabilities I			
Constant	−0.9185	−0.7997	−0.8179*
U_t^{adj}	0.0261	0.0511	0.0225
$Prob_{1,t}$	19.5006*	17.4143*	17.5990*
$U_t \times Prob_{1,t}$	0.4395***	0.4739***	0.4872***
Adjusted R^2	17.02%	18.50%	18.08%
Panel D. Business Cycle Indicator: Real-Time Recession Probabilities II			
Constant	−0.7838	−0.6997	−0.7357*
U_t^{adj}	0.0298	0.0097	0.0090
$Prob_{2,t}$	15.5379**	13.4220**	14.2224***
$U_t \times Prob_{2,t}$	0.2855***	0.3098***	0.3554***
Adjusted R^2	16.89%	16.84%	17.66%

Note: This table presents the effect of risk-adjusted unexpected changes in the Fed funds target rate on changes in credit spreads over the business cycle. U_t^{adj} is the risk-adjusted unexpected change in the Fed funds rate in month t. The Fed funds futures are adjusted for a constant risk premium in column (1), for a countercylical risk premium based on NBER recessions in column (2), and for a countercyclical risk premium based on lag employment growth in column (3). Panel A presents results based on the NBER recession dummy variable ($NBER_t$), which equals 1 if the economy is in a recession in month t as defined by the NBER, and 0 otherwise. Panel B presents results based on the (log) growth rate of industrial production ($\Delta \ln IP_t$). Panel C presents results based on the real-time recession probabilities from the estimation of equation (1). Panel D presents results based on the real-time recession probabilities from Chauvet and Piger (2008). The coefficients are estimated via OLS with HAC standard errors.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Taylor rules that take these variables into account when setting monetary policy. For example, these rules suggest cutting the target rate if credit spreads increase while inflation expectations and the output gap remain unchanged. Curdia and Woodford (2010) analyze the usefulness of such monetary policy rules in a simple dynamic stochastic general equilibrium model with credit frictions. They argue that these modified monetary policy rules can improve the equilibrium responses of economic variables to financial shocks.

TABLE 6. The Effect of Economic News on Unexpected Changes in the Fed Funds Rate and Credit Spreads.

	U_t	$\Delta(Baa_t - Aaa_t)$	$\Delta(Baa_t - Aa_t)$	$\Delta(Baa_t - A_t)$
Headline CPI	−0.1768	0.6367	1.0738**	0.7155
Core CPI	−1.1878	−1.1757	−1.1101	−1.1329*
Headline PPI	0.4248	−0.7710	−0.6510	−0.9541
Core PPI	−1.2095	1.3990	0.9062	0.5803
Nonfarm payrolls	1.3164	−0.4371	−0.1511	−0.2327
Industrial production	2.0319**	−2.0654	−1.9111	−1.5298*
Retail sales	−1.3015*	−0.6983	−0.3105	−0.1106
Retail sales, ex. autos	0.6112	−1.2434	−0.8282	−0.3588
Adjusted R^2	6.78%	6.48%	5.42%	6.35%

Note: This table presents coefficient estimates from a regression of the variable listed in the column headings on a constant and news about the variables listed in rows. The news variable for each macroeconomic variable is calculated as the difference between the actual realization and the expected value from the MMS database standardized by their corresponding in-sample standard deviations. The coefficients are estimated via OLS with HAC standard errors.

**Significant at the 5% level.

*Significant at the 10% level.

A monetary policy rule that takes credit spreads into account suggests that the Fed must be contemporaneously responding to credit spreads. This in turn implies that the actual and expected changes in the Fed funds target rate are determined by, hence endogenous to, credit spreads. However, these suggested monetary policy rules do not necessarily imply the endogeneity of unexpected changes. Thus, unexpected changes might not suffer as much from the endogeneity problem as actual and expected changes. Furthermore, in unreported analysis, we find no significant relation between credit spreads and unexpected changes in the Fed funds target rate between January 2007 and December 2008, a period during which the Fed might have been paying closer attention to credit spreads.

We now turn our attention to the joint and contemporaneous reaction of monetary policy and credit spreads to new economic information. Unexpected bad economic news might result in an increase in credit spreads and make the Fed more likely to decrease the target rate. Hence, we analyze the reaction of unexpected changes in the Fed funds target rate and credit spreads to economic news. To this extent, we define news for a macroeconomic variable as the difference between the announced value and the median survey expectation extracted from the Money Market Services International (MMS) data. We normalize news variables by dividing them by their corresponding standard deviations. This allows us to compare the magnitude of reactions to macroeconomic variables with different scales. Table 6 presents the coefficient estimates from a regression of unexpected changes in the Fed funds target rate or monthly changes in credit spreads on news about the macroeconomic variables considered in Bernanke and Kuttner (2005). We find that news about two variables, industrial production and retail sales, have a significant effect on unexpected changes in the Fed funds target rate with the latter having the wrong negative sign as in Bernanke and Kuttner. However, in contrast to Bernanke and Kuttner, we do not find employees on nonfarm payrolls and core PPI to have a significant effect. More important, credit spreads do not react significantly to news about these two variables, suggesting that unexpected changes in the Fed funds target rate and credit spreads do not react jointly and contemporaneously to news about the same macroeconomic variables.

We turn our attention to the possible endogeneity of BCI. In this section, we first discuss why our real-time BCI do not suffer from an endogeneity problem. We then analyze the endogeneity of ex post BCI in a TSLS framework.

To understand why real-time recession probabilities do not suffer from an endogeneity problem, recall our approach to estimate recession probabilities using real-time data. For a given month, say May 1989, we use data as it would have been available in that month. However, for the macroeconomic variables used for estimating the recession probabilities, the latest information available in May 1989 is data on these variables for April 1989. In other words, our real-time recession probabilities are based on a lagged information set. Thus, they do not have any contemporaneous relation with credit spreads and do not suffer from an endogeneity problem.

To analyze the endogeneity of ex post BCI, we estimate the empirical specification in equation (5) with TSLS. To this extent, we assume that unexpected change in the Fed funds target rate is exogenous. On the other hand, both the business cycle indicator and the interaction term are assumed to be endogenous variables. When we consider the growth rate of industrial production as the business cycle indicator, our instrumental variables include lagged changes in employment numbers, log industrial production, consumer price index, and housing starts and the interaction terms between these variables and unexpected changes in the Fed funds target rate. We exclude lagged log industrial production and its interaction with the unexpected change in the Fed funds target rate from instrumental variables when we use NBER recession dates as the business cycle indicator. This allows us to ensure the validity of our instruments based on the Sargan–Hansen J-statistic in both cases. Table 7 presents the coefficient estimates from the TSLS estimation of equation (5) with HAC standard errors along with some diagnostic statistics.[11] Before analyzing the significance of our coefficient estimates in the TSLS framework, we briefly discuss several diagnostic statistics that provide useful information about the validity of the instruments and the model as well as the endogeneity of the ex post BCI. The null hypothesis for the Kleibergen–Paap rank-Lagrange multiplier (LM) test statistic stipulates that the model is unidentified. The Kleibergen–Paap rank-LM test statistic for both ex post indicators reject the null hypothesis and suggest that our models are identified. The Sargan–Hansen J-statistic is a test of overidentifying restrictions where the joint null hypothesis is that the instruments are valid and that the excluded instruments are correctly excluded from the estimated equation. We fail to reject the null hypothesis, suggesting that our instruments for both ex post BCI are valid (i.e., uncorrelated with the residuals). Finally, the Durbin–Wu–Hausman statistic tests the exogeneity of the variables believed to be endogenous by checking for a statistically significant difference between the OLS and TSLS estimates of the coefficients on these variables. A statistically significant test statistic rejects the null hypothesis that the vari-

[11] We estimate a linear first-stage specification for both ex post business cycle indicators. Although a linear specification is reasonable for the log growth rate of industrial production, the same cannot be said for the NBER dummy variable. A probit or a logit specification might provide a better fit for the NBER dummy variable. However, plugging in the fitted values from a first-stage probit or logit specification does not work in our empirical specification with an interaction term. This is the well-known forbidden regression problem that does not allow the fitted values to be used in a nonlinear specification in the second stage.

TABLE 7. The Effect of Unexpected Changes in the Fed Funds Rate on Credit Spreads in a Two-Stage Least Squares Framework.

	$\Delta(Baa_t - Aaa_t)$	$\Delta(Baa_t - Aa_t)$	$\Delta(Baa - A_t)$
Panel A. Business Cycle Indicator: NBER			
Constant	−0.6903	−0.3429	−0.5141
U_t	−0.0151	0.0007	−0.0610
$NBER_t$	15.5777**	10.3247**	8.1689**
$U_t \times NBER_t$	0.4100**	0.2505*	0.2745**
Sargan-Hansen J-statistic	6.8330	5.2600	3.1550
Durbin-Wu-Hausman statistic	0.5170	0.0370	1.3150
Kleibergen-Paap rank-LM statistic		9.9040*	
Panel B. Business Cycle Indicator: Industrial Production			
Constant	2.1542**	1.3831*	0.9028
U_t	0.0440	0.0360	−0.0103
$\Delta \ln(IP_t)$	−6.8644***	−3.4621*	−3.1611*
$U_t \times \Delta \ln(IP_t)$	−0.3364***	−0.1967**	−0.2110***
Sargan-Hansen J-statistic	8.8720	9.0160	6.7400
Durbin-Wu-Hausman statistic	4.1690	3.2090	3.2350
Kleibergen-Paap rank-LM statistic		13.8860*	

Note: This table presents the effect of unexpected changes in the Fed funds rate on changes in credit spreads over the business cycle in a two-stage least squares framework. The endogenous variables are the business cycle indicator and its interaction term with unexpected change in the Fed funds rate. The instruments include lagged changes in employment numbers, log industrial production, consumer price index, and housing starts and the interaction terms between these variables and unexpected changes in the Fed funds rate as instrumental variables when the business cycle indicator is the growth rate of industrial production. When we use NBER recession periods as the business cycle indicator, we exclude log industrial production and its interaction with the unexpected change in the Fed funds rate from the list of instrumental variables. Panels A and B present coefficient estimates along with diagnostic statistics from the TSLS estimation of equation (5) for NBER recession dummy variable and growth rate of industrial production, respectively. Kleibergen-Paap rank-LM statistic is a test of the null hypothesis that the model is unidentified. The Sargan-Hansen J-statistic is a test of overidentifying restrictions where the joint null hypothesis is that the instruments are valid instruments and that the excluded instruments are correctly excluded from the estimated equation. The Durbin-Wu-Hausman statistic is a test of exogeneity. The diagnostic statistics are χ^2 distributed.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

ables are exogenous. Our results suggest that both ex post BCI are not endogenous. We now turn our attention to the coefficient estimates from the TSLS estimation. Our results on the effect of unexpected changes in the Fed funds target rate on credit spreads during periods of economic slowdown continue to hold in the TSLS framework. Specifically, credit spreads widen (narrow) following an unexpected monetary policy tightening (easing) during recessions even when we control for the possible endogeneity of economic conditions in an instrumental variables framework.

Alternative Empirical Specification

As discussed previously, not only the mean but also the volatility of credit spreads varies with the business cycle with higher volatility in recessions. So far, we focused on the effect of unexpected changes in the Fed funds target rate on the level of credit spreads for several reasons. First, the theory does not provide any clear predictions on the effect of monetary policy on credit spread volatility over the business cycle. Furthermore, a linear specification without time-varying volatility allowed us to compare our empirical results with those in the previous literature. Hence, we decided to use an empirical specification with time-varying volatility as a robustness check rather than as the main empirical specification. We estimate the following empirical specification similar to that in equation (5) where the error term follows an EGARCH specification of Nelson (1991):[12]

$$\begin{aligned} \Delta Spread_t &= \beta_0 + \beta_1 U_t + \beta_2 BCI_t + \beta_3 (U_t \times BCI_t) + \varepsilon_t, \\ \ln\left(\sigma_t^2\right) &= \gamma_0 + \gamma_1 U_t + \gamma_2 BCI_t + \gamma_3 \left(U_t \times BCI_t\right) \\ &\quad + \gamma_4 \ln\left(\sigma_{\mathrm{t}-1}^2\right) + \gamma_5 \left|\varepsilon_{\mathrm{t}-1}/\sigma_{\mathrm{t}-1}\right| + \gamma_6 \left(\varepsilon_{\mathrm{t}-1}/\sigma_{\mathrm{t}-1}\right), \end{aligned} \tag{10}$$

where σ_t^2 is the conditional variance of ε_t, which is assumed to be normally distributed.[13] We estimate the empirical specification via maximum likelihood with Bollerslev–Wooldridge robust standard errors. This specification allows to analyze the effect of unexpected changes in the Fed funds target rate on both level and volatility of credit spread changes over the business cycle.

Table 8 presents our empirical results for the credit spread between Baa- and Aaa-rated bonds.[14] Our main results on the effect of unexpected changes in the Fed funds target rate on credit spreads during economic recessions do not change even when we control for time-varying conditional volatility of credit spreads. In other words, credit spreads continue to widen (narrow) following an unexpected monetary policy tightening (easing) during economic recessions. One should always keep in mind that the coefficient estimates on the growth rate of industrial production should have the opposite sign of the coefficient estimates on other BCI because a lower or negative growth rate of industrial production signifies economic recessions. Several interesting facts about the conditional volatility of credit spreads emerge from the estimation of equation (10). First, lagged conditional volatility and lagged absolute residual have significant coefficient estimates, suggesting that conditional volatility of credit spreads is time varying. Second, the conditional volatility of credit spread changes are higher during economic recessions as suggested by the positive and significant coefficient estimate of BCI in the variance equation except when the business cycle indicator is the growth rate of industrial production. More important, the conditional volatility of credit spreads increases following an unexpected

[12]We also estimated a similar specification without any explanatory variables in the conditional variance equation except the terms related to the EGARCH specification. Our results on the effect of unexpected changes in the Fed funds target rate on credit spreads over the business cycle do not change significantly and credit spreads continue to widen following an unexpected monetary policy tightening during economic recessions.

[13]We also estimated the model assuming that the error term (ε_t) is distributed with a generalized error distribution. Our results are similar to those presented in Table 8 and are available upon request.

[14]For the sake of brevity, we choose to present our results only for the credit spread between Baa- and Aaa-rated bonds. Our results are similar for the two other definitions of the credit spread and available from the authors upon request.

TABLE 8. The Effect of Unexpected Changes in the Fed Funds Rate on Credit Spreads over the Business Cycle in an EGARCH Framework.

	$NBER_t$	$\Delta \ln(IP_t)$	$Prob_{1,t}$	$Prob_{2,t}$
		Mean Equation		
Constant	−0.2565	0.8924**	−0.4052	−0.4885*
U_t	−0.0030	−0.0398	−0.0064	−0.0146
BCI_t	5.9445***	−1.2321***	8.3705**	11.9890***
$U_t \times BCI_t$	0.2625**	0.0489	0.5598**	0.2901**
		Conditional Variance Equation		
Constant	−0.0038	−0.1817	0.9280***	0.0828
U_t	0.0169**	−0.0138	0.0416***	0.0222*
BCI_t	0.6966***	0.3876**	1.6537*	0.8518***
$U_t \times BCI_t$	−0.0059	0.0363**	−0.0885***	−0.0418**
$\ln(\sigma_{t-1}^2)$	0.8996***	0.6696***	0.5201***	0.8402***
$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	0.4509***	1.7408***	0.8362***	0.5617***
$\varepsilon_{t-1}/\sigma_{t-1}$	−0.1373	0.0092	−0.0124	−0.1409

Note: This table presents the effect of unexpected changes in the Fed funds rate on monthly changes in credit spreads between Baa- and Aaa-rated bonds over the business cycle in an EGARCH framework. The coefficient estimates are from a maximum likelihood estimation of equation (10) with Bollerslev–Wooldridge HAC standard errors.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

monetary policy tightening, which might be mainly due to the fact that conditional volatility in financial markets generally increases following news. This effect becomes negative during economic recessions and the conditional volatility decreases (increases) following unexpected monetary policy tightening (easing). This negative effect might be due to the effect of unexpected monetary policy shocks on investors' uncertainty in recessions. Volatility in financial markets generally depends on the market participants' uncertainty about the state of the economy (e.g., Veronesi 1999; David 2008). Market participants are generally more uncertain about the state of the economy in recessions (e.g., Veronesi 1999). An unexpected monetary policy tightening (easing) can be generally considered bad (good) news for credit spreads. However, in recessions, it might also signal that the Fed is expecting the economy to recover sooner (later) than expected. Hence, an unexpected monetary policy tightening (easing) might decrease (increase) investors' uncertainty during economic recessions when it is generally higher. This, in turn, might explain the reaction of conditional volatility to unexpected changes in the Fed funds target rate in recessions.

Control Variables

One might argue that the significant effect of unexpected changes in the Fed funds target rate on credit spreads in recessions might be due to the lack of control variables in our empirical specification. In this section, we analyze the relation between unexpected changes in monetary policy and credit spreads in an empirical specification where we control for other variables that might affect credit spreads. To this extent, we include variables discussed in Collin-Dufresne, Goldstein, and Martin (2001) as controls in our empirical specification. We choose to present these results as a robustness check rather than as our main empirical results in Section IV. This choice is mainly due to possible endogeneity of these variables and the difficulty in finding instrumental variables for them.

We estimate the following empirical specification:

$$\begin{aligned}\Delta Spread_t = \beta_0 + \beta_1 U_t + \beta_2 BCI_t + \beta_3 (U_t \times BCI_t) \\ + \beta_4 \Delta r_{10,t} + \beta_5 (\Delta r_{10,t})^2 + \beta_6 \Delta (r_{10,t} - r_{2,t}) \\ + \beta_7 \Delta VIX_t + \beta_8 SP500_t + \varepsilon_t,\end{aligned} \tag{11}$$

where $r_{10,t}$ and $r_{2,t}$ are yields on the 10- and 2-year Treasury bonds, respectively. Monthly yields on Treasury bonds are available to us from the Federal Reserve Bank of St. Louis. VIX_t is a volatility index based on implied volatility from S&P 500 index options traded on Chicago Board of Option Exchange and captures market's expectations about future market volatility. $SP500_t$ is the monthly return on the S&P 500 index and captures the market's expectations about current and future business conditions. We have all but two of the variables used in Collin-Dufresne, Goldstein, and Martin (2001), change in the firm leverage ratio and slope of the volatility smirk implied by options on S&P 500 index futures. We refer the reader to Collin-Dufresne, Goldstein, and Martin for theoretical motivations for using these variables.

We estimate the empirical specification in equation (11) via OLS with HAC standard errors for a sample period between February 1990 and December 2008, which is determined by the availability of the VIX index. Table 9 presents our empirical results. First, the adjusted R^2s of our empirical specifications with control variables are slightly higher than those without control variables, suggesting that the control variables contribute to explaining the variation in credit spreads. Second, almost all variables have the correct sign predicted by structural models of credit spreads as discussed in Collin-Dufresne, Goldstein, and Martin (2001). The only control variable that has a significant effect (at the 5% significance level) on credit spreads is the return on the S&P 500 index, and the negative coefficient estimate confirms our previous findings that credit spreads widen during periods of bad economic climate. More important, our results from Section IV remain unchanged, and unexpected changes in the Fed funds target rate continue to have a significant and positive effect on credit spreads in recessions even when we control for other variables implied by structural models of credit spreads. Because Collin-Dufresne, Goldstein, and Martin (2001) use S&P 500 returns as a measure of business conditions, one might argue that S&P 500 returns and our measures of business conditions capture the same factor in the economy. However, our measures of business conditions continue to have a significant effect on credit spreads even when we include S&P 500 returns in our empirical specifications. Furthermore, S&P 500 returns capture the market's expectation on current and future economic conditions and might also depend on the market participants' sentiments about the economy. On the other hand, our BCI capture only the current economic conditions and do not possibly depend on market

TABLE 9. The Effect of Unexpected Changes in the Fed Funds Rate on Credit Spreads over the Business Cycle with Control Variables.

Panel A. Business Cycle Indicator: NBER

Variable	Constant	U_t	$NBER_t$	$U_t \times NBER_t$	$\Delta r_{10,t}$	$(\Delta r_{10,t})2$	$\Delta(r_{10,t} - r_{2,t})$	ΔVIX_t	$SP500_t$	Adjusted R^2
$\Delta(Baa_t - Aaa_t)$	−0.3841	0.0478	8.1772**	0.2251**	−0.0219	0.0014	0.0804	0.2366	−25.0999	17.30%
$\Delta(Baa_t - Aa_t)$	−0.1428	0.0238	7.2816***	0.1983***	−0.0032	0.0007	0.0947	0.1284	−28.4986	19.16%
$\Delta(Baa_t - A_t)$	−0.2999	−0.0299	4.5171***	0.1599***	−0.0046	0.0007	0.0473	0.0803	−23.8578	12.89%

Panel B. Business Cycle Indicator: Industrial Production

Variable	Constant	U_t	$\Delta\ln(IP_t)$	$U_t \times \Delta\ln(IP_t)$	$\Delta r_{10,t}$	$(\Delta r_{10,t})^2$	$\Delta(r_{10,t} - r_{2,t})$	ΔVIX_t	$SP500_t$	Adjusted R^2
$\Delta(Baa_t - Aaa_t)$	1.2308***	0.0371	−2.9665***	−0.4213	−0.0039	0.0006	0.1234	0.1979	−32.8608	20.15%
$\Delta(Baa_t - Aa_t)$	01.2956**	0.0204	−2.5789***	−0.3341	0.0109	0.0001	0.1321*	0.0827	−36.8140**	20.56%
$\Delta(Baa_t - A_t)$	0.7379	−0.0237	−2.1850***	−0.2474**	0.0086	0.0002	0.0686*	0.0629	−27.7060**	16.65%

Panel C. Business Cycle Indicator: Real-Time Recession Probabilities I

Variable	Constant	U_t	$Prob_{1,t}$	$U_t \times Prob_{1,t}$	$\Delta r_{10,t}$	$(\Delta r_{10,t})^2$	$\Delta(r_{10,t} - r_{2,t})$	ΔVIX_t	$SP500_t$	Adjusted R^2
$\Delta(Baa_t - Aaa_t)$	−0.9499	0.0511	18.0532**	0.4024***	−0.0239	0.0009	0.0945	0.2638	−23.5631	22.74%
$\Delta(Baa_t - Aa_t)$	−0.1201	0.0530	10.3910	0.2138**	−0.0099	0.0005	0.1178**	0.0791	−35.0081*	17.53%
$\Delta(Baa_t - A_t)$	−0.3001	−0.0232	6.5749	0.2100***	−0.0078	0.0006	0.0615*	0.0581	−27.5238**	11.94%

Panel D. Business Cycle Indicator: Real-Time Recession Probabilities II

Variable	Constant	U_t	$Prob_{2,t}$	$U_t \times Prob_{2,t}$	$\Delta r_{10,t}$	$(\Delta r_{10,t})^2$	$\Delta(r_{10,t} - r_{2,t})$	ΔVIX_t	$SP500_t$	Adjusted R^2
$\Delta(Baa_t - Aaa_t)$	−0.9475*	0.0470	13.6191***	0.2804**	−0.0108	0.0011	0.0731	0.2969	−13.4077	20.44%
$\Delta(Baa_t - Aa_t)$	−0.4598	0.0303	10.5994***	0.2172***	0.0036	0.0005	0.0943	0.1537	−21.9910	20.15%
$\Delta(Baa_t - A_t)$	−0.5249	−0.0166	6.9516***	0.1574**	−0.0001	0.0006	0.0461	0.0969	−19.0282	14.01%

Note: This table presents the effect of unexpected changes in the Fed funds rate on changes in credit spreads over the business cycle where we control for other variables that might affect credit spreads. U_t is the monthly unexpected change in the Fed funds rate. $r_{10,t}$ and $r_{2,t}$ are the yields on the 10- and 2-year Treasury bonds, respectively. VIX_t is a volatility index based on implied volatility from S&P 500 index options traded on Chicago Board of Option Exchange. $SP500_t$ is the monthly return on the S&P 500 index. Panel A presents results based on the NBER recession dummy variable ($NBER_t$), which equals 1 if the economy is in a recession in month t as defined by the NBER, and 0 otherwise. Panel B presents results based on the (log) growth rate of industrial production ($\Delta \ln IP_t$). Panel C presents results based on the real-time recession probabilities from the estimation of equation (1). Panel D presents results based on the real-time recession probabilities from Chauvet and Piger (2008). The coefficients are estimated via OLS with HAC standard errors.

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

participants' sentiments. Finally, we also estimate the empirical specification in equation (5) with monthly returns on the S&P 500 index as another business cycle indicator (not presented here) and the results are not significant. These results suggest that our measures of business conditions and S&P 500 index returns do not seem to capture the same factor in the economy although they are positively correlated.

VI. Conclusion

In this article, we analyze the effect of monetary policy on credit spreads. Specifically, we analyze how unexpected changes in the Fed funds target rate affects changes in yield spreads between corporate bonds of firms with different credit ratings. We use the Fed funds futures to distinguish between expected and unexpected changes in the Fed funds target rate. We find that credit spreads significantly increase (decrease) following an unexpected monetary policy tightening (easing) during periods of economic slowdown. These results are in line with the imperfect capital market theories that predict that firms with lower credit ratings would be more sensitive to unexpected changes in monetary policy than firms with high credit ratings. These models also predict that this effect would be more pronounced during periods of deteriorating market conditions. In this article, we consider bond indices rather than individual bonds. One might obtain a richer set of results in terms of the effect of monetary policy on the cross-section of individual bonds. For example, an analysis using individual bonds might allow one to distinguish the effect of monetary policy on credit spreads through the balance sheet or the bank lending channels. Finally, one can also consider the effect of monetary policy on credit spreads over the credit cycle, which is known to be related but not perfectly correlated with the business cycle.

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