

Macroeconomic Announcements and Risk Premia in the Treasury Bond Market

Fabio Moneta*

May 2009

Abstract

The bond risk premia associated with important macroeconomic variables are examined in this paper. The main question is whether a risk premium is earned by risk-averse agents investing in Government bonds exposed to macroeconomic news. The news measures are based on macroeconomic announcements and market consensus forecasts covering more than twenty-five years of data (1983-2008) and more than twenty types of announcements. Procyclical variables are found to carry a statistically significant price of risk. This result is confirmed by examining both cross-sectional regressions and the expected returns of maximum-correlation portfolios mimicking the macroeconomic variables. This result is also robust controlling for the effects of other risk factors. Advantages of using high frequency data are documented. Among the different announcements, the most important appear to be the labor market and business confidence announcements. One factor appears sufficient to explain the cross-section of average returns on Government bonds. Time variation in the risk premia is also documented.

JEL classification: G14, E44

Keywords: Macroeconomic news; Economic risk premia; Bond returns

*Ph.D. candidate in Finance, Carroll School of Management, Boston College, 140 Commonwealth Avenue, Chestnut Hill, MA 02467-3808. E-mail: moneta@bc.edu. I am very grateful to Pierluigi Balduzzi, David Chapman, Wayne Ferson, Robert King, Alan Marcus, and seminar participants at the Boston College finance seminar and Boston University Macro Workshop for their valuable comments and suggestions. I also thank Pierluigi Balduzzi for kindly providing some of the data and, together with Alan Marcus, for the financial support to purchase the intra-day futures data.

1 Introduction

This paper investigates whether innovations in macroeconomic variables are priced factors for Treasury bond returns. Economic intuition would suggest that this should be the case. However, for both equity and bond returns, it has been challenging to obtain robust findings. Higher frequency data than the monthly or quarterly frequency used in the literature will be used in this study. I will focus on Government bond returns. These are assets for which better estimates of expected returns can be obtained from realized returns (see Elton, 1999). Government bonds have indeed little asset-specific information and are significantly affected by important new information about macroeconomic fundamentals. Scheduled economic announcements and consensus forecasts are used to calculate macroeconomic news.

Particular attention has been paid in the recent literature to macroeconomic interpretations of asset pricing factors and tests of whether macroeconomic factors are priced in the security market. This seems to be an old question (see for example Chen et al., 1986), but as Cochrane (2005, p. 61) concludes in his review paper: “Though this review may seem extensive and exhausting, it is clear at the end that work has barely begun. The challenge is straightforward: we need to understand what macroeconomic risks underlie the ‘factor risk premia’, the average returns on special portfolios that finance research uses to crystallize the cross-section of assets”. This search has been carried out in both the equity market and the fixed income market. For the equity market, papers such as Vassalou (2003) and Petkova (2006) showed that the Fama-French factors could be replaced by innovations in macroeconomic variables. For the fixed income market this analysis has been recently carried out within sophisticated no-arbitrage models of the term structure.

Research started with Ang and Piazzesi (2001), develops no-arbitrage affine term structure models for Treasury yields which include macroeconomic information.¹ These term structure models allow the estimation of the market prices of risk associated with macroeconomic variables. These studies provide evidence of the importance of using macroeconomic factors to model the term structure of interest rates (some successes include better model fit and improved out-of-sample forecasts). However, they provide mixed results regarding the prices of risk attached to these factors. In Ang and Piazzesi (2001) the estimates "differ enormously" across two different specifications of the model. The market prices of risk coefficients associated with inflation and real activity are indeed both negative and significant in the specification of the model that does not include lagged macro variables and positive and significant in the specification that includes

¹See, among others, Hördahl et al. (2006), Rudebusch and Wu (2003), Dai and Philippon (2005), Ang et al. (2007), Beekaert et al. (2005), Bikbov and Chernov (2006), Dewachter and Lyrio (2006), and Gallmeyer et al. (2005).

lagged macro variables.² Moreover, Duffee (2006 and 2007) finds only weak links between macroeconomic variables and bond risk premia.

What are the possible reasons for such different results? One reason is that these models impose a lot of structure: not only do these models parameterize the price of risk, but they also parameterize the relation between state variables and interest rates and the dynamics of the state variables. Since all these parameters are estimated together, it is possible that misspecification of a portion of the model contaminates estimates of the risk premia. I only focus on the parameterization of the risk premia without examining the dynamics of the factors or the relation between factors and short-term interest rates. Another advantage of my approach is that I do not need to make ad hoc hypotheses for the estimation such as assuming that the model perfectly fits some yields and that other yields have measurement error (see Ang and Piazzesi 2001).

A contribution of this paper is to use data at high frequency in the context of studying bond risk premia. This allows for more precise estimates of the exposure of bond returns to macroeconomic shocks (the beta coefficients) to be obtained which will likely improve the estimation of the risk premia (the lambda coefficients). High-frequency data have already been used in the literature investigating the impact of macro news on prices and returns.³ I will follow this literature by using intra-day and daily data together with macroeconomic surprises to estimate the sensitivity of bond returns to macro news. As shown by Balduzzi et al. (2001), it is possible to obtain a precise estimate of the sensitivity of bond returns to macro news using a short window around the announcements. However, the novelty introduced by this paper is to use returns data to quantify the risk premia associated with macroeconomic variables rather than quantify the reaction to announcement surprises. The risk premia are estimated using all available data because every day there are revisions about macro variables although we can only observe these revisions during announcements.

Macroeconomic announcements are events whose timing is known in advance, and that convey new information to the market which affects securities prices. Announcements can also reduce uncertainty and cause investors who had different expectations to adjust their portfolios. Therefore, announcements are associated with higher volatility in the security prices. If this incremental risk is not totally diversifiable, risk-averse investors would require a reward (a risk premium). This premium is like a "jump" or announcement risk premium that only occurs during announcements. Jones et al. (1998) found significant excess Treasury bond holding returns on the release dates of Employ-

²In Bikbov and Chernov (2006) and Dai and Philippon (2005) the market price of risk associated with inflation and real activity have opposite signs.

³An extensive literature (see among others Fleming and Remolona, 1997, and Balduzzi et al. 2001) provides evidence that macroeconomic surprises - measured as the difference between the headline figure and expectations taken from surveys conducted before the releases - have a significant impact on bond prices and returns using high-frequency data.

ment and Producer Price Index (PPI) data. Although I will reexamine this finding using a richer data set, I will focus on the economic risk premia that should be earned during all trading days. The risk premia will also be allowed to vary daily and jump during event days.

It is important to understand which macroeconomic surprises are priced. If some economic risks are priced, it is relevant to know what the reward for bearing those risks is. This can improve our understanding of expected returns and asset pricing considering the importance of returns on default-free bonds to price other financial assets. This study may also indicate hedging strategies for investors as suggested by the composition of the maximum-correlation portfolios mimicking the macroeconomic news. Finally, when identifying economic state variables I provide some guidance about the specification of the market price of risk in a term structure model that includes macroeconomic state variables.

If factors were tradeable, the risk premia could be obtained by calculating the average of the factors. However, for non-traded factors such as macroeconomic surprises, the risk premia can be estimated by running a cross-sectional regression of average returns on beta and testing whether there is a significant relation between exposure to macroeconomic announcements (the beta coefficients) and expected returns. This is the two-pass cross-sectional (CS) regression method developed by Fama and MacBeth (1973). An alternative is to construct mimicking portfolios projecting the factors onto the span of returns augmented with a constant. Mimicking portfolios are the maximum-correlation portfolios of Breeden et al. (1989). They estimated a portfolio that is maximally correlated with current consumption to test the Consumption Capital Asset Pricing Model.⁴ Balduzzi and Robotti (2008a) compared two formulations of the multifactor model with non-traded factors (the cross-sectional regression versus the maximum-correlation mimicking portfolios) supporting the mimicking portfolios formulation. Although the alphas are the same in the two formulations when Generalized Least Square is used, the maximum-correlation portfolios present several advantages such as the lack of dependence on a particular asset pricing model used (see also Balduzzi and Robotti, 2008b).

Both the Fama-MacBeth and mimicking portfolio approaches will be presented. I plan to estimate the time-series betas and the composition of the mimicking portfolios using only returns data around the announcements. This composition should be estimated with sufficient precision if high frequency data such as daily or intra-day data is used. Then, once betas are obtained it is possible to examine the relationship between excess

⁴Lamont (2001) estimated what he called economic tracking portfolios. These are mimicking portfolios which track unexpected components of future macro variables. The author showed that these portfolios can be useful to forecast macroeconomic variables. Ferson et al. (2006) studied mimicking portfolios with time-varying weights in the presence of conditioning information. Using the same data as Lamont, they showed that using conditioning information they could improve the correlation significantly with the macroeconomic factors.

returns and sensitivity to the news (estimating the lambdas) using all trading days. For the mimicking portfolios I will examine their average returns calculated using all trading days. I will then allow the risk premium to change during announcement days by introducing a dummy variable.

This study focuses on the Government bond market. The choice of this market is motivated by evidence from Andersen et al. (2007) that revealed that the response to real-time US macroeconomic news is larger in the bond market than in the stock market. Indeed, the link between macroeconomic fundamentals and the bond market is clear: unexpected increases in real activity and inflation increase bond yields and decrease prices. Price movements in the fixed income market, especially in the Treasury market, are driven by public information. A cross section of 7 daily bond returns from 6 months maturity to 10 years is used. I also employ a separate data set of intra-day futures. These data include 30-year T-bonds, 10-year, 5-year, and 2-year T-notes futures. In this way, I can examine the advantages of having a shorter window to calculate the sensitivity to macroeconomic news (or, similarly, the composition of the unit beta and mimicking portfolios).

The main findings of this paper can be summarized as follows: Procyclical variables such as employment, inflation, real activity, and business confidence are priced in the Treasury bond market. They have a negative price of risk so that a unit beta portfolio exposed to macroeconomic shocks is a hedge against the performance of the bond market. Bond returns, however, have a negative exposure to shocks to procyclical variables. Therefore, their risk premium (equals to beta times the price of risk) is positive. This explains why long-term bonds have higher returns than short-term bonds. Indeed, long-term bonds have higher exposure (betas) to macroeconomic news than short-term bonds. This result is confirmed using the mimicking portfolios approach, controlling for other factors, and using a dynamic factor model and the Kalman filter to extract a latent macroeconomic variable. Monetary policy shocks instead, although they are important to explain the time-series variations of bond returns, are not priced in the cross-section. This paper also documents that it is important to use high-frequency data to obtain precise estimates of exposure and price of risk.

Furthermore, it appears that the macroeconomic factors exhibit a very similar price of risk. I carry out a test inspired by Zhou (1994 and 1999) to examine whether a single factor is sufficient to explain expected bond returns. I find that one single factor is sufficient and it includes as main determinants the labor market and business confidence factors. This result is consistent with Cochrane and Piazzesi (1998) finding that a bond risk premium is earned as compensation of only one main factor called a “level” shock. In this paper I characterize this level shock as coming from procyclical variables. Finally, some evidence is presented that the economic risk premia are time-varying and their variations are associated with the term-spread and the presence of announcements. In

particular, an increase in the term spread and the presence of an announcement are associated with an increase in the economic risk premium (in absolute value).

2 Related literature

This paper primarily builds on two strands of literature. The first strand examines multifactor asset pricing models which include economic variables. The research design of this paper is closely aligned with the equity literature, but I will also refer to the recent term structure literature that uses macroeconomic factors. The second strand of literature studies the impact of macroeconomic announcements on returns and prices. This section presents a brief review of this literature.

2.1 Economic fundamentals and asset pricing

Many empirical studies relate state variables in a multifactor asset pricing model to macroeconomic factors. (For a more complete literature review, see Cochrane, 2005.) These studies typically focus on equity portfolios, although some studies include bond portfolios. Chen et al. (1986) analyze the following economic factors: the term and default spreads, expected and unexpected inflation, and industrial production. They concluded that industrial production, and the default and term spreads are priced factors, whereas the evidence for inflation as a priced factor is weaker. Ferson and Harvey (1991) also found significant risk premia associated with similar economic variables and documented a time variation in risk premia which helped to explain predictable variation in asset returns. They also included three bond portfolios in their analyses: Government, corporate, and Treasury bill portfolios. Campbell (1996) used similar base assets to estimate an equilibrium multifactor model which included revisions in the forecasts of future labor income growth (proxies for the return on human capital that is an important component of wealth) as priced factors. Fama and French (1993) identified five factors in the returns on stocks and bonds: the market, size, value, term and default factors. They included the excess returns on two government and five corporate bond portfolios and they found that stock returns were linked to bond returns through shared variation in the two term-structure factors. Vassalou (2003) and Petkova (2006) showed that the Fama-French Factors are correlated with and could be replaced respectively by innovations in GDP, shocks to the aggregate dividend yield, term spread, default spread, and the one-month T-bill yield.

Many studies explain returns with other current returns and not with contemporaneous economic variables as macroeconomic factors perform poorly in explaining returns. There is only scant direct evidence of economic risk premia. Indeed, the main asset pric-

ing models in the bond area are continuous-time models which consider the short-term interest rate as a fundamental building block.⁵

More recently, however, a growing strand of literature has focused on the links between macro variables and the yield curve. Ang and Piazzesi (2003) incorporated macro variables as factors in a term structure model. More specifically, they estimated a VAR that included three latent variables and two macro factors, extracted as the first principal components from three measures of inflation and from four real activity variables. Cross-equation restrictions implied by no-arbitrage were imposed in this estimation. The authors used a discrete-time affine term structure model, which, under Gaussianity, reduces to a VAR with cross-equation restrictions. They showed that macroeconomic variables have an important explanatory role for yields and, that the inclusion of such variables in a term structure model can improve the forecasting performance. However, Ang and Piazzesi did not provide a clear macroeconomic interpretation for the unobservable factors that accounted for most of the movement at the long end of the curve.

Other papers have put more theoretical structure on the relationship between interest rates and the macroeconomy. In this way, it is possible to create feedback from the interest rates to the macroeconomy that was absent in the Ang and Piazzesi paper. In Hördahl et al. (2006) a small structural model of the macroeconomy was combined with an arbitrage-free model of bond yields. Using German data, Hördahl et al. showed that macroeconomic factors affect the term-structure in different ways. While monetary policy shocks have an impact on yields at short maturities, inflation and output shocks mostly affect yields at medium-term maturities. Changes in the perceived inflation target tend to have a stronger influence on longer-term yields.

Rudebusch and Wu (2003) developed a macro-finance model and examined the joint movement of the term structure and macroeconomic variables. The macro model is a New-Keynesian forward-looking model and the finance model is a discrete-time affine term structure model. They showed that the “level” factor is closely associated with the central bank’s long-run inflation target and that the “slope” factor captures the central bank’s responses to cyclical variations in inflation and output gaps. Next, they incorporated such relationships in a term structure model estimated with data on both yields and macroeconomic variables. Dewachter and Lyrio (2006) provided a similar interpretation for the level factor, although they showed that the slope appears to be related to business cycle conditions, and the “curvature” to the monetary stance of the central bank.

As previously mentioned in the introduction, the findings on the market prices of risk associated with macroeconomic variables are inconclusive. This is perhaps due to over-parameterization and potential misspecification, which contaminates the estimates

⁵One exception is Elton et al (1995) that showed the importance of using unanticipated changes in economic variables to explain the cross-section of expected bond returns.

of the market prices of risk.⁶ I will use high-frequency data and I will focus on macroeconomic announcements. Therefore, I extract macroeconomic news in a different way. Macroeconomic news is calculated in this study as the difference between the headline figures of macroeconomic announcements and the expected values based on survey data.

Another way to extract macro news is from innovations obtained from a time-series model of the relevant economic variables. This approach is used for example by Campbell (1996) and more recently by Petkova (2006).⁷ They use a vector autoregressive (VAR) approach to obtain the surprise components of economic variables. However, one assumption of this approach is that all relevant information available to investors is used in the VAR system. Surveys may avoid this potential misspecification. Another advantage of using news from macroeconomic announcements is that it is possible to analyze many more news types and to use higher frequency data. Indeed, whereas the number of variables that can be included in a VAR system is limited, I analyze more than twenty different types of news in this study. I use daily and intra-day data instead of the monthly or quarterly frequencies used in the previous literature. High-frequency returns should reflect the impact of macroeconomic shocks more clearly whereas monthly stock returns incorporate a lot of different types of information that occur during the month. Finally, another advantage of using macroeconomic announcements stems from the use of data available in real time to construct news, rather than revised data. Christoffersen et al. (2002), using the same framework of Chen et al. (1986), present evidence that the use of real time data can change the significance of the rewards to macroeconomic risk changes. They do not however use surveys or high-frequency data.

The methodology adopted in this paper is closely related to what is used in the cross-sectional studies of stock returns. There are only few recent studies that study the cross-section of bond returns. Gebhardt et al. (2005) for example study the cross-section of expected corporate bond returns using bond characteristics. Li et al. (2009) document that the systematic liquidity risk of Pastor and Stambaugh and an information risk measure is priced in the Treasury bond market. They also used a Fama MacBeth (1973) methodology. One limitation of this approach is that yield cross-equation restrictions coming from no-arbitrage are not imposed. However, as showed by Adrian and Moench (2008) a dynamic Fama MacBeth approach can generate a term structure of interest rates with small yields when compared with models that impose no-arbitrage restrictions.

⁶This problem is also recognized by Ang, Dong, and Piazzesi (2007). They suggest using a Bayesian approach to handle this problem. As noted by Bikbov and Chernov (2006) "risk premia are hard to estimate in practice despite their theoretical identification. Typically, one encounters multiple local optima that have similar likelihood values, but imply dramatically different estimates of the risk premia. Additionally, a rich specification of market prices of risk might be a reason for concern, because they could be compensating for the misspecification of the factors dynamics instead of measuring the compensation for risk."

⁷Evans and Marshall (2007) and Diebold et al. (2006) also use a VAR framework to investigate the link between macroeconomic shocks and the term structure of interest rates.

2.2 Macroeconomic announcements

The literature on macroeconomic announcements tends to focus on the impact of unexpected announcements on prices and returns. Evidence shows that macroeconomic surprises have an impact on asset returns (for Treasury returns see, *inter alia*, Balduzzi et al. 2001). This finding, however, does not answer the question of whether these surprises can be viewed as systematic risks and whether investors are compensated for holding securities which are more exposed to these risks. Jones et al. (1998) found significant excess Treasury bond holding returns on the release dates of Employment and Producer Price Index (PPI) data.⁸ They did not, however, test whether these risks were priced in accordance with their exposure. Moreover, their focus was on an announcement risk premia rather than an economic risk premia that should be earned every day and not only during announcement days.

An extensive literature has documented the impact of macroeconomic announcements on security returns for the U.S. and other main industrialized countries. The strand of literature focusing on the U.S. markets can be classified in at least three different ways.⁹

A first classification is based on which moments of the returns the researchers focused their attention on. Many studies estimate by OLS the following type of regression:

$$\Delta y_t = \alpha + \beta \text{surprise}_t + \varepsilon_t, \quad (1)$$

where the dependent variable is the change in the asset price or return around the macroeconomic announcement and the independent variable is the macroeconomic surprise calculated as the standardized difference between the actual headline figures and the expectation which is generally obtained by a survey. Balduzzi et al. (2001) also controlled for contemporaneous releases which are added to the right-hand side of the regression. Another approach is to use announcement dummy variables instead of the surprises, however, this does not allow for the separation of the impact of contemporaneous macroeconomic releases. Studies that have examined the first moment have found an immediate impact of macroeconomic news on asset prices. The impact of the macroeconomic surprises on returns volatility has also been investigated extensively. A GARCH specification was used in the literature to model the conditional variance of the errors in (1). The impact of the macroeconomic releases on the volatility was gauged using dummy variables for the macroeconomic announcements which were entered as exogenous variables into the conditional variance equation. This type of analysis has been performed for example by Jones et al. (1998) and De Goeij and Marquering (2006) for the bond market, and by Flannery and Protopapadakis (2002) for the stock market. Volatility appeared to be

⁸Li and Engle (1998) considered only three announcements and did not find a statistically significant risk premium on the release dates in the Treasury futures market.

⁹Fleming and Remolona (1997) and Andersen et al. (2005), provide a more detailed review of this literature.

significantly affected by the main macroeconomic announcements. Finally, few studies also considered the impact of the macroeconomic announcements on the correlation between stocks and bonds. For instance Brenner et al. (2006) found that conditional excess return co-movement between stock and bond markets decreased on announcement days.

A second classification of the literature is based on the market or asset class studied. Different market and asset classes such as stock, bond and currency markets are usually considered in isolation. Exceptions are Anderson et al. (2005) and Kim et al (2004) who consider a broader perspective by examining the response of stock, bond and foreign exchange markets to US macroeconomic news using intra-day and daily data, respectively.¹⁰ They found that the bond market reacted the strongest to news followed by foreign exchange and equity markets. Focusing on the fixed income markets and using intra-day data, Fleming and Remolona (1999a) and Balduzzi et al. (2001) studied the links between macroeconomic news and Treasury bill and bond price changes. The latter study found that 17 macroeconomic news announcements had a significant impact on the price of at least one of the instruments examined (3-month T-bill, 2-year and 10-year note, and 30-year bond). The new information captured by the surprise component of the macroeconomic announcements was incorporated very quickly into prices (one minute or less). Ramchander et al. (2005) studied the impact of macroeconomic news on term and quality spread. Similar to Barnhill et al. (2000) they used cointegration techniques to investigate these links. They estimated different specifications of a Vector Error Correction Model which included a Federal funds rate, Treasury rates for different maturities, the prime interest rate and the Moody's Baa corporate bond rate. Finally, Ramchander et al. (2003) and Xu and Fung (2005) used monthly data to show that mortgage rates and mortgage-backed securities indices are also influenced by macroeconomic news. As expected, the significant impact of macroeconomic announcements on asset prices was not limited to the Treasury market but rather was also expanded to other fixed income asset classes.

The last method that has been used to classify the literature is based on the frequency of data. While previous works have generally used low frequency data, more recent studies use intra-day data (see *inter alia* papers quoted above). High frequency data such as tick-by-tick data allow researchers to better pinpoint the reaction of the price to the arrival of the news because a short window around the announcement is used. Researchers have found that by using intra-day data, more types of announcements impact asset prices and the explained variance is larger.

Another related question addressed in the literature is whether the response of the asset price to the macro surprises depends on the state of the business cycle. Veronesi (1999) showed theoretically that both investors' uncertainty over important factors af-

¹⁰Brenner et al. (2006) also used daily data to examine the impact of the main US macroeconomic news on stock, Treasury, and corporate bond markets.

fecting the economy and investors' willingness to hedge, make stock prices overreact to bad news in good times and underreact to good news in bad times. McQueen and Roley (1993) showed that allowing for business cycle variation in the response of stock prices to news makes this response more evident. Boyd and Jagannathan (2004) found that the reaction to unemployment news was similar across different states of the business cycle for the bond market, whereas the stock market reaction to an unexpected increase in unemployment was positive during economic expansions and negative during economic contractions. This is due to the fact that stocks are affected by both shocks to expected corporate earnings and to the discount rate that can have opposite effects.

3 Data

Three different data sets are used in the current study. The first consists of the macroeconomic announcements data. The last two consist of Government bond data from the spot and futures markets.

4 Macroeconomic announcements data

Macroeconomic announcements are publicized events which happen on pre-scheduled dates. I focus on the headline figures for which market expectations are available. The sources of the date, time, announcement values and forecasted values are Money Market Services (MMS) and Bloomberg. MMS data have been used extensively in the literature. Data were collected from the beginning of the 1980s via weekly telephone surveys. The MMS data that I obtained were used by Balduzzi et al. 2001. This data set covers the period from January 1983 to September 1995. Bloomberg provides data from the beginning of January 1997 to the end of September 2006. The forecasts are from the median expectation of surveys prepared by Bloomberg News. The survey responses are collected until one business day before the economic release. Major Wall Street firms participate in the survey. The number of participants depends on the announcements. Participation rates have increased during the most recent period. To fill in the gap between the MMS data and Bloomberg data, I hand-collected consensus forecasts and actual releases from Factiva.¹¹ For the monetary policy expectations, I followed Kuttner (2001) by estimating these expectations using data from the futures market for Federal funds and updating the data set of Gürkaynak et al. (2006). These data start on February 1994 when the Federal Open Market Committee (FOMC) began to explicitly announce

¹¹Whenever available I used the MMS forecast. For instance, the "week ahead" section of Business Week provided MMS forecasts. Some missing values in the MMS or Bloomberg data have also been filled using Factiva.

changes in its target for the federal fund rates and hold regularly scheduled meetings.

The final data set includes data from the 25 macroeconomic announcements listed in Table I. As is common in the literature (see Balduzzi et al. 2001) standardized surprises are calculated as the difference between the announced and the forecasted value (the survey median), divided by its standard deviation. The starting dates vary from the beginning of the 1980s to January 1997 (Table II). The total number of announcements is more than 6000. These are generally released monthly, except for initial jobless claims (released weekly) and a few other indicators released less often (Employment Cost Index, FOMC interest rate decision, Nonfarm Productivity). The economic indicators considered in this study tend to be released during the second half of the week. Often the day of the announcement coincides with other announcements. This always happens for few announcements that are released at the same time. These are Non-farm Payrolls and Unemployment rate which are released together, and GDP and GDP Deflator.¹²

4.1 Government bond Data

The primary data set contains seven daily Government bond returns for the following maturities: 6-month, 1-year, 2-year, 3-year, 5-year, 7-year and 10-year.¹³ Following the approach used in Jones et al. (1999), returns are calculated using daily constant maturity interest rate series from FRED St. Louis database. The excess returns are calculated from the yields using a hypothetical par bond with the stated maturity over a 3-month spot rate also obtained from FRED.

Table III provides summary statistics for the total sample and for the sample divided in two: one sample only includes announcement days and another sample only includes non-announcement days. The data are from January 3, 1983 to March 31, 2008. Although the response of bond returns to macroeconomic announcements is supposed to be very rapid (within few minutes), there are still important differences looking at the daily frequency between announcement days and non-announcement days. Indeed, during announcement days the both the mean and the standard deviation are significantly higher than during non-announcement days. The Sharpe ratios are also higher during announcement days than non-announcement days, although this difference is statistically significant only for the 6-month and 1-year maturities. Higher moments, like skewness and kurtosis, are also different and a non-parametric test (the Kolmogorov-Smirnov test) rejects the null hypothesis that the two samples come from the same distribution. Figure 1 shows the empirical probability density obtained using a Kernel-smoothing method for

¹²CPI and PPI are released together with a measure that excludes food and energy (core measure). The non-core measures were selected because they include a longer time-series.

¹³A 30-year rate is also available but it has been discontinued between February 2002 and February 2006.

5-year excess returns. The distribution for the non-announcement days is concentrated around the mean, whereas the announcement days distribution is more dispersed.

To show the advantages of using high-frequency data I will compound the daily returns into monthly returns. I will also use bond futures data to compare the analysis using daily returns with the analysis using intra-day returns. Indeed, the results of Balduzzi et al. (2001) suggest that most of the action happens within a short window around the announcement. Perhaps using daily data it is insufficient to obtain a precise estimate of the sensitivity to macroeconomic shocks. To test this, 30-year T-bonds, 10-year, 5-year, and 2-year T-notes futures were collected. Daily data were provided by Datastream and intra-day data were bought from TickData with a sample starting in March of 1993. The underlying source of uncertainty is the same in the futures and spot bond market, but microstructure differences can affect the results. Using futures data instead of spot-market data present pros and cons. One advantage is that information processing in the open outcry system of the CBOT market should be more efficient than the inter-dealer cash market.¹⁴ As shown by Mizrach and Neely (2007) the futures market contributes substantially to price discovery often dominating the cash market for long maturities. This can be explained by the high liquidity and low transaction costs of the long-maturity contracts. Moreover, Kamara (1988) and Hess and Kamara (2005) documented that the spot T-bill term premia include a default premia component due to the risk that the counterpart may default. This is absent in the futures markets because they have a clearing association that serves as the guarantor of every contract and they employ mechanisms that virtually eliminate default risk. However, a disadvantage of using futures data stems from the effects of contract expiration. U.S. T-bond and T-note futures have a quarterly delivery cycle March, June, September, and December. In order to create a continuous series, price information is usually obtained from the nearest-to-maturity futures, which are generally the most traded contracts. The switch to the next maturity contract is chosen either as the first day of the expiration month (Li and Engle, 1998) or five days before the delivery date (Andersen et al., 2007) or when the trading volume of the second nearby contract exceeds the nearby contract (Ederington and Lee, 1993 and 1995). In this paper, I will adopt this latter approach. Another issue with using futures is the optionality features embedded in futures contracts. The underlying is indeed not a bond but a basket of bonds. The seller can choose which bond to deliver (quality option) and when to deliver during the delivery month (timing option). The quality option can have substantial value (see, for example, Kane and Marcus, 1986).

Intra-day futures returns are calculated using the price at the end and at the begin-

¹⁴Starting in 1999 the secondary Treasury market experienced a change to electronic trading. The two main trading platforms (eSpeed and BroketTec) have captured almost the entire market for the on-the-run Treasuries. Therefore GovPX (a database which consolidated voice-brokered interdealer quotes and trades), which has been used extensively in the literature, does not provide a reliable indicator of transactions during the most recent years. For a study see Mizrach and Neely (2006).

ning of a 30-minute interval around the announcement (similar to Balduzzi et al. 2001). I consider five minutes before the announcement and twenty-five minutes after the announcement. For the daily futures the settlement prices are used so their returns can be compared with the spot returns.

5 Empirical analysis

This section first presents the results of the two-pass cross-sectional regression method developed by Fama and MacBeth (1973). The goal is to examine whether different sensitivities (betas) to macroeconomic announcement surprises are associated with different expected returns. Betas are estimated in the first pass with a time-series regression and then betas are used as independent variables in a cross-sectional regression. More precisely, according to multi-beta linear asset pricing models such as the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973) or the Asset Pricing Model (APT) of Ross (1976), there is a linear relationship between expected return and betas. I assume therefore that the model for the expected excess returns on asset or portfolio i , $E(r_i)$ is:

$$E(r_i) = \sum_K \lambda_{SK} \beta_{i,SK}, \forall i, \quad (2)$$

where λ_{SK} is the price of risk for innovations in the macroeconomic state variable K . The betas are the slope coefficients from the following regression of the excess return on asset i on the standardized innovations to the state variable K , S_t^K (calculated as the difference between the actual value of the macroeconomic variable and the median forecast divided by the standard deviation of this difference):

$$r_{i,t} = \alpha_i + \sum_K \beta_{i,SK} S_t^K + \varepsilon_{i,t}, \forall i, \quad (3)$$

An assumption in my analysis is that the announcement betas $\beta_{i,SK}$ are not time-varying. These betas are estimated using announcement days but I assume that they do not change during non-announcement days. During non-announcement days there are revisions about macro variables although they can not be observed. The sensitivity to these shocks can be estimated only when I observe the shocks (during announcement days) but I assume that this sensitivity does not change during non-announcement days. Under this assumption, I can use all trading days to estimate the risk premium parameters. The idea is that market participants are constantly revising their expectations about macroeconomic variables whether or not there is an official pre-scheduled announcement on a particular day. In this paper the interest is on economic risk premia that should be present daily. In the main analysis I will also consider one factor model, using a different macroeconomic surprise each time.

As a robustness check, I will estimate the composition of the mimicking portfolios tracking the main macroeconomic surprises by performing a regression of standardized surprises on bond excess returns:

$$S_t^K = a_i + \sum_i w_{i,S^K} r_{i,t} + \varepsilon_{i,t}, \forall K \quad (4)$$

Once I have the composition of the mimicking portfolios (the vector of slope coefficients $\hat{\mathbf{w}}_{S^K}$), I can calculate portfolio returns as $r_{p^K,t} = \frac{1}{|\hat{\mathbf{w}}_{S^K}^\top \mathbf{1}|} \hat{\mathbf{w}}_{S^K}^\top \mathbf{r}_t$, that track the K macroeconomic news. The division by $|\hat{\mathbf{w}}_{S^K}^\top \mathbf{1}|$ normalizes the slope coefficients so they have a weight interpretation. Similar to the betas the composition of the mimicking portfolios is estimated using only announcement data whereas the returns of the mimicking portfolios (similar to the lambdas) are calculated using all trading days.

5.1 Time-series analysis

Following the specification used by Balduzzi et al. (2001), for any economic announcement a regression is estimated using only the announcement days controlling for surprises in variables announced simultaneously. As in Balduzzi et al. (2001), concurrent announcement is included in the regression if it occurs at least 10% of the times the announcement under analysis is released. Table IV using a short window around the announcements shows the betas obtained in the time series regression of bond indices returns on macroeconomic news (the standardized surprises). As found in the literature, the majority of the macroeconomic surprises significantly affect bond indices excess returns. An unexpected increase in a procyclical variable such as a real economy indicator or inflationary variable has a negative impact on excess total returns. Only seven betas are never significant. They are Business Inventories, Existing Home Sales, Housing Starts, Factory Order, GDP Deflator, Non-farm Productivity and Wholesale Inventories. For the announcements with significant betas, the slope coefficients are increasing (in absolute value) in accordance with the maturity of the bond. An interesting effect is that of the monetary policy announcements (FOMC) which significantly enter in the regression only for the short-term returns. This is consistent with recent works such as Gürkaynak et al. (2006) who show that the long end of the yield curve is affected by changes in expectations of future policy actions and affected less by unexpected changes in the federal fund rate target.

Since there are many announcements with similar information content that also have a similar impact on bond returns, it seems natural to aggregate some announcements. One issue is how to aggregate different types of announcements which happen on the same day. For the sake of simplicity, I took the sum of the standardized and demeaned

surprises. Table V shows the different components of the aggregate announcements. The aggregation criteria are similarities in information content and in the betas. Table VI shows the time-series results for the aggregate announcements and for some announcements that did not fit in any of the groups. Only for three announcements (Inventories, Housing Starts, and Non-farm Productivity) the returns are not significantly affected by the news. The results confirm that shocks to procyclical variables negatively impact bond returns and that betas increase in absolute value with maturity.

5.2 Cross-sectional analysis

Following Fama and MacBeth (1973) a regression is performed of bond excess returns on the betas estimated above for each t . I also include an intercept in equation (2) to test whether it is significantly different from zero. Since I have only 7 observations in the cross section, I consider one factor model at a time, similar to Ferson and Harvey (1991). Table VII presents the results of this CS regression: the estimated coefficients together with Fama-MacBeth t-statistics adjusted with the Shanken (1992) correction that takes into account the errors-in-variables problem in the standard errors.

The risk premia associated with labor market, prices, aggregate demand, real activity, business confidence and home sales news are negative and statistically significant. The risk premia for budget deficit, for which the betas were positive in Table VI, is instead positive and statistically significant. Monetary policy shocks instead are not priced in the cross-section as suggested by the insignificant lambda associated to the FOMC announcements. The lambdas are divided by the time-series standard deviation to allow comparison. The magnitudes are very similar for the significant coefficients with the largest value for the labor market factor (-0.041). The intercepts are not significant for labor market, prices, aggregate demand, and real activity. Therefore, procyclical variables that had a negative beta exhibit a negative lambda so the product of beta with lambda is positive. Long-term bonds that had a higher exposure (beta) to news are rewarded with a positive risk premium. The lambdas have a portfolio interpretation as a portfolio with a beta equal to one. These unit beta portfolios are hedge portfolios (since the sign is negative) that hedge against the bond market performance.¹⁵ These results are consistent with the findings of Cochrane and Piazzesi (2008) and Kojien et al. (2009). They find that the risk premium associated with the level of the term structure is also negative. As suggested by Kojien et al. (2009, p. 13), “investors are willing to pay for assets with high returns when yields increase, which are times in which wealth decreases and marginal utility increases. Long bonds have more negative level betas: their returns fall by more when yields increase and hence they earn higher average returns.” Shocks to procyclical variables are like shocks to the level of the term structure. A positive shock

¹⁵I also performed a GLS style regression and obtained similar results.

to a procyclical variable increases the yields and a negative shock decreases the yields across all the maturities. This effect is greater for long maturity bonds which mirrors the greater response of long duration bonds to level movements.

One way to gauge the economic significance of the estimated lambdas is to use the spread in estimated betas. For instance, the spread in Table VI for the betas associated with real activity is equal to -0.09 and the excess return of the 10-year bond over the 6-month bond is 5.7% annualized (Table III). The non-standardized lambda for real activity is equal to -0.17. Therefore, the negative spread beta combined with the negative lambda allows the one-factor model to capture 97% ($(-0.09 \times -0.17) * 365 = 5.55\%$) of the observed spread between the excess return on the 10-year bond and 6-month bond. For the other significant macroeconomic announcements the proportion of the explained spread is also close to 100%.

The cross-sectional adjusted R-squared coefficients (average of each R-squared coefficient obtained in the cross sectional regressions) suggest good explanatory power. However, given the small variability in bond portfolios and the strong factor structure, it is important to provide a p-value associated with the coefficients (see Lewellen et al. 2006). Therefore, a simulation analysis was performed following Jagannathan and Wang (2007). I bootstrapped the factors and conducted 2000 time series regressions with the simulated series. Since these new factors are composed of surprises picked up at random they should not be able to explain the cross section of bond excess returns. The probability of obtaining an adjusted R-squared coefficient greater than what I obtained in the actual data can be rather large. In other words it is easy to obtain a high R-squared coefficient. Only for Prices, Business Confidence, Home Sales, and Consumer Confidence the probability of getting such a high value using random factors is very small. Using this bootstrapping approach, p-values were calculated for the adjusted t-statistics.¹⁶ The p-values indicate the probability of obtaining a bootstrapped t-statistic greater (lower) than the sample t-statistic when the sample t-statistic is positive (negative). For the intercept t-statistics, the simulation suggests that it is not difficult to obtain the sample t-statistics. Concerning the lambdas, the probability of getting a t-statistic of the magnitude obtained in the regression during the bootstrapping simulation is below 1% for significant t-statistics. The only exception is Budget for which the p-value is almost 10%. These results also suggest that Consumer Confidence is significantly priced with a negative risk premium.

¹⁶I also tried to estimate the standard errors by GMM which is robust to the distributional assumption. The same moment conditions and weighting matrix as in Balduzzi and Robotti (2008a) were used. The results are comparable.

6 Frequency comparison

One of the advantages of my approach is that it allows the use of high frequency data to estimate betas. This should provide more precise estimates of betas which will likely improve the estimation of lambdas. To support this argument, the daily results are compared to those obtained using monthly return data. When monthly returns data are used monthly macroeconomic shocks are needed. I follow the literature in using an autoregressive process of order one to extract the innovations to the macroeconomic variables. For this analysis I only focus on the monthly announcements without aggregation. Table VIII presents the time-series results. Compared to Table IV the significance is lower. Now, there are more non-significant announcements. The t-statistics are also much lower. This lower precision in the estimates will potentially affect the cross-sectional regression results. Indeed, Table IX shows that using monthly data, it is not possible to obtain significant priced lambdas whereas using daily data I obtained significant results.

It therefore appears that it is better to have high frequency data for estimating betas and lambdas. Is this also true for intra-day versus daily data? To answer this question, I compare the results using daily and intra-day futures data. Table X shows the time-series results for the two different frequencies. The precision is improved using intra-day data. The t-statistics are higher and the R-squared coefficients are also higher. However, the coefficients for the significant betas are very similar. It is not surprising then that in the cross-section the results are similar (Table XI). Daily returns were always used to calculate lambdas because I wanted to capture the risk premium for all the periods not only during a short window around the announcement.

In conclusion, to estimate the risk premium attached to macroeconomic variables it appears important to use daily data instead of monthly data which was done in past studies. Moreover, daily data seems to provide sufficient precision to estimate the betas without contaminating the estimation of the risk premia.¹⁷ Accordingly, considering also the presence of a larger cross-section for the spot data, in this paper I used the daily spot data in the main analyses.

7 Robustness checks

Balduzzi and Robotti (2008a) suggest that estimating mimicking portfolios should be considered in addition to (or even instead of) the two-pass regression. As a robustness check, a regression of the standardized surprises was performed on the excess returns as described in (4). In this way the (squared) correlation between news and returns

¹⁷An advantage of daily data is that intra-day data can present potential overshooting effects in the very short run. Moreover, microstructure frictions are more serious for higher frequency data.

is maximized. First, I tested whether the mimicking portfolios "track" the surprises by doing a jointly test on the portfolio weights (the slope coefficients) estimated in the regression. An F-test is therefore performed to examine whether the slope coefficients as a group are significantly different from zero. The F-test (see Table XII) suggests that with the exception of Inventories, Budget and Housing Starts for which the null hypothesis is not rejected, the mimicking portfolios track the main macroeconomic news. The mean excess returns for the tracking portfolios are also reported. It is confirmed that the risk premia for procyclical variables are negative and significant. The Sharpe ratios are very similar across the main announcements mirroring what was found in the cross-sectional analysis. The mimicking portfolios returns are zero investment portfolios. The mean of the mimicking portfolio returns associated with the first five announcements ranges between -1% and -2.2% annualized. These figures appear to be economically significant for the Treasury market.

Next, I also include other factors in addition to the macroeconomic factors. First, I include as an additional factor the term spread (the difference between 10-year and the 3-month rate) and the change in the term spread following Ferson and Harvey (1991). Since these factors are also affected by the macro surprises, I first regress the term spread and the change in the term spread on the surprises and then I consider the residual plus the intercept as an additional regression in the time-series regression. Table XIII confirms that the macroeconomic shocks are priced in the cross-section of bond returns although the results are somewhat weaker when the change in the term spread is included as a factor. I also control for portfolio characteristics as suggested by Jagannathan and Wang (1998). In the case of bond returns the main portfolio characteristic is the maturity. Therefore, I include the maturity as an additional regressor in the cross-section. Table XIII panel C shows that this does not change the main result.

One concern in the previous analyses is that betas can be time-varying. The period under analysis is after the monetary experiment of 1979-1982 and it is characterized by a relative homogenous monetary policy and relationship between interest rates and macroeconomic variables (see for example Clarida et al. 2000). However, between 1983 and 2008 there were few changes in the business cycle and one might wonder whether the announcement betas vary with the business cycle. Table XIV presents the results of a time-series regression that includes a dummy variable for recession and shows that for the main announcements there are no dramatic changes. The dummy variable depends on the value of the Chicago Fed National Activity Index (CFNAI) index. The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity. It is constructed by the Federal Reserve Bank of Chicago to have an average value of zero and a standard deviation of one. A recession is defined when the 3-month moving average of this index is less than -0.7 which historically is an indication of recession (see Evans et al. 2002).

A related concern is that the assumption of stability of the relation between returns and shocks is not accurate. Since I observe the shocks only during announcement days it is challenging to provide convincing tests to support this assumption. One possibility is to use a latent factor model estimated with the Kalman filter. The advantages of this approach are to obtain shocks for every day and at the same time one or two common factors can be extracted in a more elegant way than what done in the above analysis from several data series. Indeed we can assume that the state of the economy is driven by a small number of systematic factors. Let M denote a set of macroeconomic variables of dimension n . These series are observed at different times and frequencies and with measurement noises. We can model M as function of k common factors Z :

$$M_t = AZ_t + \varepsilon_t$$

where A is a $(n \times k)$ matrix of factor loadings and ε_t denotes a vector of measurement noises. The common factors in turn can be modeled as an autoregressive process:

$$Z_t = BZ_{t-1} + \eta_t$$

The Kalman filter can be used to estimate the common factors. The Kalman filter provides the optimal filter. The daily series in M_t have many missing values. The Kalman filter can accommodate missing data. When there are missing data the filter produces a forecast of the common factors.

Estimating the state space model, a daily time series of the macroeconomic factors can be obtained. Lu and Wu (2006) for example estimate two latent factors from a sample of 17 macroeconomic releases. I can also obtain a vector of innovations to the latent systematic economic factors as the difference between the ex-post updates and the ex-ante forecasts on the economic factors. One issue is that when I have missing data there is no update and therefore the shocks are zero. One possibility is to use more information using asset price data as observables following Ghysels and Wright (2009) and Aruoba et al. (2009).¹⁸ In particular let r be a vector of daily returns on bond portfolios. The daily returns provide a noisy signal about the systematic factor Z_t . Defining $y = [r_t \ M_t]^\top$, the state space model becomes

$$\begin{aligned} y_t &= \Phi Z_t + \Gamma y_{t-1} + \varepsilon_t \\ Z_t &= BZ_{t-1} + \eta_t \\ e_t &\sim N(0, H), \quad \eta_t \sim N(0, I) \end{aligned}$$

¹⁸Ghysels and Wright (2009) estimate a state space model that includes a financial variable and macro expectations to obtain a daily estimate of the macroeconomic forecasts. Aruoba et al. (2009) also estimate a dynamic factor model with one latent factor that represents the state of the real activity. They use the following observable variables observed at different frequencies: GDP (observed at quarterly frequency), non-farm payrolls (observed at monthly frequency), Initial jobless claims (observed at weekly frequency), and the yield curve term premium (observed at daily frequency).

where an autoregressive component of order one is also included in the observation equation. The matrix Γ is assumed to be a diagonal matrix. In the As in Ghysels and Wright (2009) and Aruoba et al. (2009) I only use one financial variable (10-year bond excess returns). The components of the aggregate announcements in Table V of the paper are used. I estimate therefore a latent daily labor market, real activity, inflation, and business confidence factor.¹⁹ Table XV provides the results estimating a state space model with one latent factor for different sets of macroeconomic variables.²⁰ The autoregressive coefficients of the observed variables Γ and the factor loadings Φ are presented. The autoregressive coefficients are highly significant and larger for the macro variable than for the bond returns. The factor loadings are positive for all the procyclical variables and statistically significant for all but two procyclical variables, whereas they are negative and significant for the countercyclical variables such as jobless claims and unemployment rate. The loading on the financial variable is negative although not statistically significant. Table XVI presents the estimation for a larger number of macroeconomic variables and considering two latent factors. It seems that the first factor is associated with inflation as suggested by the positive and significant loadings of the first factor on inflation variables. The second factor is associated with real activity as suggested by the positive and significant loadings of the second factor on real activity variables. Once the latent factors are reconstructed with the Kalman filter, a series of shocks can be obtained. These shocks are in general much smaller in magnitude when only the financial variable is observed (during non-announcement days), but at least they provide a continuous series. Table XVII shows the results of the Fama-MacBeth regressions using the betas obtained by regressing the bond excess returns on the latent macro shocks extracted with the Kalman filter. The standardized lambdas are negative and significant (at least marginally) for procyclical variables and very similar in magnitude. This confirms the main results of the paper.

¹⁹To increase the number of variables I put together the aggregate demand announcements with the real activity announcements. For the same reason, the sample period considered starts on April 1988 for the real activity factor and on April 1993 for the other factors. Moreover, following Lu and Wu (2006) the growth macro variables were converted in year-over-year percentage changes and for the non-farm payrolls the 12-month cumulative change was computed.

²⁰The parameters were estimated by maximum likelihood. As in Monfort et al. (2003), a two-step procedure is used for the purpose of maximization: First, the Expectations Maximization (EM) algorithm is applied, which generates estimates in the region of the maximum reasonably quickly even from poor starting values. However, the EM algorithm does not have quadratic convergence properties and thus converges only slowly in the vicinity of the maximum. Moreover, the EM algorithm does not provide an estimate of the information matrix. In a second step, the numerical maximization algorithm provided by Matlab is applied.

8 One factor model test

It appears that the different procyclical variables considered so far (labor market, prices, aggregate demand, real activity, business confidence, and home sales) behave similarly and they exhibit a negative and similar price of risk. For example, Figure 2 graphs the slope coefficients of Table VI for the main macroeconomic variables. The pattern in the beta coefficients is very similar all decreasing together with the maturity. Is it possible that only one factor is in play to explain expected returns? Let's assume that there are M observable economic factors f and that the returns are generated by the factors,

$$r_{it} = \alpha_i + \beta_{i1}f_{1t} + \cdots + \beta_{iM}f_{Mt} + \varepsilon_{it}, \quad i = 1, \dots, N$$

or in matrix form

$$\mathbf{r}_t = \alpha + \beta \mathbf{f}_t + \varepsilon_t \quad (5)$$

We posit that there is one latent factor y that is a linear combination of the economic factors

$$\begin{aligned} y_t &= c_1 f_{1t} + \cdots + c_M f_{Mt} \\ y_t &= \mathbf{c}^\top \mathbf{f}_t \end{aligned}$$

then (5) can be rewritten as

$$\mathbf{r}_t = \alpha + \mathbf{a} \mathbf{c}^\top \mathbf{f}_t + \varepsilon_t$$

Therefore, the restriction is that

$$H_0 : \beta = \mathbf{a} \mathbf{c}^\top$$

where \mathbf{a} is a $n \times 1$ vector and \mathbf{c} is a $m \times 1$ vector.

As shown by Zhou (1994 and 1999) this is equivalent to a rank restriction on β (rank equals to 1). The author shows how to estimate the parameters by generalized method of moments (GMM) and test whether one factor is sufficient to explain the returns.

The moment conditions are

$$E \left[\begin{array}{c} \mathbf{r}_t - \alpha - \mathbf{a} \mathbf{c}^\top \mathbf{f}_t \\ (\mathbf{r}_t - \alpha - \mathbf{a} \mathbf{c}^\top \mathbf{f}_t) \otimes \mathbf{f}_t \end{array} \right] = 0$$

for a total of $(N+N \times M)$ moment conditions and $(N+N+M)$ parameters to estimate. Zhou (1994 and 1999) provides the analytical solution of this GMM problem and a test of overidentifying restrictions. The analytical solution is obtained by using not the optimal weighting matrix, but one with a structure of this type

$$W \equiv W_1 \otimes W_2, \quad W_1 : N \times N, \quad W_2 : L \times L$$

where L is the number of instrumental variables.

The estimates of \mathbf{a} and \mathbf{c} are not unique since I can multiply \mathbf{a} by a scalar and divide \mathbf{c} by the same scalar and obtain the same matrix β . However, they are unique under a normalization that $\check{\mathbf{a}} = [1, \mathbf{a}_2]$ and then the estimator will be unique. There is then one parameter less to estimate.

Table XVIII presents the test statistics of the rank restriction based on GMM. This statistic is asymptotically χ^2 distributed with degree of freedom equal to $NL - q$ where q is the number of parameters to estimate. The results suggest that one factor is sufficient to explain bond returns (the null hypothesis cannot be rejected). The Table also reports the estimates of the vector \mathbf{c} (the loadings of the economic factors on the latent factor). As suggested by Zhou (1999) the latent factor can be interpreted as an economic index that drives the returns and the coefficients as weights or the contributions of the individual economic variables to the index. I focus on the announcements that were significant in the cross sectional regression and I consider two periods: From the beginning of 1985 when labor market announcement data are available and from the beginning of 1990 when all the surprises under analysis are available. The coefficients are all significant and labor market and business confidence have the largest weights.

The one factor result is a bit surprising considering the stylized fact that we need three factors to model the term structure of interest rates (see Litterman and Scheinkman 1996; Knez et al. 1994) although the first factor is considered the most important one. However what I am trying to explain is not the cross-section of yields but the cross-section of expected excess returns. As shown for example by Cochrane and Piazzesi (2008, p. 16) “a single factor accounts for all of the economically-interesting variation in expected excess returns”. Indeed, the first factor from a principal component decomposition of the expected excess returns accounts for 99.9% of the variance of expected returns, whereas this figure is in general lower when yields are used in the decomposition. The results of my paper are consistent with Cochrane and Piazzesi’ finding that a bond risk premium is earned as compensation for a “level” shock. In my paper I characterize this level shock as coming from procyclical variables. As suggested by Cochrane and Piazzesi (2008) it is statistically possible to provide evidence of additional factors. Indeed, when the change in the term spread is added to Zhou’s methodology I found evidence in an untabulated analysis that a one factor model is rejected. However, looking to the loadings it appears that the loading on the change of slope is one of the least important. The two-factor model is not rejected as suggested by the test statistics, but it is still true that the main macroeconomic variables appear to work through only one factor.

9 Time-varying risk premia

Does the bond market systematically price new information about macroeconomic fundamentals released during the scheduled announcements? If so, we should expect a change in the risk premium during the announcements. The risk premium is therefore allowed to vary daily during event days and its variation is related to the arrival of macroeconomic news.²¹

Table XIX reports the results of a regression of the returns on the unit beta portfolios (the time-series of lambdas) on predetermined variables. The high-frequency limits the choices of predetermined variables. I use the term spread (defined as the difference between the 10-year and 1-year rate) the curvature (equal to the difference between the 3-year rate minus the difference between the 7-year rate and twice the 1-year rate divided by 3) and an announcement dummy. All of these variables are lagged one day except the dummy variable which is deterministic. The term spread appears to be the best predictor of the economic risk premia. The risk premia of prices, real activity, business confidence and housing starts vary significantly if there is a scheduled announcement. This should capture an announcement risk premium documented in Table III. The curvature is only significant for the Nonfarm Productivity risk premium. The term spread is usually positively associated with a change in the investors' risk aversion. Therefore, if the risk aversion increases, the risk premium associated with procyclical variables such as labor market news increases in absolute value.

10 Conclusions

In summary, using high frequency data and macroeconomic news obtained from announcements and surveys, I provide evidence of significant economic risk premia in the Government bond market. In particular, procyclical variables carry a statistically significant negative price of risk. Long-term bonds that are more exposed than short-term bonds to macroeconomic shocks, exhibiting a higher beta, are rewarded with a positive risk premium. This is documented both with a two-pass cross-sectional regression and calculating premia on mimicking portfolios. Furthermore, this result is robust controlling for other risk factors and using a latent macroeconomic factor extracted with the Kalman filter. I also show that there are advantages of using high-frequency data such as daily or intra-day data in comparison with monthly data.

The risk premia associated with macroeconomic variables appear to be very similar. A test was carried out to examine whether a one-factor model was sufficient to explain

²¹Ample evidence is also provided in the literature of time-varying risk premium in the bond market (see among others Fama 1984, Stambaugh 1988, Fama and Bliss 1987, and Cochrane and Piazzesi, 2005).

the expected returns. The null hypothesis cannot be rejected. The loadings on a single latent factor show that the most important announcements are labor market and business confidence. Finally, I examine whether the return of the unit beta portfolios are time varying. Important predictors of risk premia changes are the term spread and the presence of an announcement. In particular, an increase in the term spread and the presence of an announcement are associated with an increase in the absolute value of the economic risk premium.

References

- Adrian T., E. Moench (2008), "Pricing the term structure with linear regressions", Federal Reserve Bank of New York Staff Reports no. 340.
- Andersen, T., Bollerslev, T., Diebold, F., Vega, C. (2007). "Real Price Discovery in Stock, Bond, and Foreign Exchange Markets", *Journal of International Economics* 73, 251–277.
- Ang, A., Dong, S., Piazzesi, M., (2007), "No-arbitrage Taylor rules", Mimeo, Columbia University.
- Ang, A. and M. Piazzesi (2003), "A no-arbitrage vector autoregression of the term structure dynamics with macroeconomic and latent variables". *Journal of Monetary Economics*, 50, 745-787.
- Aruoba, S.B., Diebold, F.X. and Scotti, C. (2009), "Real-Time Measurement of Business Conditions," *Journal of Business and Economic Statistics*, forthcoming.
- Balduzzi, P. and C. Robotti (2008a), "Mimicking portfolios, Economic risk premia, and tests of multi-beta models", forthcoming *Journal of Business and Economic Statistics*.
- Balduzzi, P. and C. Robotti (2008b), "Asset-pricing models and economic risk premia: A decomposition", Working Paper Boston College.
- Balduzzi, P., E. J. Elton, and T. C. Green, (2001), "Economic news and bond prices: evidence from the U.S. Treasury market", *Journal of Financial and Quantitative Analysis*, 36, 523-543.
- Barnhill, T. M., F. L. Joutz, and W. F. Maxwell, (2000) "Factors affecting the yields on noninvestment grade bond indices: A cointegration analysis", *Journal of Empirical Finance*, 7, 57-86.
- Beckaert, G., Cho, S., Moreno, A., (2005), "New-Keynesian macroeconomics and the term structure", NBER Working Paper No. 11340.
- Bikbov, R., Chernov, M., (2006), "No-arbitrage macroeconomic determinants of the yield curve", mimeo Columbia University.
- Boyd, J., Hu, J., Jagannathan, R. (2004), "The Stock Market's Reaction to Unemployment News: Why Bad News is Usually Good for Stocks?" *Journal of Finance*, 15, 649-672.
- Breeden, Douglas T., Michael R. Gibbons and Robert H. Litzenberger (1989), "Empirical tests of the consumption-oriented CAPM", *Journal of Finance* 44, 231-62.
- Brenner, M., P. Pasquariello, and M. Subrahmanyam (2006), "Financial Markets and

the Macro Economy", Working Paper Stern School of Business, New York University.

Campbell, J. (1996), "Understanding risk and return", *Journal of Political Economy*, 104, 298–345.

Chan, L. K., J. Karceski, and J. Lakonishok (1998), "The risk and return from factors", *Journal of Financial and Quantitative Analysis*, 33, 159-188.

Chen, Nai-fu, Roll, Richard R. and Ross, Stephen A. (1986). "Economic Forces and the Stock Market", *Journal of Business*, 59, 383-403.

Christoffersen P., E. Ghysels, NR. Swanson (2002), "Let's Get 'Real' About Using Economic Data", *Journal of Empirical Finance*, 9, 343-360.

Clarida, R., Galí, J., Gertler, M., (2000), "Monetary policy rules and macroeconomic stability: evidence and some theory", *Quarterly Journal of Economics* 115, 147–180.

Cochrane, J. and M. Piazzesi, (2005), "Bond risk premia", *American Economic Review* 95, 138-160.

Cochrane, J. H. (2005), "Financial Market and the Real Economy", NBER Working Paper No. 11193.

Cochrane, J. and M. Piazzesi, (2008), "Decomposing the yield curve", University of Chicago mimeo.

Dai, Q., Philippon, T., (2005), "Fiscal policy and the term structure of interest rates", NBER Working Paper No. 11574.

De Goeij, P., and W. Marquering (2006), "Macroeconomic announcements and asymmetric volatility in bond returns", *Journal of Banking and Finance*, 30, 2659-2680.

Dewachter, H. and M. Lyrio, (2006), "Macro factors and the term structure of interest rates", *Journal of Money, Credit, and Banking*, 38, 119-140.

Diebold, F. X., G. D. Rudebusch, S. B. Aruoba (2006), "The macroeconomy and the yield curve: a dynamic latent factor approach", *Journal of Econometrics* 131, 309–338.

Ederington, L. and Lee, J., (1993), "How markets process information: news releases and volatility". *Journal of Finance* 48, 1161–1191.

Ederington, L. and Lee, J., (1995), "The short-run dynamics of the price adjustment to new information". *Journal of Financial and Quantitative Analysis* 30, 117–134.

Elton, E. J., M. J. Gruber, C. R. Blake, (1995) "Fundamental Economic Variables, Expected Returns, and Bond Fund Performance", *Journal of Finance*, 50, 1229-1256.

Elton, E., (1999), "Expected Return, Realized Return, and Asset Pricing Tests" *Journal of Finance* 54, 1199-1220.

Evans, C. L. and D. A. Marshall, (2007), "Economic determinants of the nominal treasury yield curve", *Journal of Monetary Economics*, 54, 1986–2003.

Evans, C. L., C. T. Liu, and G. Pham-Kanter (2002), "The 2001 recession and the Chicago Fed National Activity Index: Identifying business cycle turning points" *Economic Perspectives* 26-43.

Fama, E. and R. Bliss, (1987), "The Information in Long-Maturity Forward Rates," *American Economic Review* 77, 680-692.

Fama, E. F. and J. D. MacBeth, (1973), "Risk, Return and Equilibrium: Empirical Tests", *Journal of Political Economy*, 81, 607-36.

Fama, E., (1984), Term premiums in bond returns, *Journal of Financial Economics* 13, 529-546.

Fama, E., and K. French (1993), "Common risk factors in the returns on bonds and stocks", *Journal of Financial Economics*, 33, 3–56.

Ferson, W. and C. R. Harvey (1991). "The Variation of Economic Risk Premiums", *Journal of Political Economy*, 99, 385-415.

Ferson, W. E., A. Siegel, and T. Xu, (2006), "Mimicking Portfolios with Conditioning Information", forthcoming in the *Journal of Financial and Quantitative Analysis*.

Flannery, M. J. and Protopapadakis, A. (2002), "Macroeconomic Factors do Influence Aggregate Stock Returns," *Review of Financial Studies*, 15, 751-782.

Fleming, M., Remolona, E. (1997), "What moves the bond market?", *Federal Reserve Bank of New York Economic Policy Review*, 31-50.

Fleming, M., Remolona, E. (1999a), "Price formation and liquidity in the U.S. Treasury market: The response to public information.", *Journal of Finance*, 54, 1901-1915.

Fleming, M., Remolona, E. (1999b), "The term structure of announcement effects", *Federal Reserve Bank of New York Staff Reports*, No. 76.

Gallmeyer, M., Hollifield, B., Zin, S.E., (2005), "Taylor rules McCallum rules and the term structure of interest rates". NBER Working Paper No. 11276.

Gebhardt, W. R., S. Hvidkjaer, and B. Swaminathan, (2005), "The cross-section of expected corporate bond returns: Betas or characteristics?", *Journal of Financial Economics* 75, 85–114.

Ghysels E. and J. Wright (2009), "Forecasting Professional Forecasters", *Journal of Business and Economic Statistics*, forthcoming.

Gürkaynak, R. S., Sack, B., and Swanson, E. T, (2006), "Do Actions Speak Louder

than Words? The Response of Asset Prices to Monetary Policy Actions and Statements", *International Journal of Central Banking*, 1, 55-93.

Hess A., A. Kamara (2000), "Conditional time-varying interest rate risk premium: Evidence from the Treasury bill futures market", *Journal of Money, Credit, and Banking*, 37, 679-698.

Hördahl, P., Tristani, O., and Vestin, D., (2006). "A joint econometric model of macroeconomic and term structure dynamics", *Journal of Econometrics* 131, 405–444.

Jagannathan, R., and Z. Wang, (1998), "Asymptotic theory for estimating beta pricing models using cross-sectional regressions", *Journal of Finance* 53, 1285–1309.

Jagannathan, R. and Y. Wang, (2007) "Lazy Investors, Discretionary Consumption, and the Cross-Section of Stock Returns" forthcoming *Journal of Finance*.

Jones, C. M., O. Lamont, and R. L. Lumsdaine, (1998), "Macroeconomic news and bond market volatility", *Journal of Financial Economics* 47, 315-337.

Kamara, A. (1988), "Market trading structures and asset pricing: evidence from the Treasury-bill markets", *Review of Financial Studies* 1, 357-375.

Kane, A. and A. J. Marcus, (1986), "The quality option in the Treasury bond futures market: An empirical assessment", *Journal of Futures Markets*, 6, 231-248.

Kim, S., McKenzie, M., Faff, R. (2004), "Macroeconomic News Announcements and the Role of Expectations: Evidence for US Bond, Stock and Foreign Exchange Markets" *Journal of Multinational Financial Management*, 14, 217-232.

Knez, P.K., R. Litterman, and J. Scheinkman, (1994), "Explorations into factors explaining money market returns", *Journal of Finance* 49, pp. 1861–1882.

Koijen, R., H. Lustig, and S. Van Nieuwerburgh (2009), "The Cross-Section and Time-Series of Stock and Bond Returns"

Kuttner, K. N. (2001), "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market", *Journal of Monetary Economics*, 47, 523-544.

Lamont, O. A. (2001), "Economic Tracking Portfolios", *Journal of Econometrics*, 105, 161-184.

Lewellen, J., S. Nagel and J. Shanken, (2006), "A skeptical appraisal of asset-pricing tests", NBER Working Paper No. 12360.

Li, H., J. Wang, C. Wu, and Y. He (2009), "Are liquidity and information risks priced in the Treasury bond market?", *Journal of Finance* 64, 467-503.

Li, L. and R. Engle (1998), "Macroeconomic announcements and volatility of treasury

futures". University of California, San Diego Discussion Paper, No. 27.

Litterman, R. and J. Scheinkman (1996), "Common factors affecting bond returns", *Journal of Fixed Income* 1, 54-61.

Lu B. and L. Wu (1996), "Systematic Movements in Macroeconomic Releases and the Term Structure of Interest Rates", Working Paper.

McQueen, G. and V. V. Roley, (1993), "Stock prices, news, and business conditions", *Review of Financial Studies*, 6, 683-707.

Merton, R., (1973), "An intertemporal capital asset-pricing model", *Econometrica* 41, 867–887.

Mizrach B. and Neely C., (2006), "The transition to Electronic Communications Networks in the secondary Treasury market", Federal Reserve Bank of St. Luis Review.

Mizrach B. and Neely C., (2007), "Information shares in the US Treasury market", Federal Reserve Bank of St. Luis Working Paper, No. 70.

Monfort, A., J. P. Renne, R. Ruffer, and G. Vitale (2003), "Is economic activity in the G7 synchronised? Common shocks versus spillover effects", CEPR Discussion Paper No. 4119.

Petkova, R. (2006), "Do the Fama–French Factors Proxy for Innovations in Predictive Variables?" *Journal of Finance*, 54, 581-612.

Ramchander, S., M. W. Simpson, and J. R. Webb, (2003) "Macroeconomic news and mortgage rates", *Journal of Real Estate Finance and Economics*, 27, 355-377.

Ramchander, S., M. W. Simpson, and M. K. Chaudhry, (2005) "The influence of macroeconomic news on term and quality spread", *The Quarterly Review of Economics and Finance*, 45, 84-104.

Ross, S. A. (1976) "The arbitrage theory of capital asset pricing", *Journal of Economic Theory* 13, 341-360.

Rudebusch, G.D., Wu, T., (2003) "A macro-finance model of the term structure, monetary policy, and the economy", Mimeo, Federal Reserve Bank of San Francisco.

Stambaugh, R. F. (1988) "The Information in Forward Rates: Implications for Models of the Term Structure." *Journal of Financial Economics*, 21(1), 41–70.

Vassalou, M., (2003), "News related to future GDP growth as a risk factor in equity returns", *Journal of Financial Economics*, 68, 47–73.

Veronesi, P. (1999), "Stock Market Overreaction to Bad News in Good Times: A Rational Expectations Equilibrium Model". *Review of Financial Studies*, 12, 975-1007.

Xu, X. E. and H-G. Fung, (2005), "What moves the mortgage-backed securities market?", *Real Estate Economics*. 33, 397-426.

Zhou, G. (1994) "Analytical GMM tests: asset pricing with time-varying risk premiums", *Review of Financial Studies*, 7, 687-709.

Zhou, G. (1995) "Small sample rank tests with applications to asset pricing", *Journal of Empirical Finance*, 2, 71-93.

Table I
U.S. Macroeconomic Announcements

This table reports a list of the macroeconomic announcements used in the paper together with their abbreviations, the unit of measure, and the sources. The Institute for Supply Management (ISM) was called National Association of Purchasing Management (NAPM) before 2002.

| Announcements Name | Abbreviation | Units | Source |
|--|--------------|---------------|--------------------------------------|
| Advance Retail Sales | RetS | (%) | Bureau of the Census |
| Business Inventories | BuInv | (%) | Bureau of the Census |
| Change in Nonfarm Payrolls | Nfarm | (thousands) | Bureau of Labor Statistics |
| Chicago Purchasing Manager Index | Chic | (number) | Institute for Supply Management |
| Consumer Confidence | CConf | (number) | Conference Board |
| Consumer Price Index | CPI | (%) | Bureau of Labor Statistics |
| Durable Goods Orders | Durab | (%) | Bureau of the Census |
| Employment Cost Index | ECI | (%) | Bureau of Labor Statistics |
| Existing Home Sales | EHS | (millions) | Bureau of the Census |
| Factory Orders | FacO | (%) | Bureau of the Census |
| Federal Open Market Committee rate decision | FOMC | (%) | Federal Reserve Board |
| Gross Domestic Product (advance, preliminary and final) | GDP | (%) | Bureau of Economic Analysis |
| GDP Price Deflator (advance, preliminary and final) | GDPDefla | (%) | Bureau of Economic Analysis |
| Housing Starts | HSt | thousands | Bureau of the Census |
| Industrial Production | IP | (%) | Federal Reserve Board |
| Initial Jobless Claims | IJob | (thousands) | Bureau of Labor Statistics |
| Leading Indicators | LInd | (%) | Conference Board |
| Monthly Treasury Budget Statement | Budge | (\$ Billions) | Department of the Treasury |
| National Association of Purchasing Management (after 1/02 ISM Manufacturing) Index | NAPM | (number) | Institute for Supply Management |
| New Home Sales | NewH | (thousands) | Bureau of the Census |
| Nonfarm Productivity | NFPro | (%) | Bureau of Labor Statistics |
| Philadelphia Fed Index | Phil | (number) | Federal Reserve Bank of Philadelphia |
| Producer Price Index | PPI | (%) | Bureau of Labor Statistics |
| Unemployment Rate | Unemp | (%) | Bureau of Labor Statistics |
| Wholesale Inventories | WInv | (%) | Bureau of the Census |

Table II
U.S. Macroeconomic Announcements: Release Dates Frequency and Distribution in the Week Days (January 1983 - March 2008)

This table reports the starting dates of the macroeconomic announcements, the frequency of the releases, the time (EST) of the releases, and the number of announcements together with their distribution in the week days.

| Announcements | Starting Date | Release | | Week Day | | | | | Total |
|---------------|---------------|------------|---------------|------------|-------------|------------|-------------|-------------|-------------|
| | | Frequency | Time | Mon | Tue | Wed | Thu | Fri | |
| RetS | Jan-83 | Monthly | 8:30 AM | 4 | 77 | 49 | 94 | 77 | 301 |
| BuInv | Apr-88 | Monthly | 10/8:30 AM | 43 | 24 | 58 | 43 | 72 | 240 |
| Nfarm | Jan-85 | Monthly | 8:30 AM | 10 | 0 | 1 | 6 | 260 | 277 |
| Chic | Jan-97 | Monthly | 10:00 AM | 17 | 18 | 22 | 23 | 55 | 135 |
| CConf | Jul-91 | Monthly | 10:00 AM | 0 | 144 | 2 | 3 | 1 | 150 |
| CPI | Jan-83 | Monthly | 8:30 AM | 1 | 79 | 91 | 48 | 84 | 303 |
| Durab | Jan-83 | Monthly | 8:30 AM | 0 | 72 | 106 | 70 | 53 | 301 |
| ECI | Jan-97 | Monthly | 8:30 AM | 0 | 9 | 2 | 25 | 9 | 45 |
| EHS | Jan-97 | Quarterly | 10:00 AM | 40 | 37 | 19 | 20 | 19 | 135 |
| FacO | Mar-88 | Monthly | 10:00 AM | 9 | 38 | 64 | 77 | 50 | 238 |
| FOMC | Feb-94 | 8 per year | 2:15 PM | 1 | 75 | 37 | 5 | 1 | 119 |
| GDP | Apr-93 | Monthly | 8:30 AM | 0 | 10 | 38 | 63 | 66 | 177 |
| GDPDefla | Apr-93 | Monthly | 8:30 AM | 0 | 10 | 38 | 63 | 66 | 177 |
| HSt | Jan-83 | Monthly | 8:30 AM | 4 | 111 | 98 | 54 | 34 | 301 |
| IP | Jan-83 | Monthly | 9:15 AM | 28 | 66 | 60 | 33 | 116 | 303 |
| IJob | Jul-91 | Weekly | 8:30 AM | 0 | 1 | 29 | 832 | 3 | 865 |
| LInd | Jan-83 | Monthly | 8:30/10:00 AM | 31 | 81 | 67 | 77 | 47 | 303 |
| Budge | Apr-88 | Monthly | 2:00 PM | 49 | 40 | 42 | 45 | 61 | 237 |
| NAPM | Jan-90 | Monthly | 10:00 AM | 83 | 40 | 31 | 34 | 30 | 218 |
| NewH | Mar-88 | Monthly | 10:00 AM | 37 | 55 | 64 | 47 | 36 | 239 |
| NFPro | Jan-97 | 8 per year | 8:30 AM | 0 | 30 | 19 | 36 | 3 | 88 |
| Phil | Jan-97 | Monthly | 12:00 PM | 0 | 0 | 0 | 135 | 0 | 135 |
| PPI | Jan-83 | Monthly | 8:30 AM | 3 | 40 | 21 | 60 | 179 | 303 |
| Unemp | Jan-83 | Monthly | 8:30 AM | 5 | 0 | 2 | 8 | 287 | 302 |
| WInv | Jan-97 | Monthly | 10:00 AM | 13 | 32 | 32 | 31 | 27 | 135 |
| Total | | | | 378 | 1089 | 992 | 1932 | 1636 | 6027 |

Table III

Summary Statistics of Daily Treasury Bond Excess Returns (3 January 1983 - 31 March 2008)

This table reports descriptive statistics for Treasury bond excess returns for seven maturities: 6-month, 1-year, 2-year, 3-year, 5-year, 7-year, and 10-year. Summary statistics are reported for the total sample and for the sample divided in two: one sample only includes announcement days and another sample only includes non-announcement days. Tests on the mean, variance, and distribution differences between announcement days and non-announcement days are also reported.

| | TRSY (6M) | TRSY (1Y) | TRSY (2Y) | TRSY (3Y) | TRSY (5Y) | TRSY (7Y) | TRSY (10Y) |
|---|--------------|--------------|--------------|--------------|--------------|--------------|---------------|
| <i>All sample (N=6307)</i> | | | | | | | |
| Mean (annual) | 0.74 | 1.36 | 2.27 | 3.14 | 4.53 | 5.40 | 6.44 |
| SD (annual) | 0.49 | 0.99 | 2.15 | 3.20 | 5.00 | 6.43 | 7.93 |
| Sharpe ratio | 1.53 | 1.37 | 1.06 | 0.98 | 0.91 | 0.84 | 0.81 |
| autocorrelation (1 lag) | 0.08 | 0.08 | 0.08 | 0.07 | 0.07 | 0.06 | 0.06 |
| Kurtosis | 20.61 | 16.16 | 11.27 | 9.35 | 8.37 | 8.17 | 8.13 |
| Skewness | 1.09 | 0.83 | 0.45 | 0.27 | 0.21 | 0.15 | 0.14 |
| <i>Only announcement days (N=3600)</i> | | | | | | | |
| Mean (annual) | 1.08 | 2.02 | 3.36 | 4.73 | 7.13 | 8.00 | 9.42 |
| SD (annual) | 0.51 | 1.09 | 2.42 | 3.62 | 5.65 | 7.21 | 8.84 |
| Sharpe ratio | 2.12 | 1.85 | 1.39 | 1.31 | 1.26 | 1.11 | 1.06 |
| autocorrelation (1 lag) | 0.08 | 0.07 | 0.05 | 0.05 | 0.04 | 0.03 | 0.02 |
| Kurtosis | 24.55 | 16.84 | 10.80 | 8.74 | 7.76 | 7.76 | 7.78 |
| Skewness | 1.47 | 1.14 | 0.59 | 0.36 | 0.27 | 0.22 | 0.21 |
| <i>Non-announcement days (N=2707)</i> | | | | | | | |
| Mean (annual) | 0.29 | 0.47 | 0.82 | 1.02 | 1.08 | 1.94 | 2.48 |
| SD (annual) | 0.45 | 0.83 | 1.71 | 2.53 | 3.95 | 5.21 | 6.51 |
| Sharpe ratio | 0.65 | 0.57 | 0.48 | 0.40 | 0.27 | 0.37 | 0.38 |
| autocorrelation (1 lag) | -0.02 | 0.02 | 0.01 | 0.03 | 0.03 | 0.01 | 0.01 |
| Kurtosis | 10.57 | 8.01 | 7.00 | 6.78 | 6.37 | 6.24 | 6.32 |
| Skewness | 0.27 | -0.33 | -0.29 | -0.28 | -0.23 | -0.18 | -0.18 |
| <i>Test mean difference announcement vs. non- announcement</i> | | | | | | | |
| P-value (one-tailed) | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 | 0.02 | 0.03 |
| <i>F-test on variance difference announcement vs. non- announcement</i> | | | | | | | |
| P-value (two-tailed) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| <i>Kolmogorov-Smirnov test: distribution of announcement vs. non-announcement</i> | | | | | | | |
| P-value (two-tailed) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table IV

Slope Coefficients from Regressions of Daily Excess Returns on Standardized Macro Surprises

This table shows the slope coefficients from OLS regressions of seven daily Treasury bond excess returns (6-month, 1-year, 2-year, 3-year, 5-year, 7-year, and 10-year maturities) on standardized macro surprises using only announcement days and controlling for surprises in variables announced simultaneously as in Balduzzi et al. (2001). T-statistics are in parentheses and are computed using White consistent standard errors. Each coefficient corresponds to a different regression. I present the average adjusted R-squared coefficients across the two dimensions (returns and announcement types).

| | TRSY (6M) | TRSY (1Y) | TRSY (2Y) | TRSY (3Y) | TRSY (5Y) | TRSY (7Y) | TRSY (10Y) | Mean Adj. R^2 |
|-------|-------------------|-------------------|-------------------|-------------------|-------------------|------------------|------------------|--------------------|
| RetS | -0.01 (-4.95) | -0.02 (-5.00) | -0.05 (-7.29) | -0.07 (-7.21) | -0.11 (-7.04) | -0.14 (-6.38) | -0.16 (-6.56) | 0.12 |
| BuInv | 0.00 (0.19) | 0.00 (0.96) | 0.01 (1.66) | 0.01 (1.39) | 0.02 (1.22) | 0.02 (1.21) | 0.02 (0.96) | 0.06 |
| Nfarm | -0.02 (-10.84) | -0.05 (-11.91) | -0.12 (-11.65) | -0.17 (-10.98) | -0.24 (-10.17) | -0.28 (-9.27) | -0.33 (-8.42) | 0.32 |
| Chic | 0.00 (-3.60) | -0.01 (-4.69) | -0.05 (-5.22) | -0.08 (-5.53) | -0.11 (-4.97) | -0.15 (-5.30) | -0.17 (-4.88) | 0.20 |
| CConf | 0.00 (-2.38) | -0.01 (-2.46) | -0.03 (-2.58) | -0.04 (-2.51) | -0.07 (-2.75) | -0.09 (-2.97) | -0.11 (-2.83) | 0.14 |
| Durab | 0.00 (-1.87) | -0.01 (-2.98) | -0.03 (-3.09) | -0.05 (-3.00) | -0.07 (-3.21) | -0.07 (-2.83) | -0.09 (-2.92) | 0.05 |
| EHS | 0.00 (-1.23) | 0.00 (-1.75) | -0.01 (-1.46) | -0.01 (-1.49) | -0.02 (-1.25) | -0.01 (-0.70) | -0.01 (-0.56) | 0.10 |
| HSt | 0.00 (0.19) | 0.00 (-0.45) | 0.00 (-0.08) | 0.00 (-0.26) | 0.00 (-0.07) | 0.00 (0.09) | 0.00 (0.08) | 0.00 |
| IP | -0.01 (-3.28) | -0.02 (-3.87) | -0.03 (-3.47) | -0.04 (-3.77) | -0.06 (-3.42) | -0.07 (-3.28) | -0.09 (-3.32) | 0.04 |
| IJob | 0.00 (4.23) | 0.01 (4.32) | 0.02 (5.70) | 0.03 (5.26) | 0.05 (5.42) | 0.07 (5.31) | 0.08 (5.13) | 0.05 |
| LInd | 0.00 (-1.86) | -0.01 (-1.63) | -0.01 (-1.76) | -0.02 (-2.19) | -0.03 (-1.67) | -0.03 (-1.17) | -0.04 (-1.44) | 0.08 |
| NAPM | -0.01 (-5.39) | -0.02 (-7.31) | -0.05 (-6.92) | -0.07 (-7.01) | -0.11 (-7.08) | -0.13 (-7.15) | -0.16 (-7.18) | 0.18 |
| NewH | 0.00 (-2.53) | -0.01 (-2.51) | -0.02 (-2.64) | -0.03 (-2.89) | -0.05 (-3.23) | -0.06 (-2.91) | -0.09 (-3.27) | 0.07 |
| Phil | -0.01 (-3.01) | -0.02 (-3.64) | -0.05 (-4.82) | -0.08 (-4.90) | -0.12 (-4.67) | -0.14 (-4.36) | -0.16 (-4.17) | 0.16 |
| PPI | 0.00 (-2.12) | -0.01 (-2.01) | -0.01 (-1.27) | -0.01 (-1.09) | -0.02 (-1.16) | -0.02 (-1.00) | -0.04 (-1.47) | 0.05 |
| Unemp | 0.01 (4.78) | 0.02 (4.68) | 0.04 (4.45) | 0.05 (3.67) | 0.07 (3.07) | 0.07 (2.57) | 0.08 (2.22) | 0.29 |
| CPI | -0.01 (-3.19) | -0.01 (-3.89) | -0.02 (-3.14) | -0.04 (-3.32) | -0.06 (-3.08) | -0.06 (-2.66) | -0.07 (-2.51) | 0.05 |

Table IV - Continued

| | TRSY (6M) | TRSY (1Y) | TRSY (2Y) | TRSY (3Y) | TRSY (5Y) | TRSY (7Y) | TRSY (10Y) | Mean Adj. R^2 |
|--------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|--------------------|
| ECI | -0.01 (-2.86) | -0.02 (-3.69) | -0.06 (-3.21) | -0.09 (-3.27) | -0.13 (-3.21) | -0.15 (-3.16) | -0.19 (-3.07) | 0.13 |
| FacO | 0.00 (0.72) | 0.00 (0.60) | 0.00 (0.21) | 0.00 (-0.21) | 0.00 (0.14) | 0.00 (-0.24) | -0.01 (-0.51) | 0.18 |
| GDP | 0.00 (-2.74) | -0.01 (-1.83) | -0.02 (-1.93) | -0.02 (-1.30) | -0.03 (-1.23) | -0.03 (-0.95) | -0.05 (-1.06) | 0.06 |
| Defla | 0.00 (-0.56) | 0.00 (-0.67) | -0.01 (-0.76) | -0.01 (-0.38) | -0.01 (-0.47) | -0.02 (-0.62) | -0.02 (-0.49) | 0.06 |
| Budge | 0.00 (1.47) | 0.00 (2.01) | 0.01 (2.82) | 0.02 (2.69) | 0.03 (2.69) | 0.03 (2.63) | 0.03 (2.50) | 0.02 |
| NFPro | 0.00 (0.89) | 0.00 (0.42) | 0.00 (0.41) | 0.01 (0.53) | -0.01 (-0.31) | 0.02 (0.69) | 0.02 (0.40) | 0.03 |
| WInv | 0.00 (-0.09) | 0.00 (-0.64) | -0.01 (-1.34) | -0.02 (-1.31) | -0.03 (-1.41) | -0.04 (-1.34) | -0.06 (-1.40) | 0.08 |
| FOMC | -0.02 (-5.26) | -0.03 (-4.66) | -0.04 (-2.50) | -0.05 (-1.95) | -0.05 (-1.09) | -0.03 (-0.44) | 0.00 (0.01) | 0.08 |
| Mean Adj. R^2 | 0.11 | 0.12 | 0.11 | 0.11 | 0.10 | 0.09 | 0.08 | |

Table V
Group Announcements by Type

The table shows the different components of the aggregate announcements. The aggregation criteria are similarities in information content and in the announcement betas. The sign of the surprises of Initial Jobless Claims was switched to have a similar interpretation as the surprises of Change in Nonfarm Payrolls.

| Aggregated Announcement Types | Announcements in each Aggregate |
|-------------------------------|--|
| Labor Market | Change in Nonfarm Payrolls Initial Jobless Claims (opposite sign) |
| Prices | Consumer Price Index Employment Cost Index GDP Price Deflator Producer Price Index |
| Aggregate Demand | Advance Retail Sales Durable Goods Orders Factory Orders |
| Real Activity | GDP Industrial Production |
| Business Confidence | Chicago Purchasing Manager Index Leading Indicators NAPM Index Philadelphia Fed Index |
| Home Sales | Existing Home Sales New Home Sales |
| Inventories | Business Inventories Wholesale Inventories |

Table VI
Slope Coefficients from Regressions of Daily Excess Returns on Aggregate Standardized Macro Surprises

This table shows the slope coefficients from OLS regressions of seven daily Treasury bond excess returns (6-month, 1-year, 2-year, 3-year, 5-year, 7-year, and 10-year maturities) on standardized aggregate macro surprises using only announcement days and controlling for surprises in variables announced simultaneously as in Balduzzi et al. (2001). T-statistics are in parentheses and are computed using White consistent standard errors. Each coefficient corresponds to a different regression. I present the average adjusted R-squared coefficients across the two dimensions (returns and announcement types).

| | TRSY (6M) | TRSY (1Y) | TRSY (2Y) | TRSY (3Y) | TRSY (5Y) | TRSY (7Y) | TRSY (10Y) | Mean Adj. R^2 |
|----------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|--------------------|
| Labor Market | -0.01 (-8.68) | -0.02 (-8.72) | -0.05 (-9.95) | -0.07 (-9.44) | -0.10 (-9.30) | -0.12 (-8.95) | -0.14 (-8.46) | 0.11 |
| Prices | 0.00 (-4.29) | -0.01 (-4.66) | -0.02 (-3.71) | -0.02 (-3.65) | -0.04 (-3.53) | -0.04 (-3.24) | -0.06 (-3.34) | 0.06 |
| Agg. Demand | -0.01 (-4.69) | -0.01 (-5.23) | -0.03 (-5.82) | -0.04 (-5.77) | -0.07 (-5.62) | -0.08 (-5.27) | -0.10 (-5.41) | 0.07 |
| Real Activity | -0.01 (-4.14) | -0.01 (-4.45) | -0.03 (-4.23) | -0.04 (-4.10) | -0.06 (-3.80) | -0.06 (-3.49) | -0.08 (-3.57) | 0.05 |
| Business Conf. | -0.01 (-5.38) | -0.01 (-6.86) | -0.03 (-7.94) | -0.05 (-8.47) | -0.08 (-7.72) | -0.10 (-7.27) | -0.12 (-7.36) | 0.13 |
| Home Sales | 0.00 (-2.65) | -0.01 (-3.06) | -0.02 (-3.08) | -0.03 (-3.26) | -0.04 (-3.45) | -0.05 (-2.92) | -0.06 (-3.24) | 0.10 |
| Inventories | 0.00 (-0.14) | 0.00 (0.21) | 0.00 (0.43) | 0.00 (0.21) | 0.00 (-0.13) | 0.00 (-0.14) | -0.01 (-0.43) | 0.04 |
| Budget | 0.00 (1.47) | 0.00 (2.01) | 0.01 (2.81) | 0.02 (2.69) | 0.03 (2.68) | 0.03 (2.63) | 0.03 (2.50) | 0.02 |
| CConf | 0.00 (-2.29) | -0.01 (-2.43) | -0.03 (-2.64) | -0.04 (-2.60) | -0.07 (-2.82) | -0.09 (-3.03) | -0.11 (-2.91) | 0.14 |
| HSt | 0.00 (0.21) | 0.00 (-0.42) | 0.00 (-0.06) | 0.00 (-0.22) | 0.00 (-0.03) | 0.00 (0.14) | 0.00 (0.14) | -0.01 |
| NFPro | 0.00 (0.91) | 0.00 (0.43) | 0.00 (0.42) | 0.01 (0.55) | -0.01 (-0.30) | 0.02 (0.73) | 0.02 (0.43) | 0.03 |
| FOMC | -0.02 (-5.29) | -0.03 (-4.68) | -0.04 (-2.50) | -0.05 (-1.94) | -0.05 (-1.08) | -0.03 (-0.43) | 0.00 (0.02) | 0.07 |
| Mean Adj. R2 | 0.08 | 0.08 | 0.07 | 0.07 | 0.06 | 0.06 | 0.05 | |

Table VII
Cross-Sectional Regression Results with One Factor

This table reports the Fama–MacBeth (1973) cross-sectional regression estimation results for the one factor model:

$$E(r) = \alpha + \lambda\beta$$

Betas are estimated by the time-series regressions of bond excess returns on each type of standardized surprise. The estimation method is the Fama–MacBeth cross-sectional regression procedure using all trading days. The lambdas are divided by their standard deviation. T-statistics are computed using Fama-MacBeth methodology and are adjusted with the Shanken (1992) correction. The adjusted R-squared coefficients are the averages of each R-squared obtained in the cross-sectional regressions. The p-values are obtained by performing a bootstrapping of the factors in the time-series regression. The p-values indicate the probability of obtaining a bootstrapped t-statistic greater (lower) than the sample t-statistic when the sample t-statistic is positive (negative). For the R-squared coefficients, the p-values indicate the probability of obtaining a bootstrapped adjusted R-squared coefficient greater than the sample adjusted R-squared coefficient.

| | Alpha | T-stat | P-value | Lambda | T-stat | P-value | Adj. R^2 | P-value |
|----------------|-------|--------|---------|--------|--------|---------|------------|---------|
| Labor Market | 0.001 | 1.405 | 0.863 | -0.041 | -3.072 | 0.000 | 0.676 | 0.208 |
| Prices | 0.001 | 1.589 | 0.843 | -0.038 | -2.911 | 0.005 | 0.681 | 0.026 |
| Agg. Demand | 0.001 | 1.737 | 0.891 | -0.039 | -3.024 | 0.000 | 0.675 | 0.122 |
| Real Activity | 0.001 | 0.661 | 0.921 | -0.039 | -2.991 | 0.000 | 0.669 | 0.208 |
| Business Conf. | 0.002 | 2.733 | 0.826 | -0.039 | -3.040 | 0.000 | 0.676 | 0.095 |
| Home Sales | 0.002 | 2.806 | 0.813 | -0.038 | -2.626 | 0.000 | 0.685 | 0.080 |
| Inventories | 0.006 | 2.825 | 0.429 | -0.038 | -1.791 | 0.378 | 0.592 | 0.547 |
| Budget | 0.001 | 2.171 | 0.850 | 0.039 | 2.529 | 0.101 | 0.670 | 0.228 |
| CConf | 0.003 | 3.537 | 0.407 | -0.033 | -1.841 | 0.002 | 0.723 | 0.003 |
| HSt | 0.005 | 2.987 | 0.639 | 0.037 | 1.855 | 0.482 | 0.595 | 0.780 |
| NFPro | 0.004 | 3.429 | 0.324 | 0.037 | 1.850 | 0.233 | 0.485 | 0.615 |
| FOMC | 0.010 | 2.247 | 0.763 | 0.025 | 1.490 | 0.444 | 0.023 | 0.914 |

Table VIII
Slope Coefficients from Regressions of Monthly Excess Returns on Standardized Macro Surprises

This table shows the slope coefficients from OLS regressions of seven monthly Treasury bond excess returns (6-month, 1-year, 2-year, 3-year, 5-year, 7-year, and 10-year maturities) on monthly standardized macro surprises. Accordingly, only announcements released at monthly frequency are considered. T-statistics are in parentheses and are computed using White consistent standard errors. Each coefficient corresponds to a different regression. I present the average adjusted R-squared across the two dimensions (returns and announcement types).

| | TRSY (6M) | TRSY (1Y) | TRSY (2Y) | TRSY (3Y) | TRSY (5Y) | TRSY (7Y) | TRSY (10Y) |
|-------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| RetS | -0.02 (-2.35) | -0.05 (-2.72) | -0.11 (-3.26) | -0.16 (-3.00) | -0.23 (-2.88) | -0.30 (-2.92) | -0.34 (-2.78) |
| BuInv | 0.01 (0.85) | 0.02 (1.08) | 0.05 (1.51) | 0.09 (1.68) | 0.15 (1.81) | 0.21 (2.02) | 0.29 (2.19) |
| Nfarm | -0.02 (-2.72) | -0.06 (-3.93) | -0.13 (-3.98) | -0.18 (-3.59) | -0.25 (-3.15) | -0.30 (-2.79) | -0.30 (-2.15) |
| Chic | -0.02 (-1.86) | -0.04 (-2.23) | -0.13 (-3.32) | -0.21 (-3.47) | -0.32 (-3.38) | -0.38 (-3.33) | -0.41 (-2.91) |
| CConf | -0.02 (-1.94) | -0.07 (-3.54) | -0.17 (-3.89) | -0.24 (-3.59) | -0.34 (-3.09) | -0.39 (-2.77) | -0.45 (-2.44) |
| Durab | 0.00 (-0.26) | 0.00 (-0.19) | -0.03 (-0.71) | -0.04 (-0.60) | -0.05 (-0.58) | -0.05 (-0.45) | -0.10 (-0.68) |
| HSt | -0.02 (-2.17) | -0.05 (-2.49) | -0.12 (-3.19) | -0.17 (-3.21) | -0.26 (-3.11) | -0.30 (-2.67) | -0.36 (-2.64) |
| IP | -0.02 (-2.35) | -0.05 (-2.40) | -0.09 (-2.32) | -0.14 (-2.36) | -0.20 (-2.24) | -0.27 (-2.39) | -0.33 (-2.46) |
| LInd | -0.02 (-1.62) | -0.04 (-1.73) | -0.07 (-1.73) | -0.10 (-1.61) | -0.16 (-1.68) | -0.22 (-1.80) | -0.22 (-1.52) |
| NAPM | -0.01 (-1.29) | -0.02 (-1.22) | -0.04 (-0.86) | -0.06 (-1.03) | -0.12 (-1.28) | -0.13 (-1.16) | -0.17 (-1.19) |
| NewH | -0.02 (-2.07) | -0.04 (-2.43) | -0.09 (-2.72) | -0.11 (-2.26) | -0.17 (-2.19) | -0.19 (-1.91) | -0.22 (-1.72) |
| Phil | -0.03 (-1.84) | -0.05 (-1.99) | -0.10 (-2.22) | -0.15 (-2.24) | -0.19 (-1.86) | -0.22 (-1.66) | -0.21 (-1.21) |
| PPI | -0.01 (-1.19) | -0.02 (-1.35) | -0.03 (-0.98) | -0.05 (-0.98) | -0.09 (-1.10) | -0.12 (-1.15) | -0.15 (-1.11) |
| Unemp | 0.02 (2.40) | 0.05 (2.39) | 0.08 (2.10) | 0.12 (2.02) | 0.17 (1.87) | 0.19 (1.59) | 0.21 (1.43) |
| CPI | 0.01 (0.85) | 0.00 (0.16) | -0.01 (-0.31) | -0.02 (-0.42) | -0.05 (-0.62) | -0.07 (-0.61) | -0.07 (-0.51) |
| ECI | -0.01 (-0.33) | -0.02 (-0.55) | -0.05 (-0.73) | -0.11 (-1.00) | -0.20 (-1.18) | -0.28 (-1.37) | -0.30 (-1.21) |

Table VIII - Continued

| | TRSY (6M) | TRSY (1Y) | TRSY (2Y) | TRSY (3Y) | TRSY (5Y) | TRSY (7Y) | TRSY (10Y) |
|-------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| FacO | 0.00 (0.40) | 0.01 (0.60) | 0.03 (0.76) | 0.05 (0.86) | 0.07 (0.78) | 0.07 (0.61) | 0.07 (0.52) |
| GDP | 0.00 (-0.16) | 0.01 (0.34) | 0.00 (0.10) | -0.01 (-0.09) | -0.01 (-0.06) | 0.01 (0.09) | -0.01 (-0.10) |
| Defla | 0.00 (-0.65) | -0.02 (-1.06) | -0.05 (-1.37) | -0.06 (-1.15) | -0.08 (-1.03) | -0.09 (-0.89) | -0.09 (-0.72) |
| Budge | 0.00 (-0.59) | 0.00 (-0.34) | 0.00 (-0.08) | 0.00 (0.04) | 0.02 (0.21) | 0.01 (0.08) | 0.00 (0.02) |
| WInv | -0.01 (-0.95) | -0.03 (-1.52) | -0.05 (-1.15) | -0.06 (-0.86) | -0.06 (-0.49) | -0.05 (-0.31) | -0.03 (-0.16) |

Table IX

Cross-Sectional Regression Results with One factor: Monthly vs. Daily Data

This table reports the Fama–MacBeth (1973) cross-sectional regression estimation results for the one factor model:

$$E(r) = \alpha + \lambda\beta$$

Betas are estimated by the time-series regressions of bond excess returns on each type of standardized surprise. When using monthly returns the macroeconomic shocks are obtained estimating an AR(1) model. The estimation method is the Fama–MacBeth cross-sectional regression procedure using monthly and daily data. The lambdas are divided by their standard deviation. T-statistics are computed using Fama-MacBeth methodology and are adjusted with the Shanken (1992) correction.

| | Using Monthly Returns Data | | | | Using Daily Returns Data | | | |
|-------|----------------------------|--------|--------|--------|--------------------------|--------|--------|--------|
| | Alpha | T-stat | Lambda | T-stat | Alpha | T-stat | Lambda | T-stat |
| RetS | 0.135 | 6.266 | -0.124 | -1.656 | 0.001 | 1.526 | -0.039 | -3.048 |
| BuInv | 0.149 | 6.226 | 0.130 | 1.494 | 0.002 | 2.479 | 0.039 | 2.432 |
| Nfarm | 0.110 | 4.335 | -0.153 | -1.776 | 0.000 | 0.619 | -0.041 | -3.100 |
| Chic | 0.107 | 4.075 | -0.135 | -1.326 | 0.002 | 2.636 | -0.037 | -1.954 |
| CConf | 0.101 | 3.485 | -0.121 | -1.294 | 0.003 | 3.537 | -0.033 | -1.841 |
| Durab | 0.165 | 3.078 | -0.134 | -0.688 | 0.001 | 1.490 | -0.039 | -3.039 |
| HSt | 0.136 | 6.522 | -0.134 | -1.776 | 0.005 | 2.987 | 0.037 | 1.855 |
| IP | 0.143 | 6.369 | -0.135 | -1.698 | 0.001 | 0.707 | -0.039 | -3.009 |
| LInd | 0.136 | 5.289 | -0.127 | -1.398 | 0.001 | 1.063 | -0.039 | -2.894 |
| NAPM | 0.129 | 3.808 | -0.142 | -1.050 | 0.002 | 2.918 | -0.038 | -2.562 |
| NewH | 0.111 | 3.767 | -0.108 | -1.154 | 0.002 | 3.584 | -0.038 | -2.639 |
| Phil | 0.064 | 0.982 | -0.137 | -0.963 | 0.002 | 2.203 | -0.037 | -1.957 |
| PPI | 0.156 | 4.682 | -0.123 | -0.991 | 0.002 | 2.712 | -0.038 | -2.773 |
| Unemp | 0.112 | 2.823 | 0.138 | 1.320 | 0.000 | -0.404 | 0.039 | 3.081 |
| CPI | 0.190 | 2.578 | -0.130 | -0.647 | 0.001 | 1.084 | -0.039 | -3.012 |
| ECI | 0.175 | 4.246 | 0.033 | 0.217 | 0.002 | 2.023 | -0.037 | -1.953 |
| FacO | 0.105 | 1.759 | 0.159 | 0.603 | 0.004 | 3.985 | -0.037 | -2.302 |
| GDP | 0.205 | 0.998 | -0.088 | -0.386 | 0.000 | 0.460 | -0.031 | -1.832 |
| Defla | 0.088 | 1.716 | -0.106 | -0.600 | 0.005 | 2.082 | -0.031 | -1.301 |
| Budge | 0.241 | 0.589 | 0.144 | 0.270 | 0.001 | 2.171 | 0.039 | 2.529 |
| WInv | 0.170 | 1.812 | -0.155 | -0.870 | 0.003 | 3.450 | -0.037 | -1.921 |

Table X
Slope Coefficients from Regressions of Daily and Intra-day Future Returns on Aggregate Standardized Macro Surprises

This table shows the slope coefficients from OLS regressions of four daily and intra-day future bond returns (2-year, 5-year, and 10-year T-notes and 30-year T-bond) on standardized aggregate macro surprises using only announcement days and controlling for surprises in variables announced simultaneously as in Balduzzi et al. (2001). The intra-day future returns are calculated using a window of 30-minutes around the announcements (5-minutes before and 25-minutes after). T-statistics are in parentheses and are computed using White consistent standard errors. Each coefficient corresponds to a different regression. I present the average adjusted R-squared coefficients across the two dimensions (returns and announcement types).

| | 2-year T-note | | 5-year T-note | | 10-year T-note | | 30-year T-bond | | Mean Adj. R^2 |
|---|---------------|--------|---------------|--------|----------------|--------|----------------|--------|-----------------|
| | Beta | T-stat | Beta | T-stat | Beta | T-stat | Beta | T-stat | |
| With Daily Returns | | | | | | | | | |
| Labor Market | -0.03 | -6.96 | -0.06 | -6.68 | -0.09 | -6.42 | -0.12 | -5.91 | 0.08 |
| Prices | -0.01 | -1.89 | -0.01 | -1.32 | -0.02 | -1.19 | -0.05 | -1.92 | 0.05 |
| Agg. Demand | -0.02 | -3.63 | -0.05 | -3.95 | -0.08 | -3.90 | -0.11 | -3.79 | 0.06 |
| Real Activity | -0.02 | -3.78 | -0.05 | -3.07 | -0.06 | -2.99 | -0.09 | -2.82 | 0.06 |
| Business Conf. | -0.04 | -9.63 | -0.09 | -9.59 | -0.12 | -9.42 | -0.18 | -9.03 | 0.16 |
| Home Sales | -0.02 | -4.04 | -0.04 | -4.27 | -0.06 | -4.19 | -0.09 | -3.74 | 0.08 |
| Inventories | -0.01 | -0.96 | -0.02 | -1.12 | -0.03 | -1.17 | -0.04 | -1.17 | 0.02 |
| Budget | 0.01 | 1.57 | 0.01 | 1.14 | 0.01 | 1.06 | 0.02 | 0.99 | 0.04 |
| CConf | -0.02 | -1.91 | -0.04 | -2.15 | -0.06 | -2.15 | -0.07 | -1.62 | 0.08 |
| HSt | -0.01 | -1.06 | -0.02 | -0.70 | -0.02 | -0.42 | 0.00 | -0.01 | 0.04 |
| NFPro | 0.00 | -0.22 | -0.02 | -0.96 | -0.01 | -0.47 | -0.01 | -0.31 | -0.03 |
| FOMC | -0.03 | -1.61 | -0.04 | -0.72 | -0.01 | -0.09 | 0.05 | 0.63 | -0.01 |
| Mean Adj. R^2 | 0.06 | | 0.05 | | 0.05 | | 0.05 | | |
| With Intra-day Returns (30-minute window) | | | | | | | | | |
| Labor Market | -0.04 | -8.13 | -0.07 | -8.01 | -0.10 | -8.23 | -0.12 | -7.74 | 0.14 |
| Prices | -0.01 | -3.97 | -0.04 | -3.92 | -0.05 | -4.09 | -0.09 | -4.19 | 0.17 |
| Agg. Demand | -0.02 | -7.04 | -0.05 | -7.11 | -0.07 | -6.37 | -0.10 | -5.83 | 0.16 |
| Real Activity | -0.02 | -7.53 | -0.04 | -6.44 | -0.06 | -6.20 | -0.08 | -5.46 | 0.15 |
| Business Conf. | -0.03 | -10.84 | -0.08 | -11.14 | -0.10 | -10.62 | -0.14 | -10.55 | 0.21 |
| Home Sales | -0.01 | -4.76 | -0.03 | -4.83 | -0.04 | -4.56 | -0.06 | -4.43 | 0.14 |
| Inventories | 0.00 | 0.12 | 0.00 | 0.25 | 0.00 | 0.41 | 0.01 | 0.57 | 0.07 |
| Budget | 0.00 | 1.81 | 0.00 | 1.46 | 0.01 | 1.33 | 0.01 | 1.75 | 0.00 |
| CConf | -0.03 | -5.12 | -0.07 | -4.97 | -0.09 | -4.96 | -0.12 | -4.74 | 0.29 |
| HSt | -0.02 | -3.31 | -0.04 | -3.30 | -0.04 | -3.01 | -0.06 | -3.04 | 0.12 |
| NFPro | 0.00 | 0.31 | 0.00 | -0.37 | 0.01 | 0.52 | 0.01 | 0.67 | -0.01 |
| FOMC | -0.02 | -2.15 | -0.02 | -1.74 | -0.01 | -0.68 | 0.02 | 0.99 | 0.00 |
| Mean Adj. R^2 | 0.12 | | 0.12 | | 0.12 | | 0.11 | | |

Table XI**Cross-Sectional Regression Results with One factor and Bond Futures Data**

This table reports the Fama–MacBeth (1973) cross-sectional regression estimation results for the one factor model:

$$E(r) = \alpha + \lambda\beta$$

Betas are estimated by the time-series regressions of bond futures returns on each type of standardized surprise. The estimation method is the Fama–MacBeth cross-sectional regression procedure using daily data. The lambdas are divided by their standard deviation. T-statistics are computed using Fama-MacBeth methodology and are adjusted with the Shanken (1992) correction.

| | With Betas Estimated from Daily Data | | | | With Betas Estimated from Intra-day Data | | | |
|----------------|--------------------------------------|--------|--------|--------|--|--------|--------|--------|
| | Alpha | T-stat | Lambda | T-stat | Alpha | T-stat | Lambda | T-stat |
| Labor Market | -0.003 | -1.278 | -0.033 | -2.003 | -0.003 | -1.277 | -0.032 | -1.973 |
| Prices | 0.002 | 1.085 | -0.034 | -1.966 | 0.000 | 0.133 | -0.033 | -2.016 |
| Agg. Demand | -0.001 | -0.606 | -0.033 | -2.022 | -0.002 | -0.948 | -0.033 | -1.987 |
| Real Activity | -0.003 | -1.205 | -0.033 | -1.955 | -0.002 | -1.066 | -0.033 | -1.956 |
| Business Conf. | -0.001 | -0.695 | -0.033 | -2.028 | -0.002 | -0.855 | -0.033 | -2.009 |
| Home Sales | -0.002 | -0.928 | -0.033 | -1.989 | -0.002 | -0.802 | -0.033 | -1.951 |
| Inventories | -0.001 | -0.461 | -0.033 | -1.904 | 0.003 | 0.645 | 0.034 | 0.962 |
| Budget | -0.005 | -1.168 | 0.034 | 1.582 | 0.001 | 0.279 | 0.034 | 1.161 |
| CConf | -0.001 | -0.551 | -0.033 | -1.794 | -0.002 | -1.052 | -0.033 | -1.990 |
| HSt | 0.012 | 1.785 | 0.035 | 1.807 | -0.002 | -0.758 | -0.033 | -1.910 |
| NFPro | 0.009 | 2.467 | -0.012 | -0.649 | 0.006 | 1.374 | 0.037 | 1.615 |
| FOMC | 0.010 | 1.990 | 0.035 | 2.034 | 0.010 | 2.049 | 0.035 | 2.068 |

Table XII
Mimicking Portfolio Results

This table reports the p-value of the F-test, the joint test on the slope coefficients of the regressions of standardized surprises on seven excess bond returns. The average return and the standardized mean of the mimicking portfolio together with the t-statistics and the 95% bootstrapped confidence interval are also reported.

| | F-test p-value | Rbar | Mean | Mean/ Sdev | T-stat | 95% Bootstrapped Confidence Interval | |
|----------------|-------------------|--------|--------|---------------|--------|---|--------|
| Labor Market | 0.000 | 0.108 | -0.003 | -0.071 | -5.403 | -0.004 | -0.002 |
| Prices | 0.027 | 0.011 | -0.003 | -0.073 | -5.766 | -0.004 | -0.002 |
| Agg. Demand | 0.000 | 0.057 | -0.003 | -0.068 | -5.420 | -0.005 | -0.002 |
| Real Activity | 0.001 | 0.037 | -0.003 | -0.071 | -5.606 | -0.004 | -0.002 |
| Business Conf. | 0.000 | 0.113 | -0.006 | -0.054 | -4.276 | -0.009 | -0.003 |
| Home Sales | 0.014 | 0.029 | -0.004 | -0.054 | -3.800 | -0.007 | -0.002 |
| Inventories | 0.833 | -0.009 | -0.002 | -0.058 | -4.073 | -0.002 | -0.001 |
| Budget | 0.704 | -0.010 | 0.013 | 0.023 | 1.591 | -0.003 | 0.029 |
| CConf | 0.100 | 0.035 | -0.006 | -0.053 | -2.960 | -0.010 | -0.002 |
| HSt | 0.656 | -0.007 | 0.000 | 0.004 | 0.313 | -0.001 | 0.001 |
| NFPro | 0.004 | 0.153 | 0.001 | 0.038 | 1.989 | 0.000 | 0.003 |
| FOMC | 0.000 | 0.416 | -0.002 | -0.083 | -4.954 | -0.003 | -0.001 |

Table XIII
Cross-Sectional Regression Results with Two Factors

This table reports the Fama–MacBeth (1973) cross-sectional regression estimation results for the two factors model:

$$E(r) = \alpha + \lambda_s \beta_s + \lambda_f \beta_f$$

Betas are estimated by the time-series regressions of bond excess returns on each type of standardized surprise and an additional factor. The additional factor is the term spread (panel A) the change in term spread (panel B) and the maturity (panel C). The maturity is only included in the cross-sectional regressions. The estimation method is the Fama–MacBeth cross-sectional regression procedure using all trading days. The lambdas are divided by their standard deviation. T-statistics for panel A and B are computed using Fama-MacBeth methodology and are adjusted with the Shanken (1992) correction. T-statistics for panel C are the asymptotic t-statistics. The adjusted R-squared coefficients are the averages of each R-squared obtained in the cross sectional regressions.

Panel A: Using the Term-spread as a Second Factor

| | Alpha | T-stat | λ Surprise | T-stat | λ Term-spread | T-stat | Adj. R^2 |
|----------------|-------|--------|--------------------|--------|-----------------------|--------|------------|
| Labor Market | 0.001 | 3.226 | -0.031 | -2.350 | -0.009 | -0.665 | 0.706 |
| Prices | 0.001 | 1.438 | -0.039 | -2.886 | 0.009 | 0.683 | 0.688 |
| Agg. Demand | 0.001 | 3.682 | -0.039 | -3.020 | -0.003 | -0.232 | 0.739 |
| Real Activity | 0.001 | 0.664 | -0.038 | -2.970 | 0.003 | 0.267 | 0.678 |
| Business Conf. | 0.002 | 4.201 | -0.024 | -1.902 | 0.002 | 0.130 | 0.744 |
| Home Sales | 0.002 | 5.647 | -0.040 | -2.755 | -0.002 | -0.110 | 0.725 |
| Inventories | 0.001 | 2.209 | 0.019 | 1.018 | -0.041 | -2.274 | 0.729 |
| Budget | 0.002 | 4.597 | 0.035 | 2.184 | 0.015 | 0.919 | 0.771 |
| CConf | 0.002 | 6.063 | -0.029 | -1.609 | 0.010 | 0.580 | 0.794 |
| HSt | 0.005 | 3.050 | 0.034 | 1.754 | -0.005 | -0.274 | 0.543 |
| NFPro | 0.001 | 0.482 | -0.038 | -1.040 | -0.038 | -1.050 | 0.678 |
| FOMC | 0.004 | 2.729 | 0.024 | 1.218 | 0.031 | 1.563 | 0.762 |

Panel B: Using the Δ in Term-spread as a Second Factor

| | Alpha | T-stat | λ Surprise | T-stat | $\lambda \Delta$ Term-spread | T-stat | Adj. R^2 |
|----------------|-------|--------|--------------------|--------|------------------------------|--------|------------|
| Labor Market | 0.002 | 3.316 | -0.026 | -1.950 | -0.010 | -0.722 | 0.706 |
| Prices | 0.001 | 0.994 | -0.029 | -2.182 | 0.004 | 0.277 | 0.688 |
| Agg. Demand | 0.001 | 2.563 | -0.025 | -1.956 | -0.003 | -0.270 | 0.739 |
| Real Activity | 0.001 | 1.891 | -0.028 | -2.228 | -0.008 | -0.608 | 0.678 |
| Business Conf. | 0.002 | 3.473 | -0.030 | -2.335 | -0.003 | -0.221 | 0.744 |
| Home Sales | 0.002 | 4.112 | -0.020 | -1.390 | -0.007 | -0.502 | 0.725 |
| Inventories | 0.003 | 5.354 | 0.026 | 1.641 | -0.041 | -2.717 | 0.729 |
| Budget | 0.002 | 5.113 | 0.028 | 1.886 | -0.015 | -1.059 | 0.771 |
| CConf | 0.003 | 3.060 | -0.012 | -0.642 | 0.000 | -0.001 | 0.794 |
| HSt | 0.003 | 4.949 | -0.030 | -2.078 | -0.043 | -3.170 | 0.543 |
| NFPro | 0.004 | 3.687 | -0.002 | -0.108 | -0.038 | -1.981 | 0.678 |
| FOMC | 0.002 | 3.602 | 0.001 | 0.048 | -0.031 | -1.843 | 0.762 |

Panel C: Using the Maturity as a Second Factor

| | Alpha | T-stat | λ Surprise | T-stat | λ Maturity | T-stat | Adj. R^2 |
|----------------|-------|--------|--------------------|--------|--------------------|--------|------------|
| Labor Market | 0.001 | 3.073 | -0.033 | -2.521 | 0.010 | 0.745 | 0.777 |
| Prices | 0.001 | 2.032 | -0.034 | -2.693 | -0.005 | -0.421 | 0.768 |
| Agg. Demand | 0.001 | 3.061 | -0.034 | -2.677 | 0.003 | 0.239 | 0.770 |
| Real Activity | 0.001 | 1.843 | -0.034 | -2.697 | 0.006 | 0.501 | 0.767 |
| Business Conf. | 0.002 | 4.019 | -0.033 | -2.648 | 0.003 | 0.235 | 0.770 |
| Home Sales | 0.002 | 4.071 | -0.030 | -2.126 | 0.004 | 0.260 | 0.777 |
| Inventories | 0.001 | 3.888 | 0.030 | 2.102 | 0.041 | 2.904 | 0.719 |
| Budget | 0.002 | 3.904 | 0.031 | 2.174 | 0.016 | 1.135 | 0.778 |
| CConf | 0.003 | 3.624 | -0.023 | -1.305 | -0.004 | -0.219 | 0.800 |
| HSt | 0.002 | 4.526 | -0.029 | -2.330 | 0.043 | 3.407 | 0.683 |
| NFPro | 0.003 | 3.121 | -0.005 | -0.247 | 0.038 | 1.989 | 0.705 |
| FOMC | 0.001 | 0.635 | -0.020 | -1.211 | 0.031 | 1.848 | 0.798 |

Table XIV

Slope Coefficients from Regressions of Daily Excess Returns on Aggregate Standardized Macro Surprises Interacting with a Recession Dummy

This table shows the slope coefficients from OLS regressions of seven daily Treasury bond excess returns (6-month, 1-year, 2-year, 3-year, 5-year, 7-year, and 10-year maturities) on standardized aggregate macro surprises using only announcement days and controlling for surprises in variables announced simultaneously as in Balduzzi et al. (2001). The regression also includes a dummy variable that is equal to one if the announcement occurs during a recession period. A recession is defined when the 3-month moving average of the Chicago Fed National Activity Index (CFNAI) is less than -0.7. T-statistics are in parentheses and are computed using White consistent standard errors. Each couple of coefficients corresponds to a different regression.

| | TRSY (6M) | | TRSY (1Y) | | TRSY (2Y) | | TRSY (3Y) | | TRSY (5Y) | | TRSY (7Y) | | TRSY (10Y) | |
|----------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| | Rec. | Exp. | Rec. | Exp. | Rec. | Exp. | Rec. | Exp. | Rec. | Exp. | Rec. | Exp. | Rec. | Exp. |
| Labor Market | -0.01 (-4.43) | -0.01 (-3.32) | -0.02 (-4.30) | -0.02 (-4.93) | -0.05 (-5.21) | -0.05 (-5.84) | -0.07 (-4.84) | -0.08 (-5.75) | -0.10 (-4.05) | -0.12 (-5.82) | -0.12 (-4.30) | -0.15 (-5.63) | -0.14 (-3.78) | -0.18 (-5.34) |
| Prices | 0.00 (-0.51) | 0.00 (-1.91) | -0.01 (-0.83) | -0.02 (-3.30) | -0.02 (-0.95) | -0.04 (-3.11) | -0.02 (-0.98) | -0.07 (-3.36) | -0.04 (-1.39) | -0.10 (-3.57) | -0.04 (-1.52) | -0.13 (-3.28) | -0.06 (-1.75) | -0.15 (-3.15) |
| Agg. Demand | -0.01 (-2.12) | 0.00 (-2.06) | -0.01 (-1.03) | -0.01 (-2.47) | -0.03 (-1.75) | -0.02 (-1.54) | -0.04 (-1.71) | -0.04 (-2.15) | -0.06 (-1.08) | -0.05 (-1.74) | -0.07 (-1.38) | -0.05 (-1.28) | -0.09 (-1.23) | -0.07 (-1.45) |
| Real Activity | -0.01 (-0.25) | 0.01 (0.86) | -0.01 (-0.25) | 0.01 (0.25) | -0.03 (-0.15) | 0.01 (0.22) | -0.04 (-0.03) | 0.00 (-0.21) | -0.06 (0.19) | 0.01 (-0.10) | -0.07 (0.33) | -0.02 (-0.47) | -0.08 (0.70) | -0.05 (-0.75) |
| Business Conf. | -0.01 (-4.01) | -0.01 (-3.20) | -0.01 (-3.50) | -0.02 (-3.57) | -0.04 (-3.70) | -0.04 (-4.16) | -0.06 (-4.11) | -0.06 (-3.67) | -0.09 (-3.35) | -0.08 (-3.40) | -0.11 (-3.51) | -0.10 (-3.10) | -0.14 (-3.97) | -0.12 (-3.17) |
| Home Sales | 0.00 (-1.04) | 0.00 (-0.77) | -0.01 (-1.84) | -0.01 (-0.95) | -0.02 (-1.78) | -0.02 (-1.09) | -0.03 (-1.80) | -0.04 (-1.41) | -0.04 (-1.68) | -0.08 (-1.84) | -0.05 (-1.26) | -0.10 (-1.56) | -0.06 (-1.43) | -0.13 (-1.83) |
| Inventories | 0.00 (-0.65) | 0.00 (-0.82) | 0.00 (-0.41) | 0.00 (-0.40) | 0.00 (0.04) | 0.00 (-0.09) | 0.00 (0.28) | -0.01 (-0.59) | 0.00 (0.21) | -0.01 (-0.17) | 0.00 (0.11) | -0.03 (-0.43) | -0.01 (0.28) | -0.06 (-1.01) |
| Budget | 0.00 (-0.96) | 0.00 (0.05) | 0.00 (-1.13) | -0.01 (-1.04) | 0.01 (0.19) | -0.04 (-1.73) | 0.02 (-0.15) | -0.07 (-1.79) | 0.03 (-0.24) | -0.12 (-2.21) | 0.03 (-0.32) | -0.16 (-2.51) | 0.03 (-0.37) | -0.15 (-2.06) |
| CConf | 0.00 (-2.85) | 0.00 (-1.49) | -0.01 (-4.24) | 0.00 (-1.80) | -0.03 (-4.48) | -0.01 (-1.64) | -0.04 (-4.27) | -0.01 (-1.59) | -0.07 (-3.52) | -0.01 (-0.91) | -0.09 (-4.83) | -0.02 (-0.85) | -0.11 (-3.95) | -0.03 (-1.09) |
| HSt | -0.01 (-4.43) | -0.01 (-3.32) | -0.02 (-4.30) | -0.02 (-4.93) | -0.05 (-5.21) | -0.05 (-5.84) | -0.07 (-4.84) | -0.08 (-5.75) | -0.10 (-4.05) | -0.12 (-5.82) | -0.12 (-4.30) | -0.15 (-5.63) | -0.14 (-3.78) | -0.18 (-5.34) |
| NFPro | 0.00 (-0.51) | 0.00 (-1.91) | -0.01 (-0.83) | -0.02 (-3.30) | -0.02 (-0.95) | -0.04 (-3.11) | -0.02 (-0.98) | -0.07 (-3.36) | -0.04 (-1.39) | -0.10 (-3.57) | -0.04 (-1.52) | -0.13 (-3.28) | -0.06 (-1.75) | -0.15 (-3.15) |
| FOMC | -0.01 (-2.12) | 0.00 (-2.06) | -0.01 (-1.03) | -0.01 (-2.47) | -0.03 (-1.75) | -0.02 (-1.54) | -0.04 (-1.71) | -0.04 (-2.15) | -0.06 (-1.08) | -0.05 (-1.74) | -0.07 (-1.38) | -0.05 (-1.28) | -0.09 (-1.23) | -0.07 (-1.45) |

Table XV
State Space Model: One Latent Factor

This table reports the results of one latent factor model estimated by Kalman filter for different set of macroeconomic variables. The model is the following:

$$y_t = \Phi Z_t + \Gamma y_{t-1} + \varepsilon_t$$

$$Z_t = BZ_{t-1} + \eta_t$$

The table reports the coefficients of the factor loadings Φ and the coefficients of the autoregressive parameters Γ together with the associated t-statistics.

| Real Activity Latent Factor | | | | |
|-----------------------------------|----------------|---------|--------------|--------|
| | Coeff Γ | T-stat | Coeff Φ | T-stat |
| TRSY (10Y) | 0.047 | 3.101 | -0.026 | -1.010 |
| RetS | 0.748 | 17.251 | 0.492 | 2.338 |
| Buinv | 0.967 | 54.607 | 0.089 | 3.014 |
| IP | 0.950 | 51.247 | 0.086 | 2.542 |
| FactO | 0.704 | 13.951 | 0.587 | 12.082 |
| GDP | 0.704 | 12.848 | 0.427 | 4.034 |
| Inflation Latent Factor | | | | |
| | Coeff Γ | T-stat | Coeff Φ | T-stat |
| TRSY (10Y) | 0.042 | 2.387 | -0.002 | -0.305 |
| PPI | 0.867 | 26.680 | 0.118 | 8.581 |
| CPI | 0.867 | 21.659 | 0.170 | 10.743 |
| Defla | 0.780 | 16.285 | 0.044 | 1.547 |
| Labor Market Latent Factor | | | | |
| | Coeff Γ | T-stat | Coeff Φ | T-stat |
| TRSY (10Y) | 0.052 | 3.881 | -0.126 | -3.274 |
| nfarm | 0.975 | 89.180 | 0.160 | 4.130 |
| ijob | 0.987 | 150.758 | -0.115 | -3.155 |
| Unemp | 0.989 | 83.310 | -0.070 | -3.572 |
| Business Confidence Latent Factor | | | | |
| | Coeff Γ | T-stat | Coeff Φ | T-stat |
| TRSY (10Y) | 0.042 | 2.526 | -0.001 | -0.446 |
| Chic | 0.293 | 4.824 | 0.064 | 7.448 |
| LInd | 0.927 | 155.002 | 0.004 | 0.509 |
| NAPM | 0.061 | 8.219 | 0.100 | 13.798 |
| Phil | 0.205 | 2.708 | 0.071 | 7.153 |

Table XVI
State Space Model: Two Latent Factors

This table reports the results of two latent factors model estimated by Kalman filter for different set of macroeconomic variables. The model is the following:

$$y_t = \Phi Z_t + \Gamma y_{t-1} + \varepsilon_t$$

$$Z_t = BZ_{t-1} + \eta_t$$

The table reports the coefficients of the factor loadings Φ for the two factors and the coefficients of the autoregressive parameters Γ together with the associated t-statistics.

| | Coeff Γ | T-stat | Coeff Φ^1 | T-stat | Coeff Φ^2 | T-stat |
|------------|----------------|--------|----------------|--------|----------------|--------|
| TRSY (10Y) | 0.042 | 2.463 | -0.001 | -0.068 | 0.000 | 0.025 |
| RetS | 0.520 | 7.054 | 0.023 | 0.789 | 0.027 | 2.429 |
| Buinv | 0.959 | 47.651 | 0.000 | -0.056 | 0.012 | 4.027 |
| Nfarm | 0.933 | 59.498 | -0.014 | -2.087 | 0.013 | 3.922 |
| Durab | 0.360 | 4.166 | -0.088 | -2.402 | 0.043 | 2.545 |
| IP | 0.793 | 26.497 | -0.016 | -1.845 | 0.029 | 4.321 |
| PPI | 0.857 | 23.970 | 0.120 | 8.787 | 0.009 | 1.283 |
| Unemp | 0.979 | 34.045 | 0.031 | 2.541 | -0.009 | -2.188 |
| CPI | 0.852 | 18.105 | 0.173 | 9.471 | 0.011 | 1.210 |
| GDP | 0.591 | 8.409 | -0.030 | -1.108 | 0.026 | 1.857 |
| Defla | 0.776 | 14.321 | 0.059 | 2.237 | 0.005 | 0.485 |

Table XVII**Cross-Sectional Regression Results with One Factor Using Latent Factor Betas**

This table reports the Fama–MacBeth (1973) cross-sectional regression estimation results for the one factor model:

$$E(r) = \alpha + \lambda\beta$$

Unconditional betas are obtained from the regression of the bond excess returns on the shocks to the latent factor estimated using the Kalman filter. The estimation method is the Fama–MacBeth cross-sectional regression procedure using all trading days. The lambdas are divided by their standard deviation. T-statistics are computed using Fama-MacBeth methodology and are adjusted with the Shanken (1992) correction.

| | Alpha | T-stat | Lambda | T-stat |
|---|-------|--------|--------|--------|
| Real Activity | 0.041 | 2.529 | -0.040 | -2.790 |
| Inflation | 0.013 | 0.764 | -0.031 | -1.898 |
| Labor Market | 0.064 | 4.855 | -0.040 | -3.016 |
| Business Confidence | 0.039 | 2.392 | -0.031 | -1.895 |
| 1 st Latent Factor (Inflation) | 0.033 | 2.036 | -0.031 | -1.878 |
| 2 nd Latent Factor (Real Activity) | 0.017 | 1.036 | -0.031 | -1.897 |

Table XVIII
Test of One Factor Model

This table reports the results of one latent factor model following Zhou (1994 and 1999). The one-factor model for the bond excess returns is the following:

$$r = \alpha + ac'f + \varepsilon.$$

The null hypothesis is that $\beta = ac'$. The test statistics for this null hypothesis is obtained by the generalized method of moments (GMM). The table also reports the coefficients of the vector c (the linear combination of the macroeconomic factors) and the associated t-statistics.

| | From 01/1985 to 03/2008 | | From 01/1990 to 03/2008 | |
|-----------------|-------------------------|--------|-------------------------|--------|
| | Coeff | T-stat | Coeff | T-stat |
| Labor | -0.008 | -8.783 | -0.006 | -7.540 |
| Prices | -0.003 | -2.986 | -0.002 | -2.434 |
| Agg. Demand | -0.004 | -4.615 | -0.004 | -4.667 |
| Real Activity | -0.005 | -4.301 | -0.004 | -3.909 |
| Business Conf. | -0.008 | -8.695 | -0.007 | -8.412 |
| Home Sales | -0.003 | -3.579 | -0.003 | -3.957 |
| Budget | 0.002 | 2.395 | 0.001 | 2.171 |
| Test Statistics | 33.750 | | 28.455 | |
| p-value | 0.576 | | 0.811 | |

Table XIX
Time Variations in the Economic Risk Premia

This table reports the results from regressions of daily unit beta portfolio excess returns on predetermined variables and announcements dummy (from January 1983 when possible). T-statistics are computed using Newey-West consistent standard errors. The term spread is the difference between the 10-year and 1-year rate. The curvature is equal to the difference between the 3-year rate minus the difference between the 7-year rate and twice the 1-year rate divided by 3.

| | Intercept | T-stat | Term- spread | T-stat | Curvature | T-stat | Announc. Dummy | T-stat | Adj. R^2 (%) |
|----------------|-----------|--------|-----------------|--------|-----------|--------|-------------------|--------|-------------------|
| Labor Market | 0.21 | 1.30 | -0.09 | -2.13 | -0.03 | -1.81 | 0.06 | 0.49 | 0.07 |
| Prices | 0.45 | 1.22 | -0.19 | -1.75 | -0.05 | -1.31 | -1.04 | -2.87 | 0.18 |
| Agg. Demand | 0.11 | 0.59 | -0.09 | -1.62 | -0.02 | -1.13 | 0.09 | 0.50 | 0.01 |
| Real Activity | 0.29 | 1.06 | -0.14 | -1.72 | -0.04 | -1.31 | -0.80 | -2.43 | 0.12 |
| Business Conf. | 0.19 | 1.25 | -0.08 | -1.83 | -0.02 | -1.44 | -0.35 | -2.55 | 0.12 |
| Home Sales | 0.38 | 1.14 | -0.17 | -1.97 | -0.06 | -1.58 | -0.06 | -0.21 | 0.01 |
| Inventories | 2.28 | 1.32 | -0.94 | -2.14 | -0.33 | -1.71 | -0.90 | -0.50 | 0.03 |
| Budget | -0.80 | -1.20 | 0.35 | 2.07 | 0.13 | 1.72 | -0.87 | -1.27 | 0.05 |
| CConf | 0.71 | 1.81 | -0.25 | -2.43 | -0.10 | -1.91 | -0.15 | -0.46 | 0.09 |
| HSt | -1.25 | -0.86 | 0.73 | 1.68 | 0.17 | 1.11 | 5.37 | 2.20 | 0.13 |
| NFPro | -2.27 | -2.18 | 0.76 | 2.78 | 0.34 | 2.33 | 0.18 | 0.19 | 0.15 |
| FOMC | -0.47 | -1.59 | 0.18 | 2.35 | 0.06 | 1.64 | -0.06 | -0.18 | 0.05 |

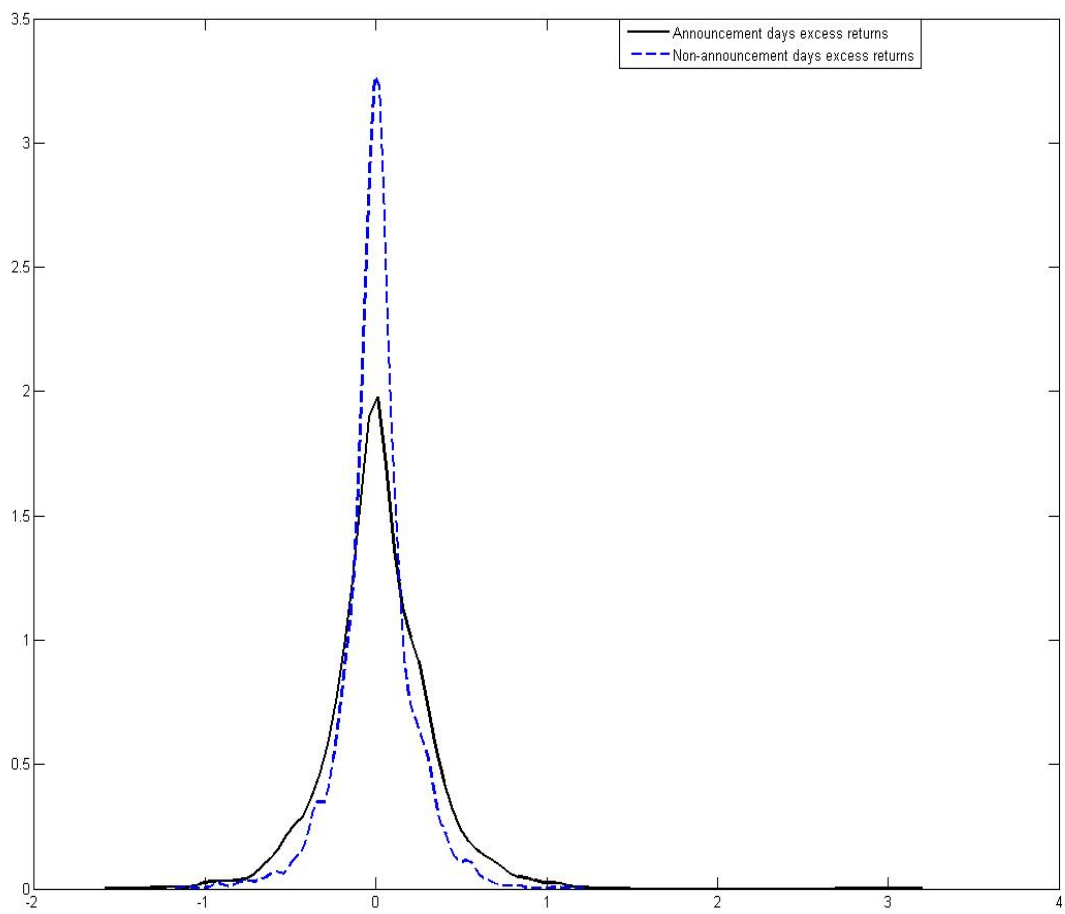


Figure 1: Probability density estimate for announcement and non-announcement days for 5-year bond excess returns. A kernel-smoothing method was used.

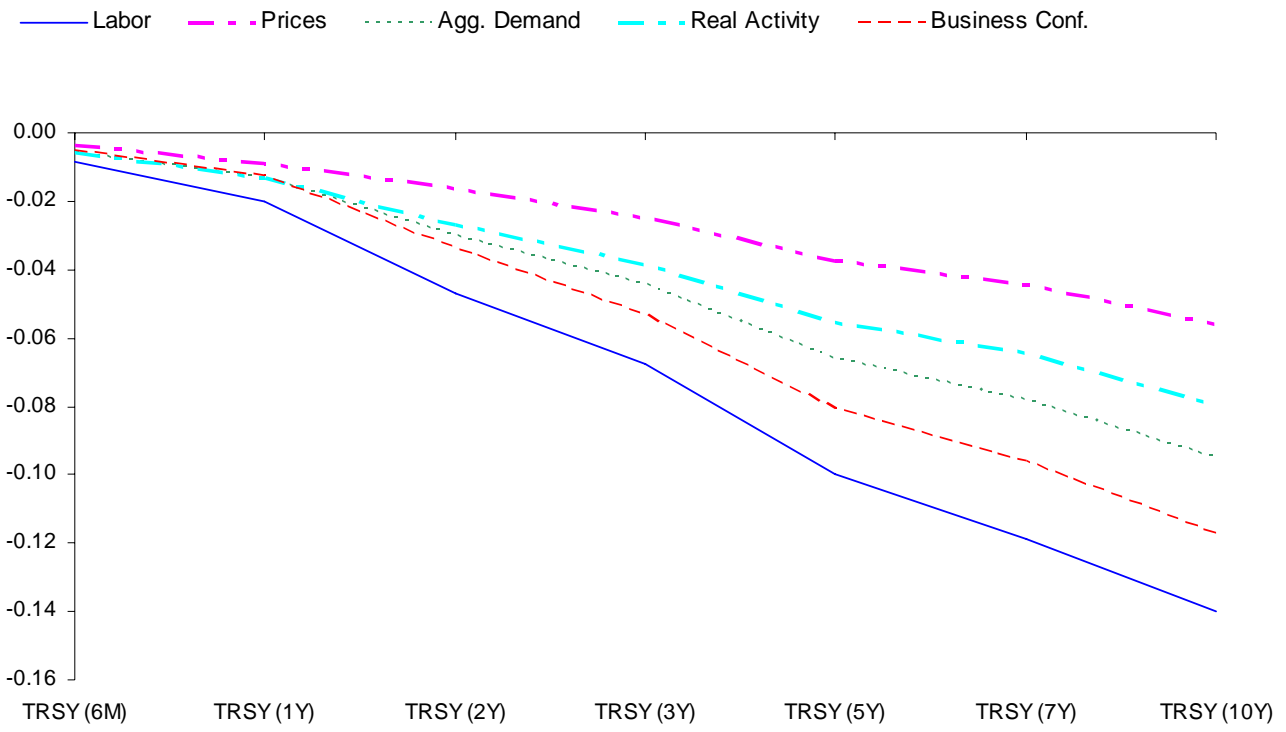


Figure 2: Regression Coefficients of Bond Excess Returns on Standardized Surprises