Economic Risk Premia in the Fixed Income Markets: The Intra-day Evidence

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ABSTRACT

We estimate the risk premia associated with macroeconomic news using intra-day bond futures data. The average conditional Sharpe ratios on portfolios mimicking the news are quite similar (in absolute value) across several types of announcements and are mainly earned on announcement days, but outside of 30-minute windows surrounding the news releases. Exposure to procyclical (countercyclical) macroeconomic variables earns negative (positive) conditional Sharpe ratios, which become more negative (positive) when the level of interest rates is high and the real economy is weak. We cannot reject the assumption that the different news announcements affect futures prices through a single latent factor. Sharpe ratios earned through exposure to this single latent factor are positive—the latent factor is rotated to be countercyclical—and, again, are mainly earned on announcement days, outside of the announcement windows. The Sharpe ratios increase with the level of interest rates and decrease with the level of economic activity. Finally, we cannot reject the assumption that the exposure to the latent factor explains the cross-section of expected bond futures returns. Our findings have implications for models of the term structure of interest rates.

JEL # G12

Keywords: macroeconomic announcements, mimicking portfolios, economic risk premia

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We estimate the risk premia associated with macroeconomic news using intra-day bond futures data. The average conditional Sharpe ratios on portfolios mimicking the news are quite similar (in absolute value) across several types of announcements and are mainly earned on announcement days, but outside of 30-minute windows surrounding the news releases. Exposure to procyclical (countercyclical) macroeconomic variables earns negative (positive) conditional Sharpe ratios, which become more negative (positive) when the level of interest rates is high and the real economy is weak. We cannot reject the assumption that the different news announcements affect futures prices through a single latent factor. Sharpe ratios earned through exposure to this single latent factor are positive—the latent factor is rotated to be countercyclical—and, again, are mainly earned on announcement days, outside of the announcement windows. The Sharpe ratios increase with the level of interest rates and decrease with the level of economic activity. Finally, we cannot reject the assumption that the exposure to the latent factor explains the cross-section of expected bond futures returns. Our findings have implications for models of the term structure of interest rates.

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1 Introduction

The recent literature has paid special attention to macroeconomic interpretations of asset pricing factors and tests of whether macroeconomic factors are priced in the security markets. This seems to be an old question, but as Cochrane (2008) states: "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 and the fixed income markets.

For the equity market, papers such as Chen et al. (1986), Ferson and Harvey (1991), McElroy and Burmeister (1988), Campbell (1996), and Jagannathan and Wang (1996), relate average excess returns to exposures to macroeconomic factors.[1] However, as pointed out by Balduzzi and Robotti (2010), the estimates of risk premia associated with macroeconomic variables—the "economic" risk premia—vary substantially in sign and statistical significance from one study to another. In addition, returns on portfolios mimicking macro variables explain little of the comovement in stock returns (see, for example, Chan et al., 1998).

For the fixed income market, traditional asset pricing models are continuous-time models that consider the short-term interest rate as a fundamental building block. However, research started with Ang and Piazzesi (2003) develops no-arbitrage affine term structure models for Treasury yields, which include macroeconomic information.[2] These term structure models allow for the estimation of the market prices of risk associated with macroeconomic variables. Overall, 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 (2003) the estimates "differ enormously" across two different specifications of the model. Indeed, the market prices of risk coefficients associated with inflation and real activity are both negative and significant in the specification of the model that does not include lagged macro variables, while they are positive and significant in the specification that includes lagged macro variables. In Dai and Philippon (2005) and Bikbov and Chernov (2006), the market prices of risk associated with inflation and real activity have opposite signs. In Lu and Wu (2009), on the other hand, the inflation and real activity factors both command a negative premium. Moreover, Duffee (2006, 2007) finds only weak links between macroeconomic variables and bond risk premia.

What are the possible reasons for such difference in results? One reason could be that these studies impose a lot of structure: not only do they impose the restrictions of asset pricing models and parameterize the price of

[1] More recently, Vassalou (2003) constructs a portfolio that tracks future GDP growth and shows that exposure to returns on this portfolio helps explain the cross-section of equity returns. Petkova (2006) shows that loadings on the shocks to the aggregate dividend yield and term spread, default spread, and one-month Treasury-bill yield explain the cross section of average equity returns better than the loadings on the Fama-French factors.

[2] See, among others, Dai and Philippon (2005), Gallmeyer et al. (2005), Bikbov and Chernov (2006), Dewachter and Lyrio (2006), Hördahl et al. (2006), Ang et al. (2007), Rudebusch and Wu (2008), Beckaert et al. (2010), Joslin et al. (2010), and Joslin et al. (2011).

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 jointly, it is possible that misspecification of a portion of the model contaminates estimates of the risk premia.[3]

This paper mainly focuses on the parameterization of the risk premia, without necessarily imposing an asset pricing model, and without examining the dynamics of the factors or the relation between factors and short-term interest rates. Specifically, we estimate the risk premia associated with macroeconomic risks using intra-day bond futures data, for the sample March 2, 1993–March 31, 2008. We consider the surprise components of 22 scheduled U.S. macroeconomic announcements, where the surprises are computed as the difference between the headline figures of the announcements and the median consensus forecasts. We use intra-day data on returns on four futures contracts on Treasury notes and bonds to obtain *precise* estimates of the composition of portfolios tracking the surprises. We consider two types of mimicking portfolios: portfolios whose returns have a beta of one with respect to the surprises, i.e., unit-beta portfolios; and portfolios whose returns are maximally correlated with the surprises, i.e., maximum-correlation portfolios. We then estimate the conditional Sharpe ratios commanded by the mimicking portfolios during *different* trading days and intervals.

We find that the average conditional Sharpe ratios on the mimicking portfolios are substantial, similar (in absolute value) across announcements, and are mainly earned on announcement days, but outside of 30-minute windows surrounding the releases. For one type of mimicking portfolios—OLS-style unit-beta mimicking portfolios—17 out of 20 annualized Sharpe ratios are in the narrow range between 0.68 and 0.72, in absolute value. Exposure to procyclical (countercyclical) variables earns negative (positive) average Sharpe ratios.

We also uncover significant patterns of time variation in the conditional Sharpe ratios. For example, during announcement days, but outside of the announcement windows, conditional Sharpe ratios on portfolios mimicking procyclical (countercyclical) economic variables are more negative (positive) when the level of interest rates is high and when the economy is weak. As in the case of average conditional Sharpe ratios, the effects are substantial and quite similar across announcements. For OLS-style unit-beta mimicking portfolios, for example, a one-standard deviation shock to the level of interest rates leads to changes in the conditional Sharpe ratios between 1.04 and 1.08 (in absolute value) in 18 out of 20 cases; and the effect of a one-standard deviation shock to an indicator of economic activity leads to changes in the conditional Sharpe ratios between 1.00 and 1.04 (in absolute value) in 17 out of 20 cases.

We then test whether economic announcements affect futures prices through a small set of latent factors. We cannot reject the presence of *a single* latent factor, and the returns on the portfolios mimicking the latent factor

[3] This problem is also recognized by Ang et al. (2007), who 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, because of the presence of multiple local optima that have similar likelihood values, but imply dramatically different estimates of the risk premia. In addition, one may end up with a specification of market prices of risk that compensates for the misspecification of other features of a term structure model.

are strongly correlated with changes in the level of the yield curve. The mimicking portfolios earn positive Sharpe ratios (the latent factor is rotated to be countercyclical). These Sharpe ratios are mainly earned on announcement days, outside of the announcement windows, increase with the level of interest rates, and decrease with economic activity. Depending on the technique used to construct mimicking portfolios, the average conditional Sharpe ratio earned on announcement days, outside of the announcement windows, ranges between 0.72 and 1.08. A one-standard deviation increase in the level of interest rates increases the Sharpe ratio by as much as 1.13, while a one-standard deviation increase in the level of economic activity has an impact as negative as -1.42. Finally, we test, and cannot reject, the null hypothesis that the cross-section of expected bond futures returns is explained by the exposures to the single latent factor.

The results above are important because existing studies have failed to uncover consistent and significant evidence of risk premia associated with explicit macroeconomic factors. In turn, reliable estimates of macroeconomic risk premia are important to understand the economic risks that agents want to avoid the most and are crucial to the pricing of securities and contracts whose payoffs are linked to macroeconomic risks. The findings of this paper also have implications for models of the term structure of interest rates and, more generally, they improve our understanding of the determinants of required expected returns on Treasury securities, which are a reference point for all financial assets.

It is worth noting that our results are conditional on the specific segment of the financial markets that we focus on, i.e., the fixed income markets. The result that exposure to pro-cyclical variables earns negative risk premia may be surprising from the perspective that positive news about the economy has a positive impact on the utility of a representative investor. Yet, for investors restricted to the fixed income markets, positive news about the economy is bad news for their investments, as this drives up the level of interest rates, and it is natural that a portfolio whose return is positively correlated with the level of interest rates should earn a negative premium. Indeed, a negative market price of interest rate risk is the commonly accepted explanation for the upward-sloping average term structure of interest rates (see, for example, the discussion in Lu and Wu, 2009).

A contribution of this paper is to use high-frequency return data combined with "real-time" data on macroeconomic announcements.[4] This allows for more precise estimates of the exposures of bond returns to the macroeconomic shocks actually observed by market participants. The improved precision of the estimates of the exposures should, in turn, translate into improved precision of the estimates of the risk premia. High-frequency data have already been used in the literature investigating the impact of macro news on prices and returns.[5] However, the novel focus of this paper is to use high-frequency returns and real-time announcement data to quantify the *risk*

[4]See Christoffersen et al. (2002) for a discussion of the effect of using real-time data in the context of Chen et al.'s (1986) analysis.

[5]An extensive literature (see, among others, Fleming and Remolona, 1997, and Balduzzi et al., 2001) provides evidence that macroeconomic news have a significant impact on bond prices using high-frequency data. The response to US macroeconomic news is stronger in the bond market than in the equity and foreign exchange markets (Andersen et al., 2007). Return volatility is also significantly affected by the main macroeconomic announcements as shown 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.

premia associated with macroeconomic variables.

Our analysis is related to Jones et al. (1998), who find significant excess Treasury bond holding returns on the release dates of Employment and Producer Price Index data.[6] They do not, however, test whether these risks are priced in accordance with their exposure. Moreover, their focus is on announcement risk premia rather than on economic risk premia that could be earned every day and not only during announcement days. Indeed, in our setting, the risk premia are estimated using all available data, on announcement and non-announcement days, because every day there are revisions of expectations on macro variables, although we can only observe these revisions during announcements.

The paper is organized as follows: Section 2 describes the methodology used. Section 3 describes the data. Section 4 discusses the empirical results. Section 5 concludes.

2 Methodology

Our empirical analysis focuses on the properties of unit-beta and maximum-correlation mimicking portfolios. As discussed in Balduzzi and Robotti (2010), there are theoretical reasons for focusing on these types of portfolios. First, if the pricing factors driving the underlying pricing kernel are the economic factors, and if the pricing kernel is affine, then the economic risk premia implied by the pricing kernel coincide with the risk premia earned by unit-beta mimicking portfolios. Second, regardless of the asset pricing model, one component of the risk premium associated with an economic—i.e., non-traded—risk factor is given by the risk premium earned by the corresponding maximum-correlation mimicking portfolio. In addition, if the pricing factors driving the pricing kernel are excess returns themselves—i.e., the pricing factors are *traded*—then the risk premia associated with the economic factors coincide with the risk premia earned by the maximum-correlation mimicking portfolios.

2.1 Unit-beta mimicking portfolios

We want the estimates of the reaction of futures prices to announcements to be as precise as possible. For this purpose, we take the following approach: i) we estimate the response of futures prices to economic announcements within a narrow window around the announcements, to avoid contaminating the estimates with return variability unrelated to the announcements; ii) we control for all the simultaneous announcements; and iii) we control for possible time variation in the response of futures prices to the announcements. Specifically, we formulate the "announcement-window" factor model

$$r^{aw}_{i,t+1} = \beta_{0,t} + \beta_t y_{i,t+1} + \epsilon^{aw}_{r,i,t+1}, \tag{1}$$

[6]See also Savor and Wilson (2012), who document higher (lower) Treasury bond (T-bill) returns on the days of macro announcements. Savor and Wilson (2012) also document higher aggregate stock market returns on macro-announcement days.

where $r^{aw}_{i,t+1}$ is a $N \times 1$ vector of continuously-compounded futures returns realized during the i-th *announcement window*, starting five minutes before the news release and ending 25 minutes after the news release, between the close on day t and the close on day $t+1$ ($i = 1, \ldots, I_{t+1}$), and $y_{i,t+1}$ is a $K \times 1$ vector of factors, given by economic surprises released during the i-th announcement window on day $t+1$. Since futures contracts are zero-net-investment positions, futures returns can be interpreted as *excess* returns. If a given announcement is not released during the i-th announcement window on day $t+1$, but some other announcements are, the corresponding surprise is assumed to be zero. W.l.o.g., each surprise released during the i-th announcement window on day t, $y_{k,i,t}$, is standardized by its standard deviation calculated over the days when the surprise is released.

Following an approach that dates back to Ferson and Harvey (1991), we model the time-varying factor loadings β_t as linear in a vector of J time-t instruments, z_t, that are observed at the daily periodicity.[7] W.l.o.g., the first element of z_t is a constant and the other elements have zero mean and unit variance. Let

$$y^z_{i,t+1} \equiv y_{i,t+1} \otimes z_t \tag{2}$$

denote the $(JK) \times 1$ vector of economic surprises interacted with the instruments. We have

$$r^{aw}_{i,t+1} = \beta_0 z_t + \beta y^z_{i,t+1} + \epsilon^{aw}_{r,i,t+1}, \tag{3}$$

where β_0 is an $N \times J$ matrix and β is an $N \times (JK)$ matrix. Hence, the time-varying $N \times K$ coefficient matrix β_t is given by

$$\beta_t = \beta(\mathbf{I}_K \otimes z_t). \tag{4}$$

Let $\beta_{k,t}$ denote the k-th column of β_t. $\beta_{k,t}$ contains the loadings of the N assets on the k-th factor. The weights of the unit-beta (Fama, 1976) portfolios tracking the k-th factor are given by the $N \times 1$ vector

$$\tilde{\gamma}_{k,t} = [(\beta^\top_{k,t} W_t \beta_{k,t})^{-1} \beta^\top_{k,t} W_t]^\top, \tag{5}$$

where W_t is a $N \times N$ weighting matrix.

Note that an alternative way to construct unit-beta portfolio weights is to define $\tilde{\gamma}_{k,t}$ as the k-th column of the matrix

$$[(\beta^\top_t W_t \beta_t)^{-1} \beta^\top_t W_t]^\top. \tag{6}$$

In this case, the resulting portfolio not only would have a beta of one with respect to $y_{ki,t}$, but would also have a beta of zero with respect to all other factors. The reason for not following this approach is that, in our main

[7]Fleming and Piazzesi (2005), for example, demonstrate the need to condition on variables describing the shape of the yields curve when modeling the reaction of bond prices to monetary policy shocks. They find that the response of bond yields to news in the monetary policy announcements depends on the steepness of the yield curve.

setting, $K > N$ and, the $K \times K$ matrix $\beta_t^\top W_t \beta_t$ would not be invertible. In addition, in the empirical analysis, we provide evidence that β_t is of rank one and, hence, even if $K \leq N$, $\beta_t^\top W_t \beta_t$ would still be (nearly) singular.

In the empirical analysis, we consider two choices of weighting matrix: $W_t = I_N$ and $W_t = \Sigma_{rr,t}^{-1}$, where $\Sigma_{rr,t}^{-1}$ is the inverse of the conditional covariance matrix of daily returns. The first choice corresponds to the construction of a unit-beta portfolio with minimum Euclidean norm; the second choice corresponds to the construction of a unit-beta portfolio with minimum variance of daily returns. We denote the unit-beta mimicking portfolios for the choice of weighting matrix $W_t = I$, "OLS-style," and for the choice $W_t = \Sigma_{rr,t}^{-1}$, "GLS-style." Depending on whether we are looking at returns during announcement days or non-announcement days, the covariance matrix has the form

$$\Sigma_{rr,t}^{a} = E_t[\epsilon_{r,t+1}^{a}(\epsilon_{r,t+1}^{a})^\top] \tag{7}$$

or

$$\Sigma_{rr,t}^{na} = E_t[\epsilon_{r,t+1}^{na}(\epsilon_{r,t+1}^{na})^\top], \tag{8}$$

respectively. The $N \times 1$ vectors $\epsilon_{r,t+1}^{a}$ and $\epsilon_{r,t+1}^{na}$ are the innovations from projecting daily returns onto the vector of instruments z_t, for announcement and non-announcement days, respectively.[8] One advantage of our approach is that, while the mimicking portfolio weights are estimated using intra-day data only for announcement days, the properties of the mimicking portfolio returns can be examined at *all* times.

Let r_t denote *all-days returns*, futures returns realized on all trading days. Let $r_t^{aw} = \sum_{i=1}^{I_t} r_{i,t}^{aw}$ denote *announcement-window returns*—cumulative futures returns during the I_t announcement windows on day t. Let r_t^{naw} denote *non-announcement-window returns*, futures returns realized during announcement days, but outside of the announcement windows.[9] Let r_t^{na} denote *non-announcement-day returns*, futures returns realized during non-announcement days. We denote

$$r_{\tilde{y}_k,t+1} \equiv \tilde{\gamma}_{k,t}^\top r_{t+1} \tag{9}$$

$$r_{\tilde{y}_k,t+1}^{aw} \equiv \tilde{\gamma}_{k,t}^\top r_{t+1}^{aw} \tag{10}$$

$$r_{\tilde{y}_k,t+1}^{naw} \equiv \tilde{\gamma}_{k,t}^\top r_{t+1}^{naw} \tag{11}$$

$$r_{\tilde{y}_k,t+1}^{na} \equiv \tilde{\gamma}_{k,t}^\top r_{t+1}^{na}, \tag{12}$$

as the unit-beta mimicking-portfolio returns on all days, at announcement times, at non-announcement times during announcement days, and on non-announcement days, respectively.

[8]This specification is consistent with the evidence of Table 2 of a significant difference between the variance of futures returns during announcement and non-announcement days.

[9]These returns are calculated as the difference between the daily returns and the returns computed during the announcement windows.

The estimation of the coefficient matrices β_0 and β can be performed by exactly-identified GMM, with orthogonality conditions

$$E(\epsilon^{aw}_{r,i,t+1} \otimes z_t) = 0 \quad (13)$$

$$E(\epsilon^{aw}_{r,i,t+1} \otimes y^{z}_{i,t+1}) = 0. \quad (14)$$

We ignore possible time variation in the covariance matrices $\Sigma^{a}_{rr,t}$ and $\Sigma^{na}_{rr,t}$, and we obtain estimates of the two matrices by computing the sample counterparts of $E[\epsilon^{a}_{r,t+1}(\epsilon^{a}_{r,t+1})^{\top}]$ and $E[\epsilon^{na}_{r,t+1}(\epsilon^{na}_{r,t+1})^{\top}]$.

2.2 Maximum-correlation mimicking portfolios

We follow Breeden et al. (1989) (see also Balduzzi and Kallal, 1997, and Balduzzi and Robotti, 2008, 2010) by also considering maximum-correlation mimicking portfolios, i.e., portfolios whose weights are obtained through a projection of the k-th economic news, released during the i-th announcement window on day t, $y_{k,i,t}$, onto the augmented span of the N announcement-window returns for the k-th economic news, $r^{aw}_{k,i,t}$. We have

$$y_{k,i,t+1} = \gamma^{\star}_{k0} + (\gamma^{\star}_{k,t})^{\top} r^{aw}_{k,i,t+1} + \epsilon_{y_k,i,t+1}, \quad (15)$$

where $\gamma^{\star}_{k,t}$ is a $N \times 1$ vector.[10]

In the empirical implementation, we model the time-varying coefficients $\gamma^{\star}_{k,t}$ as linear in z_t. We have

$$y_{k,i,t+1} = \gamma^{\star}_{k0} + (\gamma^{\star}_{k})^{\top}(r^{aw}_{k,i,t+1} \otimes z_t) + \epsilon_{y_k,i,t+1}, \quad (16)$$

where $\gamma^{\star}_{k}$ is a $(NJ) \times 1$ vector. Hence, the time-varying $N \times 1$ coefficient vector $\gamma^{\star}_{k,t}$ is given by

$$\gamma^{\star}_{k,t} = (\mathbf{I}_N \otimes z_t^{\top})\gamma^{\star}_{k}. \quad (17)$$

As in the case of unit-beta portfolios, we can evaluate the properties of maximum-correlation mimicking-portfolio returns at all times. We define

$$r_{y^{\star}_k,t+1} \equiv (\gamma^{\star}_{k,t})^{\top} r_{t+1} \quad (18)$$

$$r^{aw}_{y^{\star}_k,t+1} \equiv (\gamma^{\star}_{k,t})^{\top} r^{aw}_{t+1} \quad (19)$$

$$r^{naw}_{y^{\star}_k,t+1} \equiv (\gamma^{\star}_{k,t})^{\top} r^{naw}_{t+1} \quad (20)$$

$$r^{na}_{y^{\star}_k,t+1} \equiv (\gamma^{\star}_{k,t})^{\top} r^{na}_{t+1}. \quad (21)$$

The estimation of the coefficient vectors $\gamma^{\star}_{k0}$ and $\gamma^{\star}_{k}$ can be performed by exactly-identified GMM, with orthogonality conditions

$$E(\epsilon_{y_k,i,t+1}) = 0 \quad (22)$$

$$E[\epsilon_{y_k,i,t+1} \otimes (r^{aw}_{k,i,t+1} \otimes z_t)] = 0 \quad (23)$$

[10] We do not include the instruments z_t as separate regressors, as economic surprises should not be predictable based on z_t.

implemented using intra-day announcement-window data for each economic news.

Balduzzi and Robotti (2008) consider the case of constant mimicking portfolio weights (z_t only includes a constant) and show that the absolute value of the Sharpe ratios of the maximum-correlation mimicking portfolios are the same as the absolute values of the Sharpe ratios of the GLS-style unit-beta mimicking portfolios.[11] Since our setting includes conditioning information, we would expect some differences between the (absolute values) of the Sharpe ratios of the two types of mimicking portfolios. Hence, considering both approaches to the construction of mimicking portfolios is a useful robustness check.

2.3 Economic risk premia

In order to estimate the time-varying risk premia $\tilde{\lambda}_{k,t}$ commanded by the unit-beta mimicking portfolios, we project the mimicking-portfolio returns onto the vector of instruments z_t:[12]

$$r_{\tilde{y}_k,t+1} = \tilde{\lambda}_{k,t} + \tilde{\lambda}_k y^a_{t+1} + \epsilon_{r_{\tilde{y}_k},t+1} \equiv (\tilde{\lambda}_{0k})^\top z_t + \tilde{\lambda}_k y^a_{t+1} + \epsilon_{r_{\tilde{y}_k},t+1} \quad (24)$$

$$r^{aw}_{\tilde{y}_k,t+1} = \tilde{\lambda}^{aw}_{k,t} + \tilde{\lambda}^{aw}_k y^a_{t+1} + \epsilon^{aw}_{r_{\tilde{y}_k},t+1} \equiv (\tilde{\lambda}^{aw}_{0k})^\top z_t + \tilde{\lambda}^{aw}_k y^a_{t+1} + \epsilon^{aw}_{r_{\tilde{y}_k},t+1} \quad (25)$$

$$r^{naw}_{\tilde{y}_k,t+1} = \tilde{\lambda}^{naw}_{k,t} + \epsilon^{naw}_{r_{\tilde{y}_k},t+1} \equiv (\tilde{\lambda}^{naw}_{0k})^\top z_t + \epsilon^{naw}_{r_{\tilde{y}_k},t+1} \quad (26)$$

$$r^{na}_{\tilde{y},t+1} = \tilde{\lambda}^{na}_{k,t} + \epsilon^{na}_{r_{\tilde{y}_k},t+1} \equiv (\tilde{\lambda}^{na}_{0k})^\top z_t + \epsilon^{na}_{r_{\tilde{y}_k},t+1}, \quad (27)$$

where y^a_{t+1} is the average of all the standardized surprises released on day $t+1$ (in taking the average, the sign of countercyclical surprises is changed; more on the definition of procyclical and countercyclical announcements below). Hence, in modeling all-days returns and announcement-window returns we control for aggregate economic surprises. As shown by Faust and Wright (2011), this approach leads to more precise estimates of the predictive relation between instruments and futures returns.

Estimates of the coefficient vectors $\tilde{\lambda}_{0k}$, $\tilde{\lambda}_k$, $\tilde{\lambda}^{aw}_{0k}$, $\tilde{\lambda}^{aw}_k$, $\tilde{\lambda}^{naw}_{0k}$, and $\tilde{\lambda}^{na}_{0k}$ can be obtained by exactly-identified GMM, with orthogonality conditions

$$E(\epsilon_{r_{\tilde{y}_k},t+1} \otimes z_t) = 0 \quad (28)$$

$$E(\epsilon_{r_{\tilde{y}_k},t+1} \otimes y^a_{t+1}) = 0 \quad (29)$$

$$E(\epsilon^{aw}_{r_{\tilde{y}_k},t+1} \otimes z_t) = 0 \quad (30)$$

$$E(\epsilon^{aw}_{r_{\tilde{y}_k},t+1} \otimes y^a_{t+1}) = 0 \quad (31)$$

$$E(\epsilon^{naw}_{r_{\tilde{y}_k},t+1} \otimes z_t) = 0 \quad (32)$$

$$E(\epsilon^{na}_{r_{\tilde{y}_k},t+1} \otimes z_t) = 0. \quad (33)$$

[11] Specifically, they show that the maximum squared Sharpe ratio attainable from a set of GLS-style unit-beta mimicking portfolios is the same as the maximum squared Sharpe ratio attainable from a set of maximum-correlation mimicking portfolios. Since we consider only one announcement at a time, their result translates into the equality of the absolute value of the Sharpe ratio of a GLS-style unit-beta portfolio and of a maximum-correlation portfolio tracking the same announcement.

[12] Our approach is analogous to the approaches used in Adrian and Moench (2008) and Balduzzi and Robotti (2010).

The interpretability of the mimicking-portfolio risk premia can be improved by computing Sharpe ratios. Therefore, we standardize the estimated expected returns by the conditional standard deviation of returns calculated as

$$
\begin{aligned}
\hat{\sigma}_{r_{\tilde{y}_k},t} &= \sqrt{\widehat{\mathrm{Var}}(\epsilon_{r_{\tilde{y}_k},t+1})} && (34)\\
\hat{\sigma}^{aw}_{r_{\tilde{y}_k},t} &= \sqrt{\widehat{\mathrm{Var}}(\epsilon^{aw}_{r_{\tilde{y}_k},t+1})} && (35)\\
\hat{\sigma}^{naw}_{r_{\tilde{y}_k},t} &= \sqrt{\widehat{\mathrm{Var}}(\epsilon^{naw}_{r_{\tilde{y}_k},t+1})} && (36)\\
\hat{\sigma}^{na}_{r_{\tilde{y}_k},t} &= \sqrt{\widehat{\mathrm{Var}}(\epsilon^{na}_{r_{\tilde{y}_k},t+1})}, && (37)
\end{aligned}
$$

for all-days returns, announcement-window returns, non-announcement-window returns, and non-announcement-day returns, respectively.[13]

The same analysis described above is performed to estimate the risk premia $(\lambda_{k,t})^{\star}$ on maximum-correlation mimicking portfolios: First, we project the returns of maximum-correlation mimicking portfolios, earned on different days and at different times, on the instruments z_t, while controlling for aggregate economic surprises in modeling all-days returns and announcement-window returns. Second, we standardize the estimated expected returns by the conditional standard deviation of returns.

2.4 Latent factors and asset pricing restrictions

So far, we have assumed that the factors driving returns are explicit macroeconomic factors. It is possible, though, that the different macroeconomic surprises are summarized by the realizations of $H < K$ latent factors $f_{i,t}$. In other words, we have

$$r^{aw}_{i,t+1} = \beta_{0,t} + \beta_t y_{i,t+1} + \epsilon^{aw}_{r,i,t+1} = \beta_{0,t} + \beta^f f_{i,t+1} + \epsilon^{aw}_{r,i,t+1}, \tag{38}$$

where β^f is an $N \times H$ matrix and

$$f_{i,t+1} = \delta_t y_{i,t+1}, \tag{39}$$

δ_t being an $H \times K$ full-rank matrix. Under the assumptions above,

$$\beta_t = \beta^f \delta_t, \tag{40}$$

where $\mathrm{rank}(\beta_t) = H < K$. Hence, we assume that the factor loadings on the latent factors are constant, but we allow the coefficients of the relationship between the latent factor and the explicit economic factors to be time-varying.

[13] Note, that in order to have a quantity observed at time t, from the variance of the residuals for all-days returns and announcement-window returns, we exclude the effect due to the aggregate surprises.

Given our assumptions on the time variation in $\beta_{0,t}$ and β_t, we have

$$\beta_{0,t} = \beta_0 z_t \tag{41}$$

and

$$\beta_t = \beta(\mathbf{I}_K \otimes z_t) = \beta^f \delta_t = \beta^f [\delta(\mathbf{I}_K \otimes z_t)], \tag{42}$$

where δ is a full-rank $H \times (KJ)$ matrix. Hence, we can write

$$\begin{aligned} r^{aw}_{i,t+1} &= \beta_{0,t} + \beta(\mathbf{I}_K \otimes z_t) y_{i,t+1} + \epsilon^{aw}_{r,i,t+1} \\ &= \beta_{0,t} + \beta y^z_{i,t+1} + \epsilon^{aw}_{r,i,t+1} \\ &= \beta_0 z_t + \beta^f \delta(\mathbf{I}_K \otimes z_t) y_{i,t+1} + \epsilon^{aw}_{r,i,t+1} \\ &= \beta_0 z_t + \beta^f \delta y^z_{i,t+1} + \epsilon^{aw}_{r,i,t+1}. \end{aligned} \tag{43}$$

We impose and test the restriction

$$\beta = \beta^f \delta, \tag{44}$$

where $\text{rank}(\beta) = H < KJ$. For identification purposes, we normalize β^f so that the first H securities have unit exposure to the H latent factors:

$$(\beta^f)^\top = [\mathbf{I}_H, (\beta^f_2)^\top]. \tag{45}$$

For example, if $H = 1$, $\beta^f_1 = 1$, and the single latent factor is perfectly correlated with the "fitted" returns on the first security.

The estimation of the coefficient matrices β^f and δ can be performed by over-identified GMM, with orthogonality conditions[14]

$$E(\epsilon^{aw}_{r,i,t+1} \otimes y^z_{i,t+1}) = 0. \tag{46}$$

Note that instead of having to estimate the NKJ parameters of the unrestricted model, we estimate $(NH - H^2) + HKJ$ parameters, leading to $NKJ - [(NH - H^2) + HKJ]$ overidentifying restrictions.

The model described above corresponds to the set-up of Zhou (1994, 1999) extended to allow for interaction terms.[15] Using a sub-optimal weighting matrix, Zhou's (1994, 1999) methodology allows us to obtain analytical closed-form solutions for the GMM estimates of β_f and δ.

[14] We take a two-step approach where we first regress $r^{aw}_{i,t+1}$ on z_t, to obtain an estimate of β_0, and we then model the residuals as $r^{aw}_{i,t+1} - \hat{\beta}_0 z_t = \beta^f \delta y^z_{i,t+1} + \epsilon^{aw}_{r,i,t+1}$.

[15] Zhou (1994) considers an application where, because of the restrictions of an asset pricing model, L instruments predict asset returns through $K < L$ factor risk premia. Zhou (1999) considers an application analogous to ours, where M explicit factors affect contemporaneous asset returns through $K < M$ latent factors.

The estimate of δ involves H eigenvectors of a $(KJ) \times (KJ)$ matrix, whereas the β^f matrix is obtained from a set of GLS-style regressions of returns on $\delta_t y_{i,t+1}$. Zhou (1994, 1999) also provides a test statistic of the overidentifying restrictions that is equivalent to a test of a rank restriction on the beta coefficients (for example, if we are testing the null hypothesis of one latent factor, the rank of the matrix β should be equal to one).

Note that an alternative approach to the extraction of latent factors would be to test whether the vector of macroeconomic surprises is itself representable by a low-dimensional factor model. The problem with this approach is that the different surprises mainly take place on different days and, when any given surprise is released, most of the other surprises are zero. This implies that the covariance matrix of the surprises is close to being diagonal, and it is not possible to extract a few dominant principal components.[16]

Given the latent-factor betas, we can construct the weights of the unit-beta mimicking portfolios as

$$\tilde{\gamma}_t^f = \{[(\beta^f)^\top W_t \beta^f]^{-1} (\beta^f)^\top W_t\}^\top. \tag{47}$$

In addition, the weights of the maximum-correlation mimicking portfolio tracking $f_{i,t}$ can be calculated as

$$(\gamma_t^f)^\star = \delta_t \gamma_t^\star, \tag{48}$$

where $\gamma_t^\star$ is the $K \times N$ matrix of mimicking portfolio weights for the explicit factors. Given the composition of the unit-beta and maximum-correlation mimicking portfolios tracking the latent factor, we can estimate the conditional risk premia $\tilde{\lambda}_t^f$ and $(\lambda_t^f)^\star$ in the same way as we did for the mimicking portfolios tracking the explicit factors.

Note that, based on (38), we can also formulate and test an asset pricing model. We can compute the residuals

$$\begin{aligned}
e_{t+1} &\equiv r_{t+1} - \beta^f \tilde{\lambda}_t^f && (49)\\
e_{t+1}^{aw} &\equiv r_{t+1}^{aw} - \beta^f \tilde{\lambda}_t^{f,aw} && (50)\\
e_{t+1}^{naw} &\equiv r_{t+1}^{naw} - \beta^f \tilde{\lambda}_t^{f,naw} && (51)\\
e_{t+1}^{na} &\equiv r_{t+1}^{na} - \beta^f \tilde{\lambda}_t^{f,na}, && (52)
\end{aligned}$$

and we can then test whether

$$\begin{aligned}
E(e_{t+1} \otimes z_t) &= 0 && (53)\\
E(e_{t+1}^{aw} \otimes z_t) &= 0 && (54)\\
E(e_{t+1}^{naw} \otimes z_t) &= 0 && (55)\\
E(e_{t+1}^{na} \otimes z_t) &= 0. && (56)
\end{aligned}$$

Hence, although the composition of the unit-beta mimicking portfolios is estimated using announcement-window returns only, the asset-pricing restrictions are tested using returns at all times.

[16]The same issue applies in the implementation of the canonical-correlation analysis approach of Ahn et al. (2009).

2.5 Bootstrap inference

We bootstrap the data under various nulls, to account for small-sample effects—e.g., the "Stambaugh" bias (Stambaugh, 1999) arising from the persistence of the instruments used to predict returns—and for the sampling variability in all estimated quantities—e.g., the sampling variability of the weights of the unit-beta and maximum-correlation mimicking portfolios (Shanken, 1992). The Appendix presents details of the various null hypotheses that we impose in bootstrapping the data.

3 Data

Our data covers the period March 2, 1993 to March 31, 2008. Three different data sets are used. The first data set consists of the macroeconomic announcements data and consensus forecasts. The second data set consists of the intra-day futures prices. The third data set consists of daily data on interest rates and macroeconomic indicators that are used as instruments in the conditional analysis.

3.1 Macroeconomic announcements

Macroeconomic announcements are publicized events, which happen on pre-scheduled dates. We 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 Action Economics after 2003.[17] MMS data have been used extensively in the literature.[18] For the monetary policy expectations, we 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 1990.[19] The final data set includes data from the 22 macroeconomic announcements listed in Table 1 with abbreviations, units, and sources.[20] The economic indicators considered in this study 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, and

[17] MMS was acquired by Informa in 2003 and no longer exists; Action Economics is now providing the same survey service. These data were purchased from Haver Analytics. Since the beginning of the 1980s, MMS surveyed around 40 market participants weekly (every Friday, except on holidays) for their forecasts of major economic indicators.

[18] See, among others, McQueen and Roley (1993), and Balduzzi et al. (2001). Another provider of announcement data is Bloomberg, but these data are only available starting in 1997. We compared the announcements and the forecasts obtained from Bloomberg with those from MMS and they appear to be very similar. Any discrepancy in the announcements was checked in Factiva to obtain the correct values.

[19] The Federal Open Market Committee (FOMC) began to explicitly announce changes in its target for the federal fund rates and hold regularly scheduled meetings only in February 1994. Before 1994, the FOMC did not explicitly announce changes in its target for the federal funds rate, but such changes were implicitly communicated to financial markets through changes in open market operations (see Gürkaynak et al., 2006, for more details).

[20] Data starting from March 1993 are available for all the announcements with the exception of the Chicago Purchasing Manager Index (starting date October 1998), the Employment Cost Index (starting date July 1994), Existing Homes Sales (starting date December 1996), and the Philadelphia Fed Index (starting date November 1998).

Nonfarm Productivity).[21] Some of the announcements are released concurrently. This always happens for a few announcements that are released at the same time such as Non-farm Payrolls and Unemployment rate, and GDP and GDP Deflator.[22]

We chose to use survey forecasts, rather than the predictions of a time-series model (see, for example, Campbell, 1996, and, more recently, Petkova, 2006), because of the potential misspecification of the time-series model. In addition, survey forecasts are available for a large cross-section of announcements. Also, note that our measures of economic surprises are based on real-time data, as opposed to revised data.

3.2 Futures prices

We purchased intra-day data on the two-, five-, and ten-year T-note futures and the 30-year T-bond futures prices from TickData.[23] We focus on the futures market because it provides a long time-series of prices from the same trading platform. The secondary market for U.S. Treasuries, on the other hand, has switched from a voice-brokered system to electronic trading starting in 1999. In addition, as shown by Mizrach and Neely (2008), 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) document that the forward and spot T-bill prices include compensation for the risk that the counterpart may default.

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 (following Ederington and Lee, 1993, 1995, we only switch to the next maturity contract when the trading volume of the second nearby contract exceeds the nearby contract). Hence, the futures contracts that we select are very close substitutes for the underlying spot instruments and we feel that our results are generalizable to bond spot markets.

Intra-day futures returns are calculated using the log of the ratio of the price at the end and at the beginning of a 30-minute interval around the announcement (five minutes before and 25 minutes after the announcement, similar to Balduzzi et al., 2001).[24,25] For the daily futures the settlement prices are used so their returns can be

[21]The GDP announcements are released monthly because, in addition to the final report, we also consider the advance and the preliminary reports.

[22]CPI and PPI are released together with a measure that excludes food and energy (core measure). We focus on the non-core measures because they allow for longer time-series.

[23]While the 30-year, the ten-year, and five-year contracts started trading in the 1980s, the two-year contract only started in the early 1990s.

[24]If there is no trade during the window, we search back in time until we find a trade or settlement price. If there is no trade exactly 25 minutes after the event, we again search back in time until the data release moment. If no trade is found, we consider it a missing value.

[25]While not reported in this paper, we also experimented with announcement-window returns calculated over a shorter window, starting five minutes before the announcements and ending ten minutes after the announcements. The results are analogous to those reported for the 30-minutes window.

compared with the spot returns. The announcement-day returns earned outside of the announcement windows are computed taking the difference between the daily returns and the announcement-window returns.

Table 2 presents summary statistics for the returns on the four futures contracts. The main feature of the data apparent from the table is that (with the exception of the 30-year contract) average daily futures returns are positive and significant, and this is due to what happens on announcement days, outside of the announcement windows.[26,27] Average futures returns during the announcement windows and on non-announcement days, on the other hand, are insignificant. Sharpe ratios can be substantial: the annualized Sharpe ratios earned on announcement days, outside of the announcement windows, range between 0.57 and 1.06, decreasing monotonically with the maturity of the contract.[28] This result refines the finding of Jones et al. (1998), who also find evidence of significant risk premia on announcement days, and not on non-announcement days, but do not distinguish between behavior during the announcement windows and outside of the announcement windows.

3.3 Instruments

We use two different sets of interest rate factors as instruments for the conditional analysis. The first set includes the first five principal components (PCs) extracted from the levels of zero-coupon Treasury yields for different maturities spanning from one year to 30 years. The data on yields are provided by Gürkaynak et al. (2007).[29,30] They estimate a daily U.S. Treasury yield curve using the Svensson (1994) six-parameter function, which is an extension of Nelson and Siegel (1987). This approach assumes that instantaneous forward rates n periods ahead, $F_t(n)$, are characterized by a continuous function with six parameters:

$$F_t(n) = b_{0,t} + b_{1,t} \exp\left(-n/\tau_1\right) + b_{2,t}\left(-n/\tau_{1,t}\right) \exp\left(-n/\tau_{1,t}\right) + b_{3,t}\left(-n/\tau_{2,t}\right) \exp\left(-n/\tau_{2,t}\right). \tag{57}$$

The second set of instruments consists of the six parameters: $b_{0,t}$, $b_{1,t}$, $b_{2,t}$, $b_{3,t}$, $\tau_{1,t}$, and $\tau_{2,t}$. We can interpret these parameters as a 6-factor model of the term structure. Diebold and Li (2006) show that the three parameters entering linearly the Nelson and Siegel (1987) specification can also be interpreted as factors related to the "level," "slope," and "curvature" of the yield curve. With six parameters it is more difficult to find an interpretation for all parameters, but $b_{0,t}$ can be interpreted as the level factor and $b_{1,t}$ is highly (negatively) correlated with the second PC (the slope factor). Using the first five PCs and the six Svensson parameters could seem unnecessary considering the stylized fact that we only need three factors to model the term structure of interest rates (see

[26]By "significant," here and in the rest of the paper, we mean a quantity with an associated bootstrap p-value at or below 5%.

[27]Note that the standard deviation is actually higher for non-announcement-window returns than for announcement-window returns. This is because non-announcement-window returns are computed over a much longer time interval. On the other hand, the standard deviation is substantially higher for announcement-day than for non-announcement-day returns.

[28]This inverse relation between Sharpe ratios and bond maturity has been documented by others; see, for example, Duffee (2010).

[29]These data are available at http://www.federalreserve.gov/econresdata/researchdata.htm.

[30]We also considered a different set of daily yields, the zero yields produced by the research department of the Federal Reserve Bank of Atlanta, which are extracted from the daily CRSP Treasury data using the "unsmoothed" Fama-Bliss approach. The sample covered by this data set ends in 2002. The results of predictive regressions for futures returns using this alternative data set and sample are similar to those obtained using the Gürkaynak et al. (2007) data set and the full sample.

Knez et al., 1994, and Litterman and Scheinkman, 1996). However, in light of Cochrane and Piazzesi (2005) and as suggested by Duffee (2011), we can have a factor that is not important to explain the cross-section, but can be important in predicting returns.[31]

In addition to interest rate factors, we also consider the daily macro factor (MF) obtained by Aruoba et al. (2009).[32] This factor, called the Aruoba-Diebold-Scotti business conditions index, is extracted using a Kalman filter from a pool of economic indicators from different frequencies: weekly Initial Jobless Claims; monthly Nonfarm Payrolls, Industrial Production, Personal Income (less transfer payments), Manufacturing and Trade Sales; and quarterly real GDP. Cooper and Priestly (2008) and Ludvigson and Ng (2009), for example, show that it is important to use information extracted from macroeconomic variables to predict bond excess returns; and Barillas (2011) shows that these predictability patterns, driven by economic variables other than bond yields, are economically valuable in an optimal portfolio exercise.[33]

Table 3 presents summary statistics for the two sets of yield factors and for the macro factor. As anticipated above, the first PC in bond yields correlates strongly with $b_{0,t}$ (with a 0.52 correlation coefficient) and the second PC correlates strongly with $b_{1,t}$ (with a -0.63 correlation coefficient).

4 Empirical results

4.1 Estimating the composition of unit-beta portfolios

The basic input for the construction of unit-beta portfolios are the betas of regressions of futures returns on all the 22 economic surprises as per equation (3). We consider three choices of instruments z_t. First, we consider the case where z_t only includes a constant and betas are constant ("Uncon"). Second, we consider the case where z_t includes a constant and the first five PCs of yields and MF ("Con1"). Third, we consider the case where z_t includes a constant, the six parameters of the extended Nelson-Siegel specification estimated by Gürkaynak et al. (2007), and MF ("Con2"). In order to limit the sampling variability in portfolio weights due to poorly estimated announcement betas, we use a specification-search algorithm that recursively eliminates the least significant regressor until all t-ratios are above one (stepwise regression).[34]

[31]We also experimented with the predictive factor of Cochrane and Piazzesi (2005), which is a linear combination of forward rates. When this factor is constructed using the daily data set of Gürkaynak et al. (2007), though, its predictive ability for futures returns is modest.

[32]The time-series of the macro factor is available at http://www.phil.frb.org/research-and-data/real-time-center/business-conditions-index.

[33]Following Buraschi and Whelan (2011), we also consider as a predictor a measure of the dispersion of survey forecasts. Specifically, we use the range—the maximum value minus the minimum value—of survey forecasts for the different announcements. This measure of forecast dispersion is collected by Bloomberg for the sample period 1997–2008, for a subset of the announcements that we consider. For each announcement, we de-mean and standardize the series of forecast ranges, to obtain a "normalized" range series. We then aggregate the normalized range series to obtain a single aggregate series. We find that, in our sample, the predictive ability of this indicator for futures returns is modest.

[34]This procedure is equivalent to choosing regressors to maximize the adjusted R-squared of the regression (Greene, 2002, Theorem 3.7).

Results of the regressions are reported in Table 4. We only report the estimates of the constant beta and of the average time-varying beta. Across announcements and futures contracts, the constant beta and the average time-varying beta are similar, but the interaction terms are always jointly significant at the 5% level or better.[35] Not surprisingly, slope coefficients tend to increase (in absolute value) with the maturity of the bond underlying the futures contract. For example, in the case of retail sales (RetS), the unconditional beta goes from −0.03 for the two-year contract to −0.09 for the 30-year contract. There is also substantial variation in the effects of the different announcements on the same contract. For example, for the two-year contract, unconditional slope coefficients range from −0.10 to 0.04.

Across contracts, RetS, Nfarm, Chic, CConf, CPI, Durab, ECI, EHS, GDP, Defla, Hst, IP, Lind, ISM, NewH, Phil, and PPI announcements have a negative impact on prices, for all choices of instruments; whereas Ijob and Unemp announcements have a positive impact. Two announcements, Buinv and Budge, do not have a t-ratio above one and are dropped by the stepwise regression. Based on the reaction of futures prices, we denote the first set of announcements—including the FOMC announcement—as *procyclical*, and the second set of announcements as *countercyclical*.

4.2 Estimating the composition of maximum-correlation mimicking portfolios

In the case of maximum-correlation mimicking portfolios, estimates of the portfolio weights are obtained directly from regressing each surprise on the announcement-window futures returns interacted with the instruments as per equation (16). As in the case of unit-beta mimicking portfolios, we consider three choices of instruments and we use a stepwise-regression approach to minimize the noise in the estimates of portfolio weights.

Table 5 reports results of the estimation.To save space, we only report the adjusted R-squared and the bootstrap p-values of a Wald test. The table highlights how different announcements are spanned by futures returns in very different ways. For example, given the first choice of instruments (Uncon), the adjusted R-squared of the regression ranges from 0.00% (Budge) to 43.70% (Nfarm). The table also highlights how introducing interaction terms improves the fit of the regression: for example, for Buinv, the adjusted R-squared increases from 0.81% to 9.80% as we add returns interacted with the five PCs of yields. On average, the adjusted R-squared almost doubles when the interaction terms are included (from 13.6% to 22.89%, for the Con1 specification, and to 21.32%, for the Con2 specification). We also test whether the mimicking portfolios "track" the surprises by performing a joint test of the significance of the portfolio weights (the slope coefficients) estimated in the regression. For both choices of instruments, the test shows that the majority of the announcements are significantly tracked by futures returns. This result is the complement of the significant reaction of futures returns to macroeconomic announcements documented in Table 4.

[35]The only exception is the beta on the 30-year contract for the FOMC announcement, that switches from positive to negative, although neither the constant or the average beta are significant at the 5% level.

The results above confirm the findings of Joslin et al. (2010), who show that measures of economic growth and inflation are poorly explained by the five PCs of bond yields, using monthly-frequency data for the January 1985-December 2007 period. In particular, when changes in the two economic measures are regressed on changes in the five PCs, the R-squareds are only 2.8% and 4.8% for economic growth and inflation, respectively. Hence, while our results show that spanning can be substantially improved when focusing on intra-day data and allowing for conditioning information, we also confirm that spanning is far from complete.

4.3 Risk premia on unit-beta portfolios

We use the betas estimated in section 4.1 to construct OLS-style and GLS-style unit-beta mimicking portfolios for 20 of the 22 announcements of Table 1. The two announcements Buinv and Budge, that were dropped in all the stepwise regressions of futures returns on surprises, are not considered. For the other announcements, if an announcement is dropped in a regression, the corresponding beta is set equal to zero in the construction of unit-beta portfolios. The properties of the returns on the mimicking portfolios are evaluated during different trading intervals: i) during all trading days; ii) during the announcement windows; iii) during announcement days, but outside of the announcement windows; and iv) during non-announcement days. We report results for the case where portfolio weights are based on the constant component of the time-varying betas: betas are estimated according to (3), allowing for time-varying betas, and portfolio weights are computed according to (5), where all instruments z_t, other than the constant, are set equal to zero. We chose this specification because Table 4 shows how the interaction terms are strongly significant and, hence, ignoring time-variation in the betas would be incorrect. At the same time, allowing for time variation in the unit-beta portfolio weights leads to less precise estimates of average conditional Sharpe ratios and of predictability patterns in conditional Sharpe ratios.[36] As to the choice of instruments, we report results for the case where the vector z_t includes a constant, the five PCs of yields, and MF.[37] In predicting all-days returns and announcement-window returns, we control for aggregate economic surprises. The inclusion of the aggregate economic surprises is the reason for the high adjusted R-squareds for those predictive regressions.

4.3.1 OLS-style unit-beta portfolios

Panel A of Table 6 reports results for the OLS-style unit-beta mimicking portfolio returns realized on all trading days. For ease of interpretation, all coefficient estimates are standardized by the standard deviation of *innovations* in the returns on the corresponding futures contract—the residuals from the predictive regressions, but excluding

[36] We do report results for the case of time-varying betas and time-varying weights in the analysis of the factor model with a single latent factor and with maximum-correlation mimicking portfolios.

[37] Here and in the rest of the paper, we choose to report the results where we use the PCs as instruments, instead of the six Svensson parameters, because, in regressions of futures returns on the two sets of instruments, the PCs almost always lead to slightly higher adjusted R-squareds. In addition, the PCs also have a slight advantage in terms of interpretability.

the effect of the aggregate news—and they are scaled by $\sqrt{250}$. As a result, given that the instruments are demeaned, and given that the aggregate surprises have mean close to zero, the intercept terms have the interpretation of average annualized conditional Sharpe ratios, and the slope coefficients have the interpretation of changes in the conditional Sharpe ratio for a one standard deviation change in the instrument. The constant component of the conditional Sharpe ratio is positive (negative) for procyclical (countercyclical) announcements. Average conditional Sharpe ratios are similar in absolute value across announcements, ranging between 0.47 (Defla) and 0.69 (EHS). For 19 announcements, bootstrap p-values are at or below 5%. As to predictability patterns, with only two exceptions, the coefficients associated with the instruments are insignificant. Interestingly, although the effects are mainly insignificant, they are quite similar (in absolute value) across announcements and substantial. For PC1, for example, a one-standard-deviation increase leads to an absolute change in the conditional Sharpe ratio between 0.51 and 0.62—this is roughly the same magnitude as the average conditional Sharpe ratios.

Panel B of Table 6 reports results for returns computed during the announcement windows. In this case, all average Sharpe ratios are insignificant, although there is significant variation driven by PC3 (all 20 coefficients): an increase in PC3 leads to an increase (decrease) in the conditional Sharpe ratios of portfolios mimicking procyclical (countercyclical) macroeconomic variables. Again, predictability patterns are similar (in absolute value) across announcements and substantial: between 0.72 and 0.90.

Panel C of Table 6 reports results for returns computed during announcement days, but outside of the announcement windows. This is the sample for which we have the more significant conditional and unconditional effects. Moreover, average Sharpe ratios and predictability patterns are substantial and similar (in absolute value) across announcements. Indeed, average conditional Sharpe ratios are negative (positive) for procyclical (countercyclical) variables, ranging between 0.57 and 1.06 in absolute value, with 19 coefficients significant at the 5% level or better. Conditional Sharpe ratios become more negative (positive) with PC1 for procyclical (countercyclical) variables. The coefficients range between 0.81 and 1.08 in absolute value, with 18 of them significant. Conditional Sharpe ratios become less negative (positive) with MF for procyclical (countercyclical) variables. The coefficients range between 0.90 and 1.46 in absolute value, with 19 of them significant.

Panel D of Table 6 reports results for returns computed during non-announcement days. In this case, average Sharpe ratios are insignificant, but there is significant variation driven by PC2 (19 significant coefficients). This effect is negative (positive) for procyclical (countercyclical) macro variables and quantitatively large, between 0.86 and 1.03 in absolute value.

4.3.2 Alternative approaches to inference

As an alternative to the bootstrap p-values for tests of the significance of the economic risk premia, we also computed *asymptotic* p-values, which are *conditional* on the composition of the mimicking portfolios. These p-

values are estimated Fama-MacBeth (FM, 1973) style, i.e., they are simply the p-values on the t-ratios from regressing the mimicking-portfolio returns on the instruments.

We find that the FM p-values are generally similar to the bootstrap p-values, although they display much less variation across announcements.[38] This is consistent with the fact that the FM p-values ignore the different degrees of precision in the estimates of portfolio weights, since they condition on the mimicking-portfolio composition. The FM p-values confirm the significant average Sharpe ratios for all-days (19 significant coefficients) and for non-announcement-window (19 significant coefficients) returns. The predictive ability of PC1 (20 significant coefficients) and MF (20 significant coefficients) for non-announcement-window returns is also confirmed. Also consistent with the bootstrap inference, we find PC3 (20 coefficients) and PC2 (20 coefficients) to be significant predictors for announcement-window and non-announcement-day returns, respectively. Unlike the bootstrap inference, though, the significance of PC1, for non-announcement-window returns, and of PC3, for announcement-window returns, carries over to all-days returns (16 significant coefficients). We attribute this result to the fact that the FM p-values underestimate the sampling variability of the estimated regression coefficients and to the Stambaugh bias arising from the high persistence in PC1.

While the bootstrap inference gives us the appropriate p-values, it does not correct the point estimates for the small-sample bias due to the persistence of the instruments that we use as predictors (Stambaugh, 1999). Hence, we follow Amihud and Hurvich's (2004) "augmented regression" approach to correct the bias in the point estimates; and we use Amihud, Hurvich, and Wang's (AHW, 2009) results to perform statistical inference on the bias-adjusted estimates.

Of the significance patterns identified with the bootstrap approach, only one disappears: the predictive power of PC3 for announcement-window returns. At the same time, one other significant pattern shows up: MF is a predictor of all-days returns (19 significant coefficients).[39]

In summary, most of the patterns documented using bootstrap-based inference are confirmed by the alternative approaches to inference used in this section. In particular, *all* the significant patterns for non-announcement-window returns are confirmed.

4.3.3 GLS-style unit-beta portfolios

Table 7 performs the same exercises discussed above, but using the returns on GLS-style, instead of OLS-style, unit-beta mimicking portfolios. In the interest of space, we only focus on the most significant results, i.e., the results obtained for non-announcement-window returns.

[38] Detailed results are not reported in the tables, but are in a separate appendix available from the authors upon request.

[39] Note that, when we implement the AHW approach, we do not use the aggregate surprise as a regressor. This is probably at the origin of some of the discrepancies relative to the bootstrap and FM approaches. Indeed, when we exclude aggregate surprises as a regressor while using the FM approach, MF also shows up as a significant predictor of all-days returns (20 coefficients).

Average conditional Sharpe ratios are negative (positive) for procyclical (countercyclical) variables, ranging between 0.21 and 1.09 in absolute value, with 14 out of 20 coefficients significant at the 5% or better. Conditional Sharpe ratios generally decrease (increase) with PC1 for procyclical (countercyclical) variables, with coefficients ranging between 0.07 and 1.10 in absolute value, although only two of them are significant. Conditional Sharpe ratios increase (decrease) with MF for procyclical (countercyclical) variables, with coefficients ranging between 0.01 and 1.45 in absolute value, with 12 of them significant. In summary, compared with OLS-style portfolios (Table 6, Panel C), these results are similar, although some of the significance of PC1 is lost and there is more variation in coefficients across announcements. This is probably due to more noise caused by the time variation in weights induced by the weighting matrix.

4.4 Risk premia on maximum-correlation portfolios

We use the portfolio weights estimated in Section 4.2 to construct maximum-correlation mimicking portfolios. As in the case of the unit-beta portfolios, we report results for the case where portfolios are constructed using the average component of the time-varying portfolio weights.[40]

Table 8 reports the Sharpe ratios from investing in maximum-correlation mimicking portfolios. In this case, in addition to Buinv and Budge, we also exclude the leading indicators (Lind) announcement because, as shown in Table 5, they are not significantly spanned by futures returns: the adjusted R-squareds are below 1%. Again, we only focus on the results for non-announcement-window returns.

Average conditional Sharpe ratios are mainly significant (14 out of 19), and they are generally positive (negative) for countercyclical (procyclical) announcements. PC1 is a significant predictor for three portfolio returns, while MF is a significant predictor for 13 mimicking portfolio returns, with the effect being generally positive (negative) for procyclical (countercyclical) variables. These effects are roughly consistent with those documented for unit-beta mimicking portfolios, particularly those constructed GLS-style.

4.5 Latent factor

4.5.1 Tests of one-factor structure

We implement the analysis of Zhou (1994, 1999) described in Section 2.4. We exclude the four announcements that are dropped in at least *two* of the regressions in Table 4 for the Con1 model (Buinv, Budge, EHS, and Defla); and we also exclude the instruments that are dropped in one or more of the regression models. We cannot reject the null hypothesis that the economic announcements affect futures prices through *a single factor* (the asymptotic p-value on the chi-squared statistic is 0.53). This implies that we cannot reject the restriction that the rank of the

[40] We do report results for the case of constant weights and for the case of time-varying weights in the analysis of the factor model with a single latent factor.

matrix β should be equal to one.

We further investigate the implication above by computing the correlation matrix of the elements of the rows of β_t, when z_t is at its unconditional mean. Results are reported in Table 9. All correlations are quite high, especially in the case where we exclude the betas associated with the FOMC announcement (in addition to the betas associated with Buinv, Budge, EHS, and Defla). In this case, the correlation coefficients range between 0.97 and 1.00. Indeed, when we follow Ahn et al. (2011) and perform a singular-value decomposition of the correlation matrix of the betas, the resulting multi-collinearity coefficient—the square root of the ratio between the maximum and the minimum eigenvalues of the correlation matrix of the betas—equals 44.6, which is strong evidence of multicollinearity.

The fact that the rank of β_t is not statistically different from one also explains the similarity of the Sharpe ratios earned by unit-beta portfolios mimicking different announcements. Indeed, consider the k-th and j-th announcement and assume $\beta_{k,t} = c\beta_{j,t}$, where c is an arbitrary constant. The coefficients of the unit-beta mimicking portfolio for the k-the announcement are given by $\tilde{\gamma}_{k,t}^{\top} = (\beta_{k,t}^{\top} W_t \beta_{k,t})^{-1} \beta_{k,t}^{\top} W_t$. Since $\beta_{k,t} = c\beta_{j,t}$, we have $\tilde{\gamma}_{k,t}^{\top} = (1/c)\tilde{\gamma}_{j,t}^{\top}$. This implies that the Sharpe ratios on the mimicking portfolios for the two announcements are the same:

$$\frac{\tilde{\gamma}_{k,t}^{\top} E_t(r_{t+1})}{\sqrt{\tilde{\gamma}_{k,t}^{\top} \Sigma_{rr,t} \tilde{\gamma}_{k,t}}} = \frac{(1/c)\tilde{\gamma}_{j,t}^{\top} E_t(r_{t+1})}{\sqrt{(1/c)^2 \tilde{\gamma}_{j,t}^{\top} \Sigma_{rr,t} \tilde{\gamma}_{j,t}}} = \frac{\tilde{\gamma}_{j,t}^{\top} E_t(r_{t+1})}{\sqrt{\tilde{\gamma}_{j,t}^{\top} \Sigma_{rr,t} \tilde{\gamma}_{j,t}}}. \tag{58}$$

Finally, we perform a principal component analysis of the *fitted* values of equation (1). We find that the first PC explains 97.77% of the variance of the fitted returns, on average. This first PC has a correlation of 0.98 with the latent factor extracted using Zhou's (1994, 1999) methodology. Overall, this evidence, and the evidence above, strongly corroborates the conclusion that economic announcements affect returns through a single dominant factor.

4.5.2 Mimicking portfolios and risk premia

We follow the approach outlined in Section 2.4 to construct unit-beta and maximum-correlation mimicking portfolios, where we use the normalization suggested in Zhou (1994, 1999) and we set the latent factor loading of the two-year futures contract equal to one. This means that the latent factor is rotated to be countercyclical. Results on the estimation of Sharpe ratios are reported in Table 10.

For this case of a single latent factor, we report results for both constant-weights and time-varying-weights maximum-correlation mimicking portfolios and also allowing for constant and time-varying δ_t in equation (48).[41] Overall, results are consistent with the results obtained for the portfolios mimicking the individual announcements: Average Sharpe ratios are significant for all-days returns and non-announcement-window returns (all six portfolios);

[41] We do not consider the case of time-varying weights for the unit-beta mimicking portfolios because we assume that the factor loadings on the latent factor are constant.

PC1 and MF are significant predictors of non-announcement-window returns (four and six portfolios, respectively); and PC3 has some predictive ability for non-announcement-day returns (two portfolios). Focusing on the results for non-announcement-window returns (Panel C), the average Sharpe ratios are positive, as high as 1.08; a one-standard deviation increase in the level of interest rates increases the conditional Sharpe ratio by as much as 1.13; while a one-standard deviation increase in economic activity has an impact as negative as -1.42.

4.5.3 Understanding the nature of the latent factor

To better understand the nature of the latent factor, we compute the correlations between the daily mimicking-portfolio returns and the daily changes in the PCs of yields. Mimicking-portfolio returns are strongly (negatively) correlated with changes in the first PC. For the case of the OLS-style unit-beta mimicking portfolio, for example, the correlation is -0.97. Hence, we can interpret the latent factor as a term structure "level" shock. An examination of the loadings of the announcements on the latent factors shows that the most important determinants are: Nfarm, followed by FOMC, and ISM—we do not show these results because they are very similar to the betas in Table 4 for the two-year futures contract.

4.5.4 Tests of the one-factor asset pricing model

We test the null hypothesis that expected futures returns obey a one-factor asset pricing model; i.e., we test whether the exposure to a single latent factor explains the cross-section of expected bond futures returns. Table 11 reports annualized pricing errors and bootstrap p-values of individual and joint tests of the asset pricing restrictions in (53)–(56).

We use the risk premium estimates from OLS-style and GLS-style unit-beta mimicking portfolios and we consider two choices of instruments: i) a constant; and ii) a constant plus the five PCs of yields and MF. We consider four samples of returns: all-days returns, announcement-window returns, non-announcement-window returns, and non-announcement-day returns. We are unable to reject the null hypothesis of zero alphas in individual and joint tests for *all* choices of mimicking portfolios, instruments, and samples.[42] Hence, we conclude that exposure to a single latent factor associated with macroeconomic announcements explains the cross-section of expected bond futures returns. This finding applies not only to non-announcement-window returns but also to all-days returns.

[42]While not reported in the tables, we also computed the adjusted R-squareds of regressing announcement-window futures returns on the estimated latent factor. These R-squareds are similar to the ones reported in Table 4, ranging between 20.51% and 33.92%. More substantial are the R-squareds of regressions of daily futures returns on the daily returns of portfolios mimicking the latent factor. In the case of the OLS-style unit-beta portfolio, for example, these R-squareds range between 74.63% (two-year futures returns as regressand) and 97.85% (ten-year futures returns as regressand), indicating that the mimicking-portfolio return is an important systematic factor.

4.6 Implications for term structure modeling

Our empirical findings have implications for models of the term structure. First, we find that macro news are only imperfectly spanned by futures returns, even allowing for interaction terms and using a narrow window around the announcements. This finding supports a model like Joslin et al.'s (2010), where macro factors are not pricing factors themselves, but they help predict the variation of the latent pricing factors that drive the short rate.[43] On the other hand, this finding does not support macro-finance term structure models where macro factors are pricing factors and are spanned by bond yields (e.g. Ang and Piazzesi, 2003; see also Joslin et al., 2011, for a canonical form).

Second, we find that the risk premia on the mimicking portfolios are time-varying as functions of both yield curve factors and a macro factor. This finding is also consistent with Joslin et al.'s (2010) term structure model, where the macro factors predict the latent factors and bond returns.[44] More specifically, we can compare our results to Joslin et al.'s (2010) estimates of the risk premium associated with innovations in the level of yields. Since changes in our latent factor are negatively related to changes in the level of yields, based on our results of Table 10, we would expect the level risk premium estimated by Joslin et al. (2010) to be negatively related to the level of yields, and to be positively related to measures of economic growth and inflation. Interestingly, this is exactly what Joslin et al. (2010) find.

Third, we find that the reaction of bond futures to macro announcements effectively takes place through one latent factor, closely related to the level of yields, and that exposure to this latent factor explains the cross-section of expected bond futures returns. This finding is consistent with Cochrane and Piazzesi (2008), who show that exposure to a level shock is sufficient to explain bond risk premia. In this paper, we characterize the level shock as a latent factor driven by macroeconomic announcements.

Finally, we find that the economic risk premia are mainly earned on announcement days, outside of the announcement windows. Indeed, this is one of the novel findings of our study. One interpretation of this finding is that our tests lack the power to detect risk premia earned at announcement times and on non-announcement days.[45] On the other hand, if we take our results at face value, then we have implications for the pricing of jump versus diffusion risk. As discussed in Johannes (2004) and Piazzesi (2005), jumps in interest rates and bond prices are likely to occur when FOMC and other macroeconomic announcements take place. Hence, announcement-window

[43] In the canonical form of Joslin et al.'s (2010), the short rate depends only on the yield-curve factors, proxying for the unobservable latent factors, and the Q-dynamics of the yield-curve factors depend only on the yield-curve factors themselves. This implies that bond yields depend on the yield-curve factors only, and explicit macro factors need not be perfectly spanned by bond yields. The unspanned macro factors of Joslin et al. (2010) correspond to "hidden" factors in the framework of Duffee (2011). In Duffee (2011), though, the hidden factors are latent factors, rather than observable macro factors.

[44] In the canonical form of Joslin et al. (2010), the P-dynamics of the yield-curve factors involve both the yield-curve factors *and* the macro factors. Since risk premia arise as a result of the difference between the Q- and P-dynamics of the yield-curve factors, this implies that both the yield-curve factors and the macro factors predict bond returns.

[45] Indeed, at announcement times, we may have two confounding effects taking place: the response of returns to news, and a change in expected returns immediately before the release of the news. (We thank Wayne Ferson for suggesting this point.)

returns are likely to be dominated by jump risk, whereas non-announcement-window and non-announcement-day returns are likely to be dominated by diffusion risk. Our results would suggest that jump risk is not priced, whereas diffusion risk is priced, although only on announcement days.[46,47]

5 Conclusions

This paper provides robust evidence that macroeconomic risks are priced in the fixed income markets. Specifically, exposure to procyclical (countercyclical) variables earns negative (positive) Sharpe ratios, and the Sharpe ratios are more negative (positive) when the level of interest rates is high and when the economy is weak. These Sharpe ratios are substantial, quite similar across several portfolios tracking different announcements, and are mainly earned on announcement days, but outside of the announcement windows. We also show that a single latent factor is responsible for the reaction of bond returns to the announcements. This latent factor has a clear macroeconomic underpinning in this paper, and it is driven by the most important macroeconomic announcements: Nonfarm Payrolls, FOMC decisions, and ISM index. The Sharpe ratios associated with exposure to the latent factor are positive—the latent factor is rotated to be countercyclical—and increase with the level of interest rates and decrease with the level of economic activity. The latent factor is strongly correlated with shocks to the level of yields and exposure to the single latent factor explains the cross-section of expected bond futures returns.

[46]In equilibrium, jump risk is priced if the pricing kernel jumps at the time when bond prices jump, and the two jumps are correlated; diffusion risk is priced if bond returns and the pricing kernel share some of the same drivers (Piazzesi, 2009). Hence, our results would suggest that at announcement times the pricing kernel does not jump, or jumps independently of bond prices; that on announcement days, but outside of the announcement windows, bond prices and the pricing kernel have correlated diffusion variability; and that on non-announcement days, the drivers of the variability of the pricing kernel and bond prices are different.

[47]Note that an alternative explanation for our evidence on risk premia may have to do with information-asymmetry effects. Indeed, other studies have documented patterns in the Treasury markets that are related to informational asymmetries; see, for example, Fleming and Remolona (1999), Balduzzi et al. (2001), Green (2004), and Pasquariello and Vega (2007). Further research could investigate this alternative explanation.

Appendix

A.1 Bootstrap procedure

In this section, we illustrate the approach to generating bootstrap samples under the different nulls tested in the different tables.

A.1.1 Table 2

In Table 2, the null hypothesis is that returns have mean zero. Hence, we bootstrap the de-meaned returns at different times.

A.1.2 Table 4

In Table 4, the null hypothesis is that returns, $r^{aw}_{i,t+1}$, are not explained either by the lagged instruments, z_t, nor by the surprises interacted with the instruments, $y^z_{i,t+1}$. Hence, we bootstrap the de-meaned returns, $r^{aw}_{i,t+1} - \hat{E}(r^{aw}_{i,t+1})$, to obtain the bootstrap returns $r^{aw,b}_{i,t+1}$ under the null.

A possible bias in our analysis arises from the persistence of the instruments, and from the correlation between innovations in the instruments and innovation in returns (Stambaugh, 1999). Hence, we model the dynamics of the instruments assuming that the (mean-zero) time-varying component of the z_t vector, $z_{tv,t}$, follows the augmented VAR

$$z_{tv,t+1} = Az_{tv,t} + B[r_{t+1} - \hat{E}(r_{t+1})] + \epsilon_{z_{tv},t+1}, \tag{A.1}$$

where the daily de-meaned returns are introduced as additional regressors to replicate the correlation between returns innovations and innovations in the instruments. Bootstrap instruments are generated using the estimated law of motion,

$$z^b_{tv,t+1} = \hat{A}z^b_{tv,t} + \hat{B}r^b_{t+1} + \hat{\epsilon}^b_{z_{tv},t+1}, \tag{A.2}$$

where we keep the first observation, $z_{tv,0}$, constant across bootstrap samples. Note that the bootstrap daily returns are constructed from the bootstrap non-announcement-day returns and the sum of the bootstrap non-announcement-window returns and the bootstrap returns $r^{aw,b}_{i,t+1}$, aggregated across announcement windows during the day. In turn, bootstrap non-announcement-window returns and bootstrap non-announcement-day returns are generated by bootstrapping the corresponding de-meaned returns. Given observations on the instruments on all days, we then select observations for announcement days. For simplicity, the surprises are kept fixed across bootstrap samples.

A.1.3 Table 5

In Table 5, the null hypothesis is that the surprises $y_{k,i,t+1}$, are unrelated to the contemporaneous returns interacted with the instruments, $r^{aw}_{k,i,t+1} \otimes z_t$. The bootstrap data generated above is consistent with this null.

A.1.4 Tables 6–8 and 10

In Tables 6–8 and 10, the null hypothesis is that mimicking-portfolio returns have zero mean and are not predicted by the lagged instruments. Hence, we estimate (3) where we only set β_0 equal to zero. We then bootstrap the residuals across announcement windows. We use this bootstrap sample together with the sample surprises and the bootstrap instruments (obtained using the same law of motion described above), to calculate a bootstrap series of the announcement window returns as

$$r^{aw,b}_{i,t+1} = \hat{\beta} y^{z,b}_{i,t+1} + \hat{\epsilon}^{aw,b}_{r,i,t+1}. \tag{A.3}$$

We aggregate the bootstrap returns $r^{aw,b}_{i,t+1}$ over the I_{t+1} announcement windows on day $t+1$, to obtain the bootstrap announcement-window returns $r^{aw,b}_{t+1}$:

$$r^{aw,b}_{t+1} \equiv \sum_{i=1}^{I_{t+1}} r^{aw,b}_{i,t+1}. \tag{A.4}$$

The other bootstrap data are generated in the same way as described above.

We then regress the bootstrap announcement-window returns $r^{aw,b}_{i,t+1}$ on the sample surprises interacted with the bootstrap instruments. We obtain bootstrap values for betas and portfolio weights. We construct unit-beta mimicking portfolios interacting the bootstrap portfolio weights with the bootstrap returns. We regress the bootstrap mimicking portfolio returns on the bootstrap instruments (and aggregate sample surprises for the case of all-days and announcement-window bootstrap returns). For the GLS case, we obtain bootstrap counterparts of the estimates of the two covariance matrices (7) and (8) as the sample covariance matrices of the de-meaned daily bootstrap returns for announcement and non-announcement days, respectively.

In the case of maximum-correlation portfolios, we regress for each announcement the sample surprises on the bootstrap announcement-window returns (for the specific announcement) interacted with bootstrap instruments, to obtain bootstrap estimates of the portfolio weights, $\hat{\gamma}^{\star,b}_k$. We apply the bootstrap estimated portfolio weights to the bootstrap returns to obtain the bootstrap mimicking portfolio returns,

$$r^{b}_{y^\star_k,t+1} = (\hat{\gamma}^{\star,b}_{k,t})^\top r^{b}_{t+1} \tag{A.5}$$

$$r^{aw,b}_{y^\star_k,t+1} = (\hat{\gamma}^{\star,b}_{k,t})^\top r^{aw,b}_{t+1} \tag{A.6}$$

$$r^{naw,b}_{y^\star_k,t+1} = (\hat{\gamma}^{\star,b}_{k,t})^\top r^{naw,b}_{t+1} \tag{A.7}$$

$$r^{na,b}_{y^\star_k,t+1} = (\hat{\gamma}^{\star,b}_{k,t})^\top r^{na,b}_{t+1}, \tag{A.8}$$

and we regress the bootstrap mimicking portfolio returns on the bootstrap instruments (and aggregate sample surprises for the case of all trading days and announcement-window bootstrap returns).

A.1.5 Table 11

In Table 11, the null hypothesis is that expected returns satisfy the restrictions of a one-factor asset pricing model. Therefore, in this case, we allow for predictability in the futures returns. We obtain bootstrap returns as

$$
\begin{aligned}
r_{i,t+1}^{aw,b} &= \frac{1}{\bar{I}}\hat{\beta}^f \hat{\hat{\lambda}}_t^{f,aw,b} + (\hat{\beta}^f \hat{\delta}_t^b) y_{i,t+1} + \hat{\epsilon}_{r,i,t+1}^{aw,b} && \text{(A.9)}\\
r_{t+1}^{aw,b} &= \hat{\beta}^f \hat{\hat{\lambda}}_t^{f,aw,b} + \sum_{i=1}^{I_{t+1}} [(\hat{\beta}^f \hat{\delta}_t^b) y_{i,t+1} + \hat{\epsilon}_{r,i,t+1}^{aw,b}] && \text{(A.10)}\\
r_{t+1}^{naw,b} &= \hat{\beta}^f \hat{\hat{\lambda}}_t^{f,naw,b} + \hat{\epsilon}_{r,t+1}^{naw,b} && \text{(A.11)}\\
r_{t+1}^{na,b} &= \hat{\beta}^f \hat{\hat{\lambda}}_t^{f,na,b} + \hat{\epsilon}_{r,t+1}^{na,b}, && \text{(A.12)}
\end{aligned}
$$

where $\bar{I}$ is the average number of announcement windows in an announcement day (we assume that the announcement-window risk premium is equally "spread" across different windows within the same day). The bootstrap residuals $\hat{\epsilon}_{r,i,t+1}^{aw,b}$ are obtained by resampling the residuals from the estimated factor model (38). The bootstrap residuals $\hat{\epsilon}_{r,t+1}^{naw,b}$ and $\hat{\epsilon}_{r,t+1}^{na,b}$ are from unrestricted predictive models for futures non-announcement-window and non-announcement-day returns (time-series regressions of futures returns on lagged instruments).

We model the dynamics of the instruments assuming that the (mean-zero) time-varying component of the z_t vector, $z_{tv,t}$, follows the augmented VAR

$$
z_{tv,t+1} = A z_{tv,t} + B \hat{\epsilon}_{r,t+1} + \epsilon_{z_{tv},t+1}, \tag{A.13}
$$

where $\hat{\epsilon}_{r,t+1}$ is the vector of estimated residuals from unrestricted predictive models for futures returns. We then generate bootstrap instruments according to

$$
z_{tv,t+1}^b = \hat{A} z_{tv,t}^b + \hat{B} \hat{\epsilon}_{r,t+1}^b + \hat{\epsilon}_{z_{tv},t+1}^b, \tag{A.14}
$$

where the innovations $\hat{\epsilon}_{r,t+1}^b$ are constructed from the innovations in bootstrap announcement-window, non-announcement-window, and non-announcement-day returns. Specifically, on announcement days, we have

$$
\hat{\epsilon}_{r,t+1}^b = \sum_{i=1}^{I_{t+1}} [(\hat{\beta}^f \hat{\delta}_t^b) y_{i,t+1} + \hat{\epsilon}_{r,i,t+1}^{aw,b}] + \hat{\epsilon}_{r,t+1}^{naw,b}, \tag{A.15}
$$

whereas on non-announcement days we simply have $\hat{\epsilon}_{r,t+1}^b = \hat{\epsilon}_{r,t+1}^{na,b}$.

A.2 Generating bootstrap p-values

It is known that bootstrapping on a *pivotal* quantity, such as the Wald or t-statistic, produces better sizes than bootstrapping on the estimated coefficients (Hall, 1992, and Hall and LePage, 1996). Our approach of bootstrapping the data under the null corresponds to the "recentering" of Hall and Horowitz (1996), and we compute the bootstrap p-value for a vector of parameter estimates $\hat{\theta}$ as

$$\Pr\left\{(\hat{\theta}^b)^\top[\widehat{\mathrm{Cov}}(\hat{\theta}^b)]^{-1}\hat{\theta}^b > \hat{\theta}^\top[\widehat{\mathrm{Cov}}(\hat{\theta})]^{-1}\hat{\theta}\right\}, \tag{A.16}$$

where $\widehat{\mathrm{Cov}}(\hat{\theta})$ denotes the estimated covariance matrix of the estimates.[48]

[48]Obviously, the same approach applies when we make inference on *individual* parameter estimates.

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Table 1: U.S. macroeconomic announcements

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

Announcement Name	**Abbreviation**	**Units**	**Source**
Advance Retail Sales	RetS	Units	Bureau of the Census
Business Inventories	Buinv	Units	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	Percentage	Bureau of Labor Statistics
Durable Goods Orders	Durab	Percentage	Bureau of the Census
Employment Cost Index	ECI	Percentage	Bureau of Labor Statistics
Existing Home Sales	EHS	Millions	Bureau of the Census
Federal Open Market Committee rate decision	FOMC	Percentage	Federal Reserve Board
Gross Domestic Product	GDP	Percentage	Bureau of Economic Analysis
GDP Price Deflator	Defla	Percentage	Bureau of Economic Analysis
Housing Starts	HSt	Thousands	Bureau of the Census
Industrial Production	IP	Percentage	Federal Reserve Board
Initial Jobless Claims	Ijob	Thousands	Bureau of Labor Statistics
Leading Indicators	Lind	Percentage	Conference Board
Monthly Treasury Budget Statement	Budge	USD Billions	Department of the Treasury
ISM Purchasing Managers' Index	ISM	Number	Institute for Supply Management
New Home Sales	NewH	Thousands	Bureau of the Census
Philadelphia Fed Index	Phil	Number	Federal Reserve Bank of Philadelphia
Producer Price Index	PPI	Percentage	Bureau of Labor Statistics
Unemployment Rate	Unemp	Percentage	Bureau of Labor Statistics

Table 2: Summary statistics of daily and intra-day futures returns

This table reports descriptive statistics for futures bond returns for four contracts: the two-year, five-year, and ten-year Treasury notes, and the 30-year Treasury bond. A 30-minute window around the announcements is considered (five minutes before and 25 minutes after the announcement). Futures returns are measured during all trading days, during announcement windows, during announcement days but outside of the announcement windows, during non-announcement days, and during announcement days. If more announcements are released on the same day, but at different times during the day, we take the sum of the different announcement-window returns. Daily continuously-compounded returns are calculated using the closing price of the same contract. This is the front contract, unless when the volume of the back contract is greater than the front contract. In this case, the back contract prices are used to calculate returns. The statistics are annualized multiplying the mean by 250 and the standard deviation by $\sqrt{250}$. Bootstrap p-values are reported. The sample starts on March 2, 1993, and ends on March 31, 2008.

	2-Year	**5-Year**	**10-Year**	**30-Year**
All-days returns				
Mean	1.183	2.257	3.338	3.796
Pvalue	0.011	0.031	0.028	0.105
SDEV	1.819	4.120	5.962	9.117
Sharpe ratio	0.651	0.548	0.560	0.416
Announcement-window returns				
Mean	-0.002	-0.322	-0.046	-0.067
Pvalue	0.996	0.697	0.970	0.968
SDEV	1.204	2.637	3.546	5.010
Sharpe ratio	-0.002	-0.122	-0.013	-0.013
Non-announcement-window returns				
Mean	1.793	3.380	4.326	4.809
Pvalue	0.001	0.006	0.013	0.076
SDEV	1.697	3.811	5.488	8.428
Sharpe ratio	1.056	0.887	0.788	0.571
Non-announcement-day returns				
Mean	0.074	1.030	1.894	2.487
Pvalue	0.894	0.455	0.375	0.463
SDEV	1.412	3.304	4.979	7.848
Sharpe ratio	0.052	0.312	0.380	0.317
Announcement-day returns				
Mean	1.800	2.939	4.140	4.524
Pvalue	0.004	0.040	0.046	0.150
SDEV	2.009	4.510	6.444	9.752
Sharpe ratio	0.896	0.652	0.642	0.464

Table 3: Summary statistics of instruments

This table reports descriptive statistics for the instruments. The instruments are: the first five principal components obtained using the yields provided by Gürkaynak et al. (2007): PC1, PC2, PC3, PC4, and PC5; the six Nelson-Siegel-Svensson coefficients also provided by Gürkaynak et al. (2007): b_0, b_1, b_2, b_3, τ_1, and τ_2; and the macro factor, MF, obtained by Aruoba et al. (2009). The sample starts on March 2, 1993, and ends on March 31, 2008.

	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**b0**	**b1**	**b2**	**b3**	**Tau1**	**Tau2**	**MF**
Mean	-0.00	0.00	-0.00	-0.00	0.00	2.56	1.43	7.21	4.39	1.63	12.76	-0.03
SDEV	5.34	2.05	0.36	0.16	0.11	2.53	2.87	23.88	27.87	1.23	8.64	0.51
Correlations												
PC1												
PC2	-0.00											
PC3	0.00	-0.00										
PC4	-0.00	0.00	-0.00									
PC5	-0.00	0.00	-0.00	0.00								
b0	0.52	0.27	-0.04	-0.36	0.63							
b1	-0.16	-0.63	0.13	0.37	-0.50	-0.84						
b2	0.23	0.35	0.23	-0.25	0.24	0.54	-0.54					
b3	-0.22	-0.37	-0.18	0.33	-0.41	-0.70	0.69	-0.97				
Tau1	0.03	-0.25	0.41	0.13	-0.19	-0.26	0.39	0.16	-0.08			
Tau2	0.10	-0.09	0.12	-0.01	-0.22	-0.17	0.20	-0.31	0.33	-0.09		
MF	0.42	-0.06	0.06	-0.02	-0.33	0.03	0.07	0.14	-0.06	0.21	0.15	

Table 4: Regressing futures returns on macro surprises

This table presents the results of regressing the four intra-day futures bond returns (two-year, five-year, and ten-year T-notes, and 30-year T-bond) on the 22 macro surprises. The intra-day futures returns are calculated using a 30-minute window around the announcements (five minutes before and 25 minutes after the news release). We consider two models with conditioning information. In the first model (Con1), the instruments are: the first five principal components extracted from the daily yields provided by Gürkaynak et al. (2007), and the macro factor of Aruoba et al. (2009). In the second model (Con2), the instruments are: the six Nelson-Siegel-Svensson parameters of Gürkaynak et al. (2007), and the macro factor of Aruoba et al. (2009). The regressors are selected using a stepwise regression technique that recursively eliminates regressors with t-ratios below one. To save space, we do not report the intercepts and for the conditional models we only report the average slope regression coefficients. Bootstrap p-values are reported in parenthesis. The adjusted R-squareds (Rbar) are expressed in percentage points. Bootstrap p-values of the joint significance of the interaction coefficients of each regression are also reported in square brackets. The sample starts on March 2, 1993, and ends on March 31, 2008.

	2Y	**2YCon1**	**2YCon2**	**5Y**	**5YCon1**	**5YCon2**	**10Y**	**10YCon1**	**10YCon2**	**30Y**	**30YCon1**	**30YCon2**
RetS	−0.03	−0.04	−0.04	−0.06	−0.08	−0.09	−0.08	−0.11	−0.11	−0.09	−0.13	−0.14
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Buinv												
Nfarm	−0.10	−0.10	−0.10	−0.21	−0.20	−0.20	−0.27	−0.26	−0.26	−0.31	−0.30	−0.30
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Chic	−0.02	−0.04		−0.04	−0.08		−0.05	−0.12		−0.07	−0.16	−0.15
	(0.00)	(0.00)		(0.00)	(0.00)		(0.01)	(0.00)		(0.01)	(0.00)	(0.02)
CConf	−0.02	−0.02	−0.02	−0.05	−0.05	−0.05	−0.07	−0.07	−0.07	−0.08	−0.09	−0.09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CPI	−0.01	−0.02	−0.01	−0.03	−0.04	−0.02	−0.04	−0.06	−0.04	−0.07	−0.09	−0.07
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Durab	−0.02	−0.02	−0.02	−0.05	−0.06	−0.05	−0.06	−0.07	−0.06	−0.08	−0.10	−0.08
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ECI	−0.03	−0.03	−0.09	−0.07	−0.08	−0.09	−0.09	−0.09		−0.14	−0.16	−0.28
	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.24)	(0.00)	(0.00)		(0.00)	(0.00)	(0.20)
EHS	−0.01	−0.01	−0.01			−0.02			−0.02			−0.13
	(0.24)	(0.21)	(0.14)			(0.16)			(0.22)			(0.13)
FOMC	−0.05	−0.07	−0.06	−0.07	−0.10	−0.09	−0.04	−0.10	−0.10	0.04		−0.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.09)		(0.18)
GDP	−0.03	−0.03	−0.03	−0.06	−0.06	−0.07	−0.08	−0.09	−0.08	−0.10	−0.12	−0.11
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Defla			−0.00	−0.01		−0.02	−0.02		−0.03	−0.04	−0.03	−0.05
			(0.26)	(0.23)		(0.08)	(0.12)		(0.05)	(0.04)	(0.21)	(0.02)
Hst	−0.01	−0.01	−0.01	−0.02	−0.03	−0.03	−0.02	−0.04	−0.03	−0.03	−0.05	−0.04
	(0.03)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.10)	(0.01)	(0.01)	(0.10)	(0.01)	(0.04)
IP	−0.01	−0.02	−0.02	−0.02	−0.03	−0.03	−0.03	−0.04	−0.04	−0.04	−0.05	−0.05
	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)
Ijob	0.01	0.01	0.01	0.03	0.03	0.03	0.04	0.04	0.04	0.05	0.05	0.05
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lind	−0.01	−0.01	−0.01	−0.01	−0.02	−0.03	−0.02	−0.03	−0.03	−0.02	−0.05	−0.04
	(0.19)	(0.06)	(0.05)	(0.18)	(0.04)	(0.04)	(0.18)	(0.04)	(0.03)	(0.22)	(0.04)	(0.04)
Budge												
ISM	−0.05	−0.05	−0.05	−0.12	−0.12	−0.12	−0.16	−0.17	−0.16	−0.22	−0.23	−0.23
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NewH	−0.02	−0.02	−0.02	−0.04	−0.05	−0.05	−0.06	−0.07	−0.07	−0.08	−0.10	−0.10
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Phil	−0.02	−0.02		−0.04	−0.05		−0.06	−0.06		−0.07	−0.07	
	(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)	
PPI	−0.02	−0.03	−0.03	−0.04	−0.07	−0.07	−0.05	−0.09	−0.09	−0.09	−0.14	−0.15
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemp	0.04	0.04	0.04	0.09	0.09	0.10	0.10	0.11	0.11	0.14	0.15	0.17
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Rbar	28.44	34.48	35.16	25.50	31.53	32.02	22.90	28.57	29.46	18.17	24.43	25.28
Pvalue		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.00]		[0.00]	[0.01]

Table 5: Regressing macro surprises on futures returns

This table presents the results of regressing the 22 macro surprises (one separate regression for each surprise) on the four intra-day futures bond returns (two-year, five-year, and ten-year T-notes, and 30-year T-bond). The intra-day futures returns are calculated using a 30-minute window around the announcements (five minutes before and 25 minutes after the news release). We consider two models with conditioning information. In the first model (Con1), the instruments are: the first five principal components extracted from the daily yields provided by Gürkaynak et al. (2007), and the macro factor of Aruoba et al. (2009). In the second model (Con2), the instruments are: the six Nelson-Siegel-Svensson parameters of Gürkaynak et al. (2007), and the macro factor of Aruoba et al. (2009). The regressors are selected using a stepwise regression technique that recursively eliminates regressors with t-ratios below one. To save space, we do not report the estimated coefficients. The adjusted R-squareds (Rbar) are expressed in percentage points. Bootstrap p-values of a test of the joint significance of all the slope coefficients of each regression are also reported. The sample starts on March 2, 1993, and ends on March 31, 2008.

	Rbar Unc	**Pvalue Unc**	**Rbar Con1**	**Pvalue Con1**	**Rbar Con2**	**Pvalue Con2**
RetS	12.44	0.00	22.14	0.01	19.01	0.01
Buinv	0.81	0.18	9.80	0.07	5.44	0.10
Nfarm	43.70	0.00	45.80	0.00	45.44	0.00
Chic	14.19	0.00	28.10	0.07	31.69	0.31
CConf	19.12	0.00	31.82	0.00	26.09	0.03
CPI	3.97	0.06	8.68	0.11	10.81	0.00
Durab	13.94	0.00	25.88	0.00	21.71	0.02
ECI	8.00	0.01	35.80	0.00	21.24	0.11
EHS	3.09	0.14	14.80	0.15	13.23	0.33
FOMC	42.87	0.00	64.01	0.00	67.79	0.00
GDP	15.59	0.01	24.22	0.04	22.65	0.02
Defla	2.39	0.25	14.83	0.27	12.07	0.52
Hst	3.84	0.03	9.91	0.02	11.18	0.03
IP	8.84	0.00	14.30	0.00	14.20	0.19
Ijob	8.70	0.00	10.65	0.00	9.89	0.00
Lind	0.28	0.06	6.48	0.04	3.74	0.11
Budge	0.00		4.07	0.43	9.15	0.70
ISM	42.43	0.00	47.43	0.00	46.73	0.00
NewH	13.93	0.00	22.24	0.00	17.89	0.03
Phil	22.23	0.00	27.28	0.04	29.83	0.02
PPI	8.51	0.00	15.73	0.02	10.26	0.13
Unemp	10.53	0.00	19.58	0.04	19.06	0.09

Table 6: Risk premia on unit-beta, OLS-style mimicking portfolios

This table presents the results of regressing the 20 unit-beta, OLS-style mimicking portfolio returns on the instruments. The mimicking portfolio returns are obtained by interacting portfolio weights with returns as explained in the text. Portfolio weights are based on announcement betas which are those reported in Table 4 for the Con1 model. Two announcements (Buinv and Budge) that were dropped by the stepwise regression of futures returns on surprises, are not included. The instruments include: the first five principal components extracted from the daily yields provided by Gürkaynak et al. (2007), and the macro factor of Aruoba et al. (2009). Mimicking portfolio returns are measured during all trading days (Panel A), during announcement windows (Panel B), during announcement days but outside of the announcement windows (Panel C), and during non-announcement days (Panel D). If more announcements are released on the same day, but at different times during the day, we take the sum of the different announcement-window returns. Following Faust and Wright (2011), the regressions in Panels A and B include as an augmenting variable (not shown in the table) the average of all the standardized announcement surprises on a given day. Regression coefficients are standardized by the conditional volatility of the mimicking portfolio returns and are annualized by multiplying by $\sqrt{250}$. Bootstrap p-values are reported in parenthesis. The adjusted R-squareds (Rbar) are expressed in percentage points. The sample starts on March 2, 1993, and ends on March 31, 2008.

Panel A: Using all-days returns

	Int	PC1	PC2	PC3	PC4	PC5	MF	Rbar
RetS	−0.55	−0.58	−0.13	0.56	0.11	0.01	0.58	3.04
	(0.03)	(0.25)	(0.70)	(0.09)	(0.68)	(0.98)	(0.12)	
Nfarm	−0.55	−0.57	−0.13	0.56	0.11	0.00	0.58	3.07
	(0.03)	(0.25)	(0.70)	(0.08)	(0.68)	(0.99)	(0.12)	
Chic	−0.54	−0.58	−0.13	0.55	0.10	0.01	0.57	2.99
	(0.03)	(0.26)	(0.68)	(0.10)	(0.68)	(0.95)	(0.12)	
CConf	−0.55	−0.58	−0.13	0.56	0.11	0.01	0.58	3.02
	(0.03)	(0.26)	(0.69)	(0.09)	(0.68)	(0.97)	(0.12)	
CPI	−0.53	−0.59	−0.13	0.54	0.10	0.03	0.55	2.89
	(0.04)	(0.25)	(0.67)	(0.10)	(0.71)	(0.92)	(0.15)	
Durab	−0.54	−0.58	−0.13	0.56	0.11	0.01	0.57	3.01
	(0.03)	(0.26)	(0.69)	(0.09)	(0.68)	(0.96)	(0.12)	
ECI	−0.54	−0.58	−0.13	0.55	0.10	0.02	0.56	2.95
	(0.03)	(0.25)	(0.68)	(0.10)	(0.69)	(0.93)	(0.13)	
EHS	−0.69	−0.51	−0.06	0.61	0.31	−0.05	0.96	4.63
	(0.00)	(0.29)	(0.86)	(0.07)	(0.28)	(0.87)	(0.01)	
FOMC	−0.63	−0.51	−0.09	0.66	0.17	−0.09	0.70	3.79
	(0.01)	(0.32)	(0.81)	(0.05)	(0.56)	(0.74)	(0.07)	
GDP	−0.54	−0.58	−0.13	0.55	0.11	0.01	0.57	3.00
	(0.03)	(0.25)	(0.69)	(0.10)	(0.69)	(0.95)	(0.13)	
Defla	−0.47	−0.62	−0.16	0.46	0.07	0.10	0.47	2.38
	(0.07)	(0.22)	(0.64)	(0.16)	(0.79)	(0.74)	(0.25)	
Hst	−0.54	−0.58	−0.13	0.56	0.11	0.01	0.58	3.02
	(0.03)	(0.25)	(0.68)	(0.09)	(0.68)	(0.95)	(0.12)	
IP	−0.54	−0.58	−0.13	0.55	0.11	0.01	0.57	3.00
	(0.03)	(0.25)	(0.69)	(0.09)	(0.69)	(0.95)	(0.12)	
Ijob	0.55	0.58	0.13	−0.56	−0.11	−0.01	−0.58	3.02
	(0.03)	(0.25)	(0.69)	(0.09)	(0.68)	(0.97)	(0.12)	
Lind	−0.54	−0.58	−0.13	0.55	0.10	0.02	0.57	2.97
	(0.03)	(0.26)	(0.68)	(0.10)	(0.69)	(0.94)	(0.13)	
ISM	−0.54	−0.58	−0.13	0.55	0.10	0.02	0.57	2.98
	(0.03)	(0.25)	(0.68)	(0.10)	(0.69)	(0.95)	(0.13)	
NewH	−0.54	−0.58	−0.13	0.55	0.10	0.01	0.57	2.98
	(0.03)	(0.25)	(0.69)	(0.10)	(0.70)	(0.96)	(0.13)	
Phil	−0.55	−0.57	−0.13	0.56	0.11	0.00	0.59	3.08
	(0.03)	(0.25)	(0.70)	(0.08)	(0.66)	(0.99)	(0.11)	
PPI	−0.53	−0.58	−0.13	0.54	0.10	0.02	0.56	2.93
	(0.03)	(0.25)	(0.67)	(0.10)	(0.70)	(0.93)	(0.13)	
Unemp	0.54	0.58	0.13	−0.55	−0.11	−0.01	−0.57	3.01
	(0.03)	(0.26)	(0.69)	(0.09)	(0.68)	(0.96)	(0.12)	

Panel B: Using announcement-window returns

	Int	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**MF**	**Rbar**
RetS	−0.05	−0.15	−0.01	0.85	0.55	0.04	−0.14	8.66
	(0.88)	(0.66)	(0.98)	(0.01)	(0.06)	(0.87)	(0.70)	
Nfarm	−0.05	−0.15	−0.01	0.84	0.55	0.04	−0.14	8.74
	(0.88)	(0.66)	(0.96)	(0.01)	(0.05)	(0.89)	(0.70)	
Chic	−0.05	−0.15	−0.00	0.85	0.55	0.06	−0.14	8.53
	(0.88)	(0.65)	(0.99)	(0.01)	(0.06)	(0.84)	(0.70)	
CConf	−0.05	−0.15	−0.01	0.85	0.55	0.05	−0.14	8.63
	(0.88)	(0.65)	(0.98)	(0.01)	(0.06)	(0.87)	(0.70)	
CPI	−0.05	−0.15	0.01	0.86	0.54	0.07	−0.14	8.28
	(0.87)	(0.66)	(0.98)	(0.01)	(0.06)	(0.80)	(0.70)	
Durab	−0.05	−0.15	−0.01	0.85	0.55	0.05	−0.14	8.59
	(0.88)	(0.66)	(0.98)	(0.01)	(0.06)	(0.86)	(0.70)	
ECI	−0.05	−0.15	0.00	0.85	0.54	0.06	−0.14	8.43
	(0.88)	(0.65)	(1.00)	(0.01)	(0.06)	(0.82)	(0.70)	
EHS	−0.04	−0.05	−0.19	0.72	0.55	−0.12	−0.11	12.29
	(0.91)	(0.91)	(0.49)	(0.04)	(0.06)	(0.72)	(0.77)	
FOMC	−0.03	−0.14	−0.11	0.74	0.58	−0.09	−0.13	10.41
	(0.93)	(0.68)	(0.70)	(0.03)	(0.03)	(0.79)	(0.70)	
GDP	−0.05	−0.15	−0.00	0.85	0.55	0.05	−0.14	8.56
	(0.88)	(0.66)	(0.99)	(0.01)	(0.06)	(0.85)	(0.70)	
Defla	−0.05	−0.15	0.08	0.90	0.50	0.17	−0.14	6.85
	(0.86)	(0.64)	(0.79)	(0.01)	(0.09)	(0.59)	(0.72)	
Hst	−0.05	−0.15	−0.01	0.85	0.55	0.05	−0.14	8.61
	(0.89)	(0.66)	(0.99)	(0.01)	(0.06)	(0.86)	(0.70)	
IP	−0.05	−0.15	−0.00	0.85	0.55	0.05	−0.14	8.57
	(0.88)	(0.66)	(0.99)	(0.01)	(0.06)	(0.86)	(0.70)	
Ijob	0.05	0.15	0.01	−0.85	−0.55	−0.05	0.14	8.61
	(0.88)	(0.65)	(0.98)	(0.01)	(0.06)	(0.86)	(0.70)	
Lind	−0.05	−0.15	−0.00	0.85	0.54	0.06	−0.14	8.49
	(0.87)	(0.65)	(1.00)	(0.01)	(0.06)	(0.85)	(0.70)	
ISM	−0.05	−0.15	−0.00	0.85	0.54	0.06	−0.14	8.51
	(0.88)	(0.65)	(0.99)	(0.01)	(0.06)	(0.84)	(0.70)	
NewH	−0.05	−0.15	−0.00	0.85	0.55	0.05	−0.14	8.51
	(0.87)	(0.66)	(1.00)	(0.01)	(0.06)	(0.85)	(0.70)	
Phil	−0.05	−0.14	−0.01	0.84	0.55	0.04	−0.14	8.76
	(0.89)	(0.66)	(0.95)	(0.01)	(0.06)	(0.89)	(0.69)	
PPI	−0.05	−0.15	0.00	0.86	0.54	0.06	−0.14	8.39
	(0.88)	(0.66)	(0.99)	(0.01)	(0.06)	(0.82)	(0.71)	
Unemp	0.04	0.15	0.01	−0.85	−0.55	−0.05	0.14	8.59
	(0.88)	(0.66)	(0.98)	(0.01)	(0.06)	(0.86)	(0.70)	

Panel C: Using non-announcement-window returns

	Int	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**MF**	**Rbar**
RetS	−0.72	−1.05	0.32	0.16	−0.22	−0.01	1.03	0.32
	(0.03)	(0.04)	(0.40)	(0.72)	(0.58)	(0.96)	(0.03)	
Nfarm	−0.72	−1.04	0.32	0.16	−0.22	−0.02	1.04	0.33
	(0.03)	(0.04)	(0.39)	(0.72)	(0.58)	(0.96)	(0.03)	
Chic	−0.70	−1.05	0.31	0.15	−0.21	−0.01	1.02	0.32
	(0.04)	(0.04)	(0.41)	(0.73)	(0.59)	(0.97)	(0.04)	
CConf	−0.71	−1.05	0.32	0.15	−0.22	−0.01	1.03	0.32
	(0.04)	(0.03)	(0.40)	(0.72)	(0.59)	(0.97)	(0.03)	
CPI	−0.68	−1.06	0.30	0.14	−0.21	−0.00	1.00	0.30
	(0.05)	(0.04)	(0.44)	(0.74)	(0.60)	(0.99)	(0.04)	
Durab	−0.71	−1.05	0.32	0.15	−0.21	−0.01	1.03	0.32
	(0.04)	(0.04)	(0.41)	(0.73)	(0.59)	(0.97)	(0.04)	
ECI	−0.70	−1.05	0.31	0.15	−0.21	−0.01	1.01	0.31
	(0.04)	(0.04)	(0.43)	(0.73)	(0.59)	(0.98)	(0.04)	
EHS	−1.06	−0.81	0.45	0.13	−0.11	0.03	1.46	0.53
	(0.00)	(0.10)	(0.23)	(0.75)	(0.77)	(0.94)	(0.01)	
FOMC	−0.87	−0.94	0.41	0.23	−0.25	−0.06	1.17	0.41
	(0.01)	(0.06)	(0.29)	(0.61)	(0.51)	(0.88)	(0.02)	
GDP	−0.71	−1.05	0.32	0.15	−0.21	−0.01	1.02	0.32
	(0.04)	(0.04)	(0.41)	(0.73)	(0.59)	(0.97)	(0.04)	
Defla	−0.57	−1.08	0.23	0.09	−0.17	0.03	0.90	0.24
	(0.08)	(0.03)	(0.54)	(0.82)	(0.66)	(0.93)	(0.06)	
Hst	−0.71	−1.05	0.32	0.15	−0.21	−0.01	1.03	0.32
	(0.04)	(0.03)	(0.40)	(0.72)	(0.59)	(0.97)	(0.04)	
IP	−0.71	−1.05	0.32	0.15	−0.21	−0.01	1.03	0.32
	(0.04)	(0.04)	(0.41)	(0.73)	(0.59)	(0.97)	(0.03)	
Ijob	0.71	1.05	−0.32	−0.15	0.22	0.01	−1.03	0.32
	(0.03)	(0.03)	(0.40)	(0.73)	(0.59)	(0.97)	(0.03)	
Lind	−0.70	−1.05	0.31	0.15	−0.21	−0.01	1.02	0.31
	(0.04)	(0.04)	(0.41)	(0.73)	(0.59)	(0.97)	(0.03)	
ISM	−0.70	−1.05	0.31	0.15	−0.21	−0.01	1.02	0.31
	(0.04)	(0.04)	(0.42)	(0.73)	(0.59)	(0.97)	(0.04)	
NewH	−0.70	−1.05	0.31	0.15	−0.21	−0.01	1.02	0.32
	(0.04)	(0.03)	(0.42)	(0.73)	(0.59)	(0.97)	(0.04)	
Phil	−0.72	−1.04	0.32	0.16	−0.22	−0.02	1.04	0.33
	(0.03)	(0.04)	(0.39)	(0.71)	(0.59)	(0.96)	(0.03)	
PPI	−0.69	−1.05	0.31	0.14	−0.21	−0.01	1.01	0.31
	(0.04)	(0.04)	(0.43)	(0.74)	(0.60)	(0.98)	(0.04)	
Unemp	0.71	1.05	−0.32	−0.15	0.21	0.01	−1.03	0.32
	(0.04)	(0.03)	(0.41)	(0.73)	(0.59)	(0.97)	(0.04)	

Panel D: Using non-announcement-day returns

	Int	PC1	PC2	PC3	PC4	PC5	MF	Rbar
RetS	−0.34	0.29	−1.02	0.42	0.03	−0.04	0.27	0.15
	(0.43)	(0.65)	(0.04)	(0.44)	(0.94)	(0.92)	(0.64)	
Nfarm	−0.34	0.29	−1.02	0.43	0.04	−0.04	0.27	0.15
	(0.43)	(0.66)	(0.04)	(0.43)	(0.91)	(0.92)	(0.63)	
Chic	−0.34	0.28	−1.02	0.40	0.02	−0.03	0.26	0.14
	(0.43)	(0.66)	(0.04)	(0.47)	(0.97)	(0.93)	(0.64)	
CConf	−0.34	0.29	−1.02	0.42	0.03	−0.03	0.26	0.14
	(0.43)	(0.66)	(0.04)	(0.45)	(0.94)	(0.92)	(0.64)	
CPI	−0.34	0.28	−1.03	0.37	−0.00	−0.02	0.25	0.12
	(0.42)	(0.66)	(0.04)	(0.50)	(1.00)	(0.96)	(0.66)	
Durab	−0.34	0.28	−1.02	0.41	0.03	−0.03	0.26	0.14
	(0.43)	(0.66)	(0.03)	(0.45)	(0.95)	(0.94)	(0.65)	
ECI	−0.34	0.28	−1.02	0.39	0.01	−0.02	0.25	0.13
	(0.42)	(0.66)	(0.04)	(0.48)	(0.98)	(0.95)	(0.65)	
EHS	−0.05	0.06	−0.86	0.77	0.58	−0.19	0.57	0.43
	(0.91)	(0.92)	(0.06)	(0.17)	(0.27)	(0.68)	(0.30)	
FOMC	−0.32	0.34	−0.95	0.70	0.25	−0.13	0.37	0.32
	(0.46)	(0.61)	(0.05)	(0.22)	(0.60)	(0.76)	(0.48)	
GDP	−0.34	0.28	−1.02	0.41	0.02	−0.03	0.26	0.14
	(0.43)	(0.66)	(0.03)	(0.45)	(0.95)	(0.93)	(0.65)	
Defla	−0.33	0.22	−1.03	0.20	−0.10	0.04	0.19	0.06
	(0.43)	(0.71)	(0.04)	(0.73)	(0.82)	(0.92)	(0.75)	
Hst	−0.34	0.28	−1.02	0.41	0.03	−0.03	0.26	0.14
	(0.43)	(0.66)	(0.03)	(0.45)	(0.95)	(0.93)	(0.64)	
IP	−0.34	0.28	−1.02	0.41	0.02	−0.03	0.26	0.14
	(0.43)	(0.66)	(0.03)	(0.46)	(0.96)	(0.94)	(0.65)	
Ijob	0.34	−0.28	1.02	−0.42	−0.03	0.03	−0.26	0.14
	(0.42)	(0.66)	(0.04)	(0.44)	(0.95)	(0.93)	(0.65)	
Lind	−0.34	0.28	−1.02	0.40	0.02	−0.03	0.26	0.14
	(0.42)	(0.65)	(0.04)	(0.47)	(0.97)	(0.94)	(0.64)	
ISM	−0.34	0.28	−1.02	0.40	0.02	−0.03	0.26	0.14
	(0.42)	(0.66)	(0.03)	(0.46)	(0.97)	(0.94)	(0.65)	
NewH	−0.34	0.28	−1.02	0.40	0.02	−0.03	0.26	0.14
	(0.42)	(0.66)	(0.03)	(0.46)	(0.97)	(0.94)	(0.65)	
Phil	−0.34	0.29	−1.02	0.43	0.04	−0.04	0.27	0.15
	(0.42)	(0.66)	(0.04)	(0.44)	(0.91)	(0.93)	(0.62)	
PPI	−0.34	0.28	−1.02	0.39	0.01	−0.02	0.25	0.13
	(0.42)	(0.66)	(0.04)	(0.49)	(0.98)	(0.95)	(0.65)	
Unemp	0.34	−0.28	1.02	−0.41	−0.03	0.03	−0.26	0.14
	(0.43)	(0.66)	(0.04)	(0.45)	(0.95)	(0.93)	(0.64)	

Table 7: Risk premia on unit-beta, GLS-style mimicking portfolios; non-announcement-window returns

This table presents the results of regressing the 20 unit-beta, GLS-style mimicking portfolio returns on the instruments. The mimicking portfolio returns are obtained by interacting portfolio weights with returns as explained in the text. Portfolio weights are based on announcement betas which are those reported in Table 4 for the Con1 model. Two announcements (Buinv and Budge) that were dropped by the stepwise regression of futures returns on surprises are not included. The instruments include: the first five principal components extracted from the daily yields provided by Gürkaynak et al. (2007), and the macro factor of Aruoba et al. (2009). Mimicking portfolio returns are measured during announcement days but outside of the announcement windows. If more announcements are released on the same day, but at different times during the day, we take the sum of the different announcement-window returns. Regression coefficients are standardized by the conditional volatility of the mimicking portfolio returns and are annualized by multiplying by $\sqrt{250}$. Bootstrap p-values are reported in parenthesis. The adjusted R-squareds (Rbar) are expressed in percentage points. The sample starts on March 2, 1993, and ends on March 31, 2008.

	Int	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**MF**	**Rbar**
RetS	−0.88	−0.69	0.62	0.23	−0.34	−0.32	1.05	0.48
	(0.01)	(0.15)	(0.10)	(0.59)	(0.33)	(0.34)	(0.05)	
Nfarm	−1.06	−0.57	0.59	0.23	−0.23	−0.18	1.31	0.55
	(0.00)	(0.24)	(0.13)	(0.57)	(0.54)	(0.61)	(0.02)	
Chic	−0.86	−0.91	0.48	−0.13	−0.02	−0.02	1.32	0.44
	(0.00)	(0.06)	(0.14)	(0.74)	(0.95)	(0.95)	(0.01)	
CConf	−1.03	−0.71	0.55	0.29	−0.28	−0.17	1.27	0.53
	(0.00)	(0.16)	(0.16)	(0.51)	(0.47)	(0.64)	(0.02)	
CPI	−0.49	−1.10	0.15	−0.18	0.04	0.19	0.96	0.22
	(0.14)	(0.03)	(0.67)	(0.64)	(0.90)	(0.57)	(0.06)	
Durab	−0.77	−0.35	0.18	0.36	−0.14	0.11	0.93	0.10
	(0.01)	(0.56)	(0.65)	(0.37)	(0.75)	(0.76)	(0.06)	
ECI	−0.40	−0.20	−0.16	0.06	0.18	0.41	0.65	−0.08
	(0.22)	(0.68)	(0.67)	(0.86)	(0.60)	(0.20)	(0.11)	
EHS	−0.39	−0.32	0.18	−0.40	0.29	0.17	0.79	0.01
	(0.21)	(0.46)	(0.58)	(0.16)	(0.39)	(0.61)	(0.07)	
FOMC	−0.87	0.16	0.42	0.22	−0.06	−0.09	0.96	0.30
	(0.01)	(0.69)	(0.34)	(0.53)	(0.87)	(0.83)	(0.10)	
GDP	−1.00	−0.73	0.40	0.26	−0.18	0.01	1.30	0.41
	(0.00)	(0.15)	(0.30)	(0.55)	(0.67)	(0.95)	(0.01)	
Defla	0.21	−0.13	−0.43	−0.25	0.35	0.49	0.01	0.00
	(0.52)	(0.74)	(0.28)	(0.54)	(0.33)	(0.14)	(0.98)	
Hst	−1.00	−0.61	0.31	0.03	0.06	0.20	1.44	0.39
	(0.00)	(0.24)	(0.39)	(0.95)	(0.85)	(0.56)	(0.01)	
IP	−0.98	−0.84	0.46	−0.07	0.00	0.05	1.45	0.49
	(0.01)	(0.08)	(0.18)	(0.85)	(1.00)	(0.92)	(0.01)	
Ijob	1.08	0.78	−0.51	−0.15	0.14	0.03	−1.45	0.57
	(0.00)	(0.13)	(0.19)	(0.71)	(0.69)	(0.94)	(0.01)	
Lind	−0.83	−0.76	0.30	0.29	−0.20	0.03	1.09	0.26
	(0.02)	(0.14)	(0.42)	(0.47)	(0.57)	(0.93)	(0.02)	
ISM	−0.97	−0.91	0.41	0.17	−0.16	0.02	1.33	0.45
	(0.00)	(0.08)	(0.28)	(0.71)	(0.68)	(0.96)	(0.02)	
NewH	−0.87	−0.97	0.56	0.17	−0.30	−0.22	1.15	0.52
	(0.00)	(0.05)	(0.14)	(0.73)	(0.42)	(0.49)	(0.04)	
Phil	−1.09	−0.56	0.56	0.15	−0.13	−0.10	1.40	0.55
	(0.00)	(0.26)	(0.11)	(0.71)	(0.69)	(0.78)	(0.01)	
PPI	−0.47	−0.47	−0.08	0.11	0.06	0.33	0.73	−0.07
	(0.16)	(0.40)	(0.84)	(0.76)	(0.86)	(0.31)	(0.09)	
Unemp	0.51	0.07	0.03	−0.32	0.03	−0.22	−0.60	−0.08
	(0.10)	(0.92)	(0.95)	(0.42)	(0.95)	(0.49)	(0.18)	

Table 8: Risk premia on maximum-correlation mimicking portfolios; non-announcement-window returns

This table presents the results of regressing the 19 maximum-correlation mimicking portfolio returns on the instruments. The mimicking portfolio returns are obtained by interacting portfolio weights with returns as explained in the text. Portfolio weights are obtained by using the Con1 model. Three announcements (Buinv, Budge, and Lind) are not included because they are poorly spanned by futures returns (adjusted R-squareds for the unconditional models less than 1%). The instruments include: the first five principal components extracted from the daily yields provided by Gürkaynak et al. (2007), and the macro factor of Aruoba et al. (2009). Mimicking portfolio returns are measured during announcement days but outside of the announcement windows. If more announcements are released on the same day, but at different times during the day, we take the sum of the different announcement-window returns. Regression coefficients are standardized by the conditional volatility of the mimicking portfolio returns and are annualized by multiplying by $\sqrt{250}$. Bootstrap p-values are reported in parenthesis. The adjusted R-squareds (Rbar) are expressed in percentage points. The sample starts on March 2, 1993, and ends on March 31, 2008.

	Int	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**MF**	**Rbar**
RetS	−0.95	−0.14	0.43	0.41	−0.23	−0.12	1.03	0.34
	(0.00)	(0.81)	(0.27)	(0.34)	(0.54)	(0.74)	(0.08)	
Nfarm	−1.07	−0.38	0.55	0.25	−0.18	−0.13	1.29	0.51
	(0.00)	(0.44)	(0.15)	(0.56)	(0.64)	(0.67)	(0.02)	
Chic	−0.77	0.04	0.14	0.34	−0.04	0.15	0.88	0.11
	(0.02)	(0.94)	(0.66)	(0.45)	(0.92)	(0.64)	(0.09)	
CConf	−1.08	−0.66	0.55	0.24	−0.22	−0.12	1.36	0.56
	(0.00)	(0.20)	(0.13)	(0.59)	(0.57)	(0.76)	(0.02)	
CPI	−0.65	−1.02	0.25	−0.24	0.10	0.17	1.18	0.29
	(0.05)	(0.05)	(0.52)	(0.54)	(0.76)	(0.61)	(0.02)	
Durab	−0.89	−0.85	0.38	0.27	−0.24	−0.04	1.16	0.37
	(0.00)	(0.10)	(0.31)	(0.55)	(0.53)	(0.92)	(0.02)	
ECI	0.07	−0.32	−0.02	0.36	−0.34	−0.15	−0.24	−0.06
	(0.79)	(0.56)	(0.96)	(0.26)	(0.34)	(0.64)	(0.60)	
EHS	−1.05	−0.46	0.36	0.18	−0.03	0.12	1.39	0.41
	(0.00)	(0.27)	(0.27)	(0.62)	(0.93)	(0.76)	(0.00)	
FOMC	−0.17	0.80	0.09	−0.00	0.15	−0.02	0.08	0.05
	(0.55)	(0.08)	(0.86)	(0.99)	(0.67)	(0.97)	(0.87)	
GDP	−1.07	−0.35	0.46	0.12	−0.02	0.02	1.39	0.47
	(0.00)	(0.53)	(0.20)	(0.75)	(0.95)	(0.96)	(0.01)	
Defla	0.59	−0.45	−0.26	−0.05	−0.11	0.00	−0.66	0.13
	(0.07)	(0.37)	(0.51)	(0.90)	(0.78)	(1.00)	(0.24)	
Hst	−0.99	−0.34	0.35	0.01	0.10	0.15	1.38	0.38
	(0.00)	(0.52)	(0.30)	(0.98)	(0.75)	(0.65)	(0.01)	
IP	−1.06	−0.81	0.45	0.13	−0.11	0.03	1.46	0.53
	(0.00)	(0.10)	(0.23)	(0.75)	(0.77)	(0.94)	(0.01)	
Ijob	0.98	0.93	−0.45	−0.17	0.18	0.02	−1.34	0.50
	(0.00)	(0.05)	(0.26)	(0.71)	(0.62)	(0.95)	(0.01)	
ISM	−0.96	−0.69	0.42	0.33	−0.25	−0.06	1.19	0.39
	(0.00)	(0.21)	(0.28)	(0.47)	(0.51)	(0.85)	(0.03)	
NewH	−0.79	−1.01	0.40	0.21	−0.27	−0.09	1.07	0.39
	(0.01)	(0.05)	(0.29)	(0.65)	(0.47)	(0.79)	(0.03)	
Phil	−0.82	−0.85	0.33	−0.20	0.12	0.16	1.35	0.36
	(0.01)	(0.10)	(0.39)	(0.60)	(0.76)	(0.65)	(0.01)	
PPI	−0.57	−1.08	0.23	0.09	−0.17	0.03	0.90	0.24
	(0.08)	(0.03)	(0.54)	(0.82)	(0.66)	(0.93)	(0.06)	
Unemp	0.93	0.60	−0.33	−0.32	0.19	−0.03	−1.17	0.30
	(0.00)	(0.25)	(0.41)	(0.45)	(0.64)	(0.93)	(0.01)	

Table 9: Correlations of announcement betas

This table shows the correlation coefficients of the average betas reported in Table 4 for the Con1 model. Two announcements (Buinv and Budge) are excluded in panel A because *all* beta coefficients are dropped by the stepwise regression. Four announcements (Buinv, EHS, Defla, and Budge) are excluded in panel B because at least *two* beta coefficients are dropped by the stepwise regression. Panel C also excludes the FOMC announcement. The sample starts on March 2, 1993, and ends on March 31, 2008.

Panel A: With 20 announcements

	2YCon1	**5YCon1**	**10YCon1**	**30YCon1**
2YCon1				
5YCon1	0.98			
10YCon1	0.95	0.99		
30YCon1	0.81	0.90	0.94	

Panel B: With 18 announcements

	2YCon1	**5YCon1**	**10YCon1**	**30YCon1**
2YCon1				
5YCon1	0.98			
10YCon1	0.95	0.99		
30YCon1	0.80	0.89	0.94	

Panel C: With 17 announcements (excluding the FOMC announcement)

	2YCon1	**5YCon1**	**10YCon1**	**30YCon1**
2YCon1				
5YCon1	0.99			
10YCon1	0.99	1.00		
30YCon1	0.97	0.98	0.98	

Table 10: Risk premia on the mimicking portfolios tracking the latent factor

This table presents the results of regressing the latent factor mimicking-portfolio returns on the instruments. The mimicking portfolios are the OLS-style and GLS-style unit-beta mimicking portfolios (UBMP), and the maximum-correlation mimicking portfolios (MCMP), with and without time-varying weights and allowing for constant and time-varying δ_t in equation (48). The latent factor is constructed using Zhou's (1994, 1999) methodology as explained in the text. Four announcements are excluded from the analysis (Buinv, Budge, EHS, and Defla) because they are dropped in at least *two* of the regressions in Table 4 for the Con1 model. We also exclude the instruments that are dropped in one or more of the regressions in Table 4 for the Con1 model. Mimicking portfolio returns are measured during all trading days (Panel A), during announcement windows (Panel B), during announcement days but outside of the announcement windows (Panel C), and during non-announcement days (Panel D). If more announcements are released on the same day, but at different times during the day, we take the sum of the different announcement-window returns. Following Faust and Wright (2011), the regressions in Panels A and B include as an augmenting variable (not shown in the table) the average of all the standardized announcement surprises on a given day. Regression coefficients are standardized by the conditional volatility of the mimicking portfolio returns and are annualized by multiplying by $\sqrt{250}$. Bootstrap p-values are reported in parenthesis. The adjusted R-squareds (Rbar) are expressed in percentage points. The sample starts on March 2, 1993, and ends on March 31, 2008.

Panel A: Using all-days returns

	Int	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**MF**	**Rbar**
UBMP OLS	0.55	0.58	0.13	−0.56	−0.11	−0.01	−0.58	3.05
	(0.03)	(0.23)	(0.68)	(0.08)	(0.69)	(0.98)	(0.10)	
UBMP GLS	0.60	0.32	0.03	−0.61	−0.46	0.14	−0.94	4.49
	(0.00)	(0.50)	(0.94)	(0.07)	(0.10)	(0.61)	(0.01)	
MCMP average weights and δ	0.68	0.37	0.02	−0.67	−0.37	0.17	−0.94	4.67
	(0.00)	(0.21)	(0.96)	(0.00)	(0.05)	(0.57)	(0.23)	
MCMP time-varying weights and average δ	0.55	0.40	−0.09	−0.58	−0.57	−0.01	−0.78	3.88
	(0.02)	(0.19)	(0.80)	(0.00)	(0.00)	(0.98)	(0.54)	
MCMP average weights and time-varying δ	0.64	0.44	−0.02	−0.63	−0.39	0.02	−1.01	4.27
	(0.03)	(0.14)	(0.94)	(0.01)	(0.13)	(0.96)	(0.21)	
MCMP time-varying weights and δ	0.47	0.74	−0.08	−0.58	−0.62	−0.32	−0.79	3.60
	(0.13)	(0.02)	(0.83)	(0.01)	(0.00)	(0.32)	(0.50)	

Panel B: Using announcement-window returns

	Int	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**MF**	**Rbar**
UBMP OLS	0.02	0.08	0.01	−0.46	−0.30	−0.02	0.08	8.70
	(0.93)	(0.73)	(0.98)	(0.00)	(0.06)	(0.90)	(0.66)	
UBMP GLS	−0.07	0.07	0.17	−0.22	−0.37	0.16	0.05	11.48
	(0.84)	(0.75)	(0.33)	(0.32)	(0.06)	(0.45)	(0.80)	
MCMP average weights and δ	−0.01	0.05	0.16	−0.32	−0.35	0.15	0.06	12.28
	(0.98)	(0.77)	(0.61)	(0.00)	(0.00)	(0.45)	(1.00)	
MCMP time-varying weights and average δ	−0.02	0.03	0.16	−0.19	−0.18	0.12	0.20	11.40
	(0.96)	(0.88)	(0.57)	(0.13)	(0.05)	(0.57)	(1.00)	
MCMP average weights and time-varying δ	0.00	0.03	0.10	−0.28	−0.36	0.09	−0.00	11.28
	(1.00)	(0.89)	(0.77)	(0.09)	(0.00)	(0.85)	(1.00)	
MCMP time-varying weights and δ	−0.00	0.14	0.10	−0.20	−0.20	−0.02	0.10	9.71
	(1.00)	(0.55)	(0.73)	(0.43)	(0.32)	(0.97)	(1.00)	

Panel C: Using non-announcement-window returns

	Int	PC1	PC2	PC3	PC4	PC5	MF	Rbar
UBMP OLS	0.72	1.04	−0.32	−0.16	0.22	0.01	−1.03	0.32
	(0.03)	(0.03)	(0.40)	(0.72)	(0.59)	(0.96)	(0.03)	
UBMP GLS	1.05	0.44	−0.39	−0.28	0.12	−0.04	−1.31	0.40
	(0.00)	(0.41)	(0.31)	(0.51)	(0.73)	(0.92)	(0.02)	
MCMP average weights and δ	1.08	0.61	−0.47	−0.25	0.16	0.02	−1.39	0.50
	(0.00)	(0.10)	(0.11)	(0.52)	(0.64)	(0.95)	(0.00)	
MCMP time-varying weights and average δ	0.89	0.73	−0.38	−0.21	−0.48	−0.07	−1.22	0.39
	(0.01)	(0.04)	(0.17)	(0.56)	(0.09)	(0.85)	(0.02)	
MCMP average weights and time-varying δ	1.04	0.84	−0.44	−0.27	0.15	−0.19	−1.42	0.49
	(0.00)	(0.03)	(0.14)	(0.45)	(0.66)	(0.59)	(0.00)	
MCMP time-varying weights and δ	0.80	1.13	−0.31	−0.22	−0.60	−0.31	−1.19	0.50
	(0.01)	(0.01)	(0.25)	(0.52)	(0.06)	(0.35)	(0.00)	

Panel D: Using non-announcement-day returns

	Int	PC1	PC2	PC3	PC4	PC5	MF	Rbar
UBMP OLS	0.34	−0.29	1.02	−0.43	−0.04	0.04	−0.27	0.15
	(0.43)	(0.66)	(0.04)	(0.44)	(0.92)	(0.92)	(0.63)	
UBMP GLS	−0.03	−0.01	0.53	−1.03	−1.06	0.27	−0.60	0.77
	(0.94)	(0.99)	(0.27)	(0.06)	(0.04)	(0.58)	(0.28)	
MCMP average weights and δ	0.08	−0.16	0.66	−1.04	−0.83	0.27	−0.58	0.70
	(0.83)	(0.76)	(0.13)	(0.05)	(0.11)	(0.52)	(0.29)	
MCMP time-varying weights and average δ	0.01	−0.27	0.12	−1.10	−0.65	−0.16	−0.46	0.38
	(0.99)	(0.58)	(0.76)	(0.03)	(0.11)	(0.73)	(0.41)	
MCMP average weights and time-varying δ	0.01	−0.29	0.56	−0.96	−0.89	0.27	−0.57	0.67
	(0.97)	(0.57)	(0.18)	(0.06)	(0.06)	(0.51)	(0.29)	
MCMP time-varying weights and δ	−0.05	−0.14	0.09	−1.04	−0.47	−0.39	−0.37	0.20
	(0.91)	(0.81)	(0.79)	(0.03)	(0.27)	(0.39)	(0.49)	

Table 11: Pricing errors and Wald test

This table presents the pricing errors (annualized multiplying by 250) and bootstrap p-values (in parenthesis) implied by a one-factor asset pricing model: see equations (53)–(56) for the case where z_t only includes the constant. The exposures to the single latent factor are obtained using Zhou's (1994, 1999) methodology and the economic risk premia associated with the latent factor are those of OLS-style (Panel A) or GLS-style (Panel B) unit-beta mimicking portfolios. The last two columns report the bootstrap p-values for the test of the joint significance of the pricing errors without (test 1) and with (test 2) conditioning information. The instruments include: the first five principal components extracted from the daily yields provided by Gürkaynak et al. (2007), and the macro factor of Aruoba et al. (2009). The sample starts on March 2, 1993, and ends on March 31, 2008.

Panel A: Using OLS-style unit-beta mimicking portfolios

	2-Year	**5-Year**	**10-Year**	**30-Year**	**Wald Test 1**	**Wald Test 2**
All days	−0.12	−0.42	−0.06	−0.25	0.69	0.86
	(0.83)	(0.55)	(0.93)	(0.74)		
Announcement windows	−0.07	−0.31	−0.01	−0.11	0.76	0.99
	(0.83)	(0.45)	(0.99)	(0.81)		
Non-announcement windows	0.23	0.09	0.16	−0.26	0.95	0.90
	(0.69)	(0.90)	(0.79)	(0.74)		
Non-announcement days	−0.60	−0.41	0.07	0.40	0.67	0.96
	(0.41)	(0.67)	(0.91)	(0.72)		

Panel B: Using GLS-style unit-beta mimicking portfolios

	2-Year	**5-Year**	**10-Year**	**30-Year**	**Wald Test 1**	**Wald Test 2**
All days	0.15	0.16	0.67	0.63	0.31	0.71
	(0.70)	(0.83)	(0.62)	(0.75)		
Announcement windows	0.13	0.11	0.52	0.53	0.45	0.96
	(0.60)	(0.83)	(0.54)	(0.65)		
Non-announcement windows	0.08	−0.25	−0.26	−0.77	0.86	0.92
	(0.85)	(0.79)	(0.85)	(0.72)		
Non-announcement days	0.11	1.08	1.96	2.69	0.39	0.91
	(0.82)	(0.38)	(0.34)	(0.42)		

Economic Risk Premia in the Fixed Income Markets:
The Intra-day Evidence

Separate Appendix

Table 1: Risk premia on unit-beta, OLS-style mimicking portfolios (Fama-MacBeth p-values)

This table presents the results of regressing the 20 unit-beta, OLS-style mimicking portfolio returns on the instruments. The mimicking portfolio returns are obtained by interacting portfolio weights with returns as explained in the text. Portfolio weights are based on announcement betas which are those reported in Table 4 for the Con1 model. Two announcements (Buinv and Budge) that were dropped by the stepwise regression of futures returns on surprises are not included. The instruments include: the first five principal components extracted from the daily yields provided by Gürkaynak et al. (2007), and the macro factor of Aruoba et al. (2009). Mimicking portfolio returns are measured during all trading days (Panel A), during announcement windows (Panel B), during announcement days but outside of the announcement windows (Panel C), and during non-announcement days (Panel D). If more announcements are released on the same day, but at different times during the day, we take the sum of the different announcement-window returns. Following Faust and Wright (2011), the regressions in Panels A and B include as an augmenting variable (not shown in the table) the average of all the standardized announcement surprises on a given day. Regression coefficients are standardized by the conditional volatility of the mimicking portfolio returns and are annualized by multiplying by $\sqrt{250}$. Fama-MacBeth p-values are reported in parenthesis. The adjusted R-squareds (Rbar) are expressed in percentage points. The sample starts on March 2, 1993, and ends on March 31, 2008.

Panel A: Using all-days returns

	Int	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**MF**	**Rbar**
RetS	−0.55	−0.58	−0.13	0.56	0.11	0.01	0.58	3.04
	(0.03)	(0.05)	(0.62)	(0.05)	(0.70)	(0.98)	(0.06)	
Nfarm	−0.55	−0.57	−0.13	0.56	0.11	0.00	0.58	3.07
	(0.03)	(0.05)	(0.63)	(0.04)	(0.69)	(0.99)	(0.06)	
Chic	−0.54	−0.58	−0.13	0.55	0.10	0.01	0.57	2.99
	(0.04)	(0.05)	(0.62)	(0.05)	(0.71)	(0.96)	(0.07)	
CConf	−0.55	−0.58	−0.13	0.56	0.11	0.01	0.58	3.02
	(0.03)	(0.05)	(0.62)	(0.05)	(0.70)	(0.97)	(0.06)	
CPI	−0.53	−0.59	−0.13	0.54	0.10	0.03	0.55	2.89
	(0.04)	(0.05)	(0.60)	(0.05)	(0.72)	(0.92)	(0.07)	
Durab	−0.54	−0.58	−0.13	0.56	0.11	0.01	0.57	3.01
	(0.04)	(0.05)	(0.62)	(0.05)	(0.70)	(0.97)	(0.06)	
ECI	−0.54	−0.58	−0.13	0.55	0.10	0.02	0.56	2.95
	(0.04)	(0.05)	(0.61)	(0.05)	(0.71)	(0.94)	(0.07)	
EHS	−0.69	−0.51	−0.06	0.61	0.31	−0.05	0.96	4.63
	(0.01)	(0.09)	(0.81)	(0.03)	(0.25)	(0.86)	(0.00)	
FOMC	−0.63	−0.51	−0.09	0.66	0.17	−0.09	0.70	3.79
	(0.02)	(0.08)	(0.73)	(0.02)	(0.54)	(0.73)	(0.03)	
GDP	−0.54	−0.58	−0.13	0.55	0.11	0.01	0.57	3.00
	(0.04)	(0.05)	(0.62)	(0.05)	(0.70)	(0.96)	(0.07)	
Defla	−0.47	−0.62	−0.16	0.46	0.07	0.10	0.47	2.38
	(0.07)	(0.04)	(0.55)	(0.10)	(0.80)	(0.73)	(0.13)	
Hst	−0.54	−0.58	−0.13	0.56	0.11	0.01	0.58	3.02
	(0.03)	(0.05)	(0.62)	(0.05)	(0.70)	(0.97)	(0.06)	
IP	−0.54	−0.58	−0.13	0.55	0.11	0.01	0.57	3.00
	(0.04)	(0.05)	(0.62)	(0.05)	(0.70)	(0.96)	(0.06)	
Ijob	0.55	0.58	0.13	−0.56	−0.11	−0.01	−0.58	3.02
	(0.03)	(0.05)	(0.62)	(0.05)	(0.70)	(0.97)	(0.06)	
Lind	−0.54	−0.58	−0.13	0.55	0.10	0.02	0.57	2.97
	(0.04)	(0.05)	(0.61)	(0.05)	(0.71)	(0.96)	(0.07)	
ISM	−0.54	−0.58	−0.13	0.55	0.10	0.02	0.57	2.98
	(0.04)	(0.05)	(0.61)	(0.05)	(0.71)	(0.96)	(0.07)	
NewH	−0.54	−0.58	−0.13	0.55	0.10	0.01	0.57	2.98
	(0.04)	(0.05)	(0.62)	(0.05)	(0.71)	(0.96)	(0.07)	
Phil	−0.55	−0.57	−0.13	0.56	0.11	0.00	0.59	3.08
	(0.03)	(0.05)	(0.63)	(0.04)	(0.69)	(0.99)	(0.06)	
PPI	−0.53	−0.58	−0.13	0.54	0.10	0.02	0.56	2.93
	(0.04)	(0.05)	(0.61)	(0.05)	(0.71)	(0.94)	(0.07)	
Unemp	0.54	0.58	0.13	−0.55	−0.11	−0.01	−0.57	3.01
	(0.04)	(0.05)	(0.62)	(0.05)	(0.70)	(0.97)	(0.06)	

Panel B: Using announcement-window returns

	Int	PC1	PC2	PC3	PC4	PC5	MF	Rbar
RetS	−0.05	−0.15	−0.01	0.85	0.55	0.04	−0.14	8.66
	(0.89)	(0.69)	(0.97)	(0.01)	(0.06)	(0.89)	(0.68)	
Nfarm	−0.05	−0.15	−0.01	0.84	0.55	0.04	−0.14	8.74
	(0.89)	(0.69)	(0.96)	(0.01)	(0.06)	(0.90)	(0.68)	
Chic	−0.05	−0.15	−0.00	0.85	0.55	0.06	−0.14	8.53
	(0.89)	(0.69)	(0.99)	(0.01)	(0.06)	(0.86)	(0.68)	
CConf	−0.05	−0.15	−0.01	0.85	0.55	0.05	−0.14	8.63
	(0.89)	(0.69)	(0.98)	(0.01)	(0.06)	(0.88)	(0.68)	
CPI	−0.05	−0.15	0.01	0.86	0.54	0.07	−0.14	8.28
	(0.88)	(0.69)	(0.98)	(0.01)	(0.06)	(0.82)	(0.67)	
Durab	−0.05	−0.15	−0.01	0.85	0.55	0.05	−0.14	8.59
	(0.89)	(0.69)	(0.98)	(0.01)	(0.06)	(0.87)	(0.68)	
ECI	−0.05	−0.15	0.00	0.85	0.54	0.06	−0.14	8.43
	(0.89)	(0.69)	(0.99)	(0.01)	(0.06)	(0.84)	(0.68)	
EHS	−0.04	−0.05	−0.19	0.72	0.55	−0.12	−0.11	12.29
	(0.91)	(0.89)	(0.50)	(0.04)	(0.06)	(0.71)	(0.75)	
FOMC	−0.03	−0.14	−0.11	0.74	0.58	−0.09	−0.13	10.41
	(0.92)	(0.71)	(0.72)	(0.02)	(0.04)	(0.78)	(0.69)	
GDP	−0.05	−0.15	−0.00	0.85	0.55	0.05	−0.14	8.56
	(0.89)	(0.69)	(0.99)	(0.01)	(0.06)	(0.87)	(0.68)	
Defla	−0.05	−0.15	0.08	0.90	0.50	0.17	−0.14	6.85
	(0.88)	(0.69)	(0.81)	(0.00)	(0.09)	(0.60)	(0.68)	
Hst	−0.05	−0.15	−0.01	0.85	0.55	0.05	−0.14	8.61
	(0.89)	(0.69)	(0.98)	(0.01)	(0.06)	(0.87)	(0.68)	
IP	−0.05	−0.15	−0.00	0.85	0.55	0.05	−0.14	8.57
	(0.89)	(0.69)	(0.99)	(0.01)	(0.06)	(0.87)	(0.68)	
Ijob	0.05	0.15	0.01	−0.85	−0.55	−0.05	0.14	8.61
	(0.89)	(0.69)	(0.98)	(0.01)	(0.06)	(0.88)	(0.68)	
Lind	−0.05	−0.15	−0.00	0.85	0.54	0.06	−0.14	8.49
	(0.89)	(0.69)	(1.00)	(0.01)	(0.06)	(0.86)	(0.68)	
ISM	−0.05	−0.15	−0.00	0.85	0.54	0.06	−0.14	8.51
	(0.89)	(0.69)	(0.99)	(0.01)	(0.06)	(0.86)	(0.68)	
NewH	−0.05	−0.15	−0.00	0.85	0.55	0.05	−0.14	8.51
	(0.89)	(0.69)	(0.99)	(0.01)	(0.06)	(0.86)	(0.67)	
Phil	−0.05	−0.14	−0.01	0.84	0.55	0.04	−0.14	8.76
	(0.89)	(0.69)	(0.96)	(0.01)	(0.06)	(0.90)	(0.68)	
PPI	−0.05	−0.15	0.00	0.86	0.54	0.06	−0.14	8.39
	(0.89)	(0.69)	(0.99)	(0.01)	(0.06)	(0.84)	(0.68)	
Unemp	0.04	0.15	0.01	−0.85	−0.55	−0.05	0.14	8.59
	(0.89)	(0.69)	(0.98)	(0.01)	(0.06)	(0.87)	(0.68)	

Panel C: Using non-announcement-window returns

	Int	PC1	PC2	PC3	PC4	PC5	MF	Rbar
RetS	−0.72	−1.05	0.32	0.16	−0.22	−0.01	1.03	0.32
	(0.03)	(0.01)	(0.33)	(0.67)	(0.55)	(0.97)	(0.01)	
Nfarm	−0.72	−1.04	0.32	0.16	−0.22	−0.02	1.04	0.33
	(0.03)	(0.01)	(0.32)	(0.66)	(0.55)	(0.96)	(0.01)	
Chic	−0.70	−1.05	0.31	0.15	−0.21	−0.01	1.02	0.32
	(0.03)	(0.00)	(0.34)	(0.68)	(0.56)	(0.98)	(0.01)	
CConf	−0.71	−1.05	0.32	0.15	−0.22	−0.01	1.03	0.32
	(0.03)	(0.01)	(0.33)	(0.67)	(0.55)	(0.97)	(0.01)	
CPI	−0.68	−1.06	0.30	0.14	−0.21	−0.00	1.00	0.30
	(0.03)	(0.00)	(0.36)	(0.70)	(0.56)	(0.99)	(0.02)	
Durab	−0.71	−1.05	0.32	0.15	−0.21	−0.01	1.03	0.32
	(0.03)	(0.01)	(0.34)	(0.67)	(0.55)	(0.97)	(0.01)	
ECI	−0.70	−1.05	0.31	0.15	−0.21	−0.01	1.01	0.31
	(0.03)	(0.00)	(0.35)	(0.69)	(0.56)	(0.99)	(0.01)	
EHS	−1.06	−0.81	0.45	0.13	−0.11	0.03	1.46	0.53
	(0.00)	(0.03)	(0.13)	(0.72)	(0.77)	(0.92)	(0.00)	
FOMC	−0.87	−0.94	0.41	0.23	−0.25	−0.06	1.17	0.41
	(0.01)	(0.01)	(0.20)	(0.54)	(0.50)	(0.87)	(0.01)	
GDP	−0.71	−1.05	0.32	0.15	−0.21	−0.01	1.02	0.32
	(0.03)	(0.00)	(0.34)	(0.67)	(0.55)	(0.97)	(0.01)	
Defla	−0.57	−1.08	0.23	0.09	−0.17	0.03	0.90	0.24
	(0.08)	(0.00)	(0.48)	(0.80)	(0.63)	(0.93)	(0.03)	
Hst	−0.71	−1.05	0.32	0.15	−0.21	−0.01	1.03	0.32
	(0.03)	(0.01)	(0.33)	(0.67)	(0.56)	(0.97)	(0.01)	
IP	−0.71	−1.05	0.32	0.15	−0.21	−0.01	1.03	0.32
	(0.03)	(0.00)	(0.34)	(0.68)	(0.56)	(0.97)	(0.01)	
Ijob	0.71	1.05	−0.32	−0.15	0.22	0.01	−1.03	0.32
	(0.03)	(0.01)	(0.33)	(0.67)	(0.55)	(0.97)	(0.01)	
Lind	−0.70	−1.05	0.31	0.15	−0.21	−0.01	1.02	0.31
	(0.03)	(0.00)	(0.34)	(0.68)	(0.56)	(0.98)	(0.01)	
ISM	−0.70	−1.05	0.31	0.15	−0.21	−0.01	1.02	0.31
	(0.03)	(0.00)	(0.34)	(0.68)	(0.56)	(0.98)	(0.01)	
NewH	−0.70	−1.05	0.31	0.15	−0.21	−0.01	1.02	0.32
	(0.03)	(0.00)	(0.34)	(0.68)	(0.56)	(0.97)	(0.01)	
Phil	−0.72	−1.04	0.32	0.16	−0.22	−0.02	1.04	0.33
	(0.02)	(0.01)	(0.32)	(0.66)	(0.55)	(0.96)	(0.01)	
PPI	−0.69	−1.05	0.31	0.14	−0.21	−0.01	1.01	0.31
	(0.03)	(0.00)	(0.35)	(0.69)	(0.56)	(0.99)	(0.01)	
Unemp	0.71	1.05	−0.32	−0.15	0.21	0.01	−1.03	0.32
	(0.03)	(0.01)	(0.34)	(0.67)	(0.55)	(0.98)	(0.01)	

Panel D: Using non-announcement-day returns

	Int	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**MF**	**Rbar**
RetS	−0.34	0.29	−1.02	0.42	0.03	−0.04	0.27	0.15
	(0.43)	(0.56)	(0.02)	(0.40)	(0.95)	(0.94)	(0.61)	
Nfarm	−0.34	0.29	−1.02	0.43	0.04	−0.04	0.27	0.15
	(0.43)	(0.55)	(0.02)	(0.39)	(0.93)	(0.94)	(0.60)	
Chic	−0.34	0.28	−1.02	0.40	0.02	−0.03	0.26	0.14
	(0.44)	(0.56)	(0.02)	(0.42)	(0.97)	(0.95)	(0.62)	
CConf	−0.34	0.29	−1.02	0.42	0.03	−0.03	0.26	0.14
	(0.43)	(0.56)	(0.02)	(0.40)	(0.95)	(0.94)	(0.61)	
CPI	−0.34	0.28	−1.03	0.37	−0.00	−0.02	0.25	0.12
	(0.43)	(0.57)	(0.02)	(0.46)	(1.00)	(0.97)	(0.63)	
Durab	−0.34	0.28	−1.02	0.41	0.03	−0.03	0.26	0.14
	(0.43)	(0.56)	(0.02)	(0.41)	(0.96)	(0.95)	(0.61)	
ECI	−0.34	0.28	−1.02	0.39	0.01	−0.02	0.25	0.13
	(0.44)	(0.57)	(0.02)	(0.44)	(0.98)	(0.96)	(0.62)	
EHS	−0.05	0.06	−0.86	0.77	0.58	−0.19	0.57	0.43
	(0.90)	(0.91)	(0.04)	(0.14)	(0.24)	(0.69)	(0.27)	
FOMC	−0.32	0.34	−0.95	0.70	0.25	−0.13	0.37	0.32
	(0.46)	(0.49)	(0.03)	(0.18)	(0.61)	(0.78)	(0.47)	
GDP	−0.34	0.28	−1.02	0.41	0.02	−0.03	0.26	0.14
	(0.43)	(0.56)	(0.02)	(0.41)	(0.96)	(0.95)	(0.61)	
Defla	−0.33	0.22	−1.03	0.20	−0.10	0.04	0.19	0.06
	(0.45)	(0.65)	(0.02)	(0.68)	(0.83)	(0.93)	(0.72)	
Hst	−0.34	0.28	−1.02	0.41	0.03	−0.03	0.26	0.14
	(0.44)	(0.56)	(0.02)	(0.41)	(0.95)	(0.95)	(0.61)	
IP	−0.34	0.28	−1.02	0.41	0.02	−0.03	0.26	0.14
	(0.44)	(0.56)	(0.02)	(0.41)	(0.96)	(0.95)	(0.61)	
Ijob	0.34	−0.28	1.02	−0.42	−0.03	0.03	−0.26	0.14
	(0.43)	(0.56)	(0.02)	(0.41)	(0.95)	(0.95)	(0.61)	
Lind	−0.34	0.28	−1.02	0.40	0.02	−0.03	0.26	0.14
	(0.43)	(0.56)	(0.02)	(0.42)	(0.97)	(0.95)	(0.62)	
ISM	−0.34	0.28	−1.02	0.40	0.02	−0.03	0.26	0.14
	(0.43)	(0.56)	(0.02)	(0.42)	(0.97)	(0.95)	(0.62)	
NewH	−0.34	0.28	−1.02	0.40	0.02	−0.03	0.26	0.14
	(0.43)	(0.56)	(0.02)	(0.42)	(0.97)	(0.95)	(0.62)	
Phil	−0.34	0.29	−1.02	0.43	0.04	−0.04	0.27	0.15
	(0.44)	(0.55)	(0.02)	(0.39)	(0.93)	(0.94)	(0.60)	
PPI	−0.34	0.28	−1.02	0.39	0.01	−0.02	0.25	0.13
	(0.43)	(0.57)	(0.02)	(0.44)	(0.99)	(0.96)	(0.63)	
Unemp	0.34	−0.28	1.02	−0.41	−0.03	0.03	−0.26	0.14
	(0.44)	(0.56)	(0.02)	(0.41)	(0.95)	(0.95)	(0.61)	

Table 2: Risk premia on unit-beta, OLS-style mimicking portfolios (Amihud-Hurvich-Wang, 2009, approach)

This table presents the results of regressing the 20 unit-beta, OLS-style mimicking portfolio returns on the instruments. We use the augmented-regression method of Amihud and Hurvich (2004) and Amihud, Hurvich, and Wang (2009). Two announcements (Buinv and Budge) that were dropped by the stepwise regression of futures returns on surprises are not included. The instruments include: the first five principal components extracted from the daily yields provided by Gürkaynak et al. (2007), and the macro factor of Aruoba et al. (2009). Mimicking portfolio returns are measured during all trading days (Panel A), during announcement windows (Panel B), during announcement days but outside of the announcement windows (Panel C), and during non-announcement days (Panel D). If more announcements are released on the same day, but at different times during the day, we take the sum of the different announcement-window returns. Regression coefficients are standardized by the conditional volatility of the mimicking portfolio returns, (obtained by taking out the effect of the augmented regressors) and are annualized by multiplying by $\sqrt{250}$. The p-values are reported in parenthesis and are obtained following Amihud, Hurvich, and Wang (2009). The adjusted R-squareds (Rbar) are expressed in percentage points. The sample starts on March 2, 1993, and ends on March 31, 2008.

Panel A: Using all-days returns

	Int	PC1	PC2	PC3	PC4	PC5	MF	Rbar
RetS	−0.51	−0.32	0.00	0.33	−0.03	−0.13	0.60	95.27
	(0.05)	(0.27)	(0.98)	(0.63)	(0.97)	(0.89)	(0.04)	
Nfarm	−0.51	−0.32	0.00	0.33	−0.03	−0.13	0.61	95.29
	(0.05)	(0.27)	(0.98)	(0.63)	(0.98)	(0.89)	(0.04)	
Chic	−0.51	−0.32	0.00	0.32	−0.03	−0.12	0.60	95.24
	(0.05)	(0.27)	(0.98)	(0.64)	(0.97)	(0.90)	(0.04)	
CConf	−0.51	−0.32	0.00	0.32	−0.03	−0.12	0.60	95.27
	(0.05)	(0.27)	(0.98)	(0.63)	(0.97)	(0.89)	(0.04)	
CPI	−0.50	−0.33	0.00	0.31	−0.04	−0.10	0.58	95.17
	(0.05)	(0.26)	(0.99)	(0.64)	(0.97)	(0.91)	(0.04)	
Durab	−0.51	−0.32	0.00	0.32	−0.03	−0.12	0.60	95.26
	(0.05)	(0.27)	(0.98)	(0.64)	(0.98)	(0.89)	(0.04)	
ECI	−0.50	−0.33	0.00	0.32	−0.03	−0.11	0.59	95.22
	(0.05)	(0.27)	(0.99)	(0.64)	(0.98)	(0.90)	(0.04)	
EHS	−0.65	−0.34	−0.02	0.33	0.12	−0.22	1.01	88.55
	(0.01)	(0.32)	(0.96)	(0.71)	(0.93)	(0.85)	(0.01)	
FOMC	−0.59	−0.29	0.01	0.38	−0.00	−0.24	0.74	95.12
	(0.02)	(0.34)	(0.98)	(0.60)	(1.00)	(0.81)	(0.02)	
GDP	−0.51	−0.32	0.00	0.32	−0.03	−0.12	0.60	95.25
	(0.05)	(0.27)	(0.98)	(0.64)	(0.97)	(0.89)	(0.04)	
Defla	−0.44	−0.34	0.00	0.26	−0.04	−0.03	0.49	94.50
	(0.09)	(0.23)	(1.00)	(0.69)	(0.97)	(0.98)	(0.08)	
Hst	−0.51	−0.32	0.00	0.32	−0.03	−0.12	0.60	95.27
	(0.05)	(0.27)	(0.98)	(0.64)	(0.98)	(0.89)	(0.04)	
IP	−0.51	−0.32	0.00	0.32	−0.03	−0.12	0.60	95.26
	(0.05)	(0.27)	(0.98)	(0.64)	(0.97)	(0.90)	(0.04)	
Ijob	0.51	0.32	−0.00	−0.32	0.03	0.12	−0.60	95.27
	(0.05)	(0.27)	(0.98)	(0.63)	(0.98)	(0.89)	(0.04)	
Lind	−0.50	−0.32	0.00	0.32	−0.04	−0.12	0.59	95.24
	(0.05)	(0.27)	(0.98)	(0.64)	(0.97)	(0.90)	(0.04)	
ISM	−0.50	−0.32	0.00	0.32	−0.03	−0.12	0.59	95.24
	(0.05)	(0.27)	(0.98)	(0.64)	(0.97)	(0.90)	(0.04)	
NewH	−0.51	−0.32	0.00	0.32	−0.04	−0.12	0.59	95.24
	(0.05)	(0.27)	(0.98)	(0.64)	(0.97)	(0.90)	(0.04)	
Phil	−0.52	−0.32	0.00	0.33	−0.03	−0.13	0.61	95.30
	(0.05)	(0.27)	(0.98)	(0.63)	(0.98)	(0.89)	(0.04)	
PPI	−0.50	−0.33	0.00	0.32	−0.04	−0.11	0.59	95.21
	(0.05)	(0.26)	(0.99)	(0.64)	(0.97)	(0.90)	(0.04)	
Unemp	0.51	0.32	−0.00	−0.32	0.03	0.12	−0.60	95.27
	(0.05)	(0.27)	(0.98)	(0.64)	(0.98)	(0.89)	(0.04)	

Panel B: Using announcement-window returns

	Int	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**MF**	**Rbar**
RetS	−0.01	−0.05	0.06	0.51	0.28	−0.23	0.12	22.67
	(0.97)	(0.88)	(0.86)	(0.37)	(0.74)	(0.74)	(0.77)	
Nfarm	−0.01	−0.05	0.06	0.50	0.28	−0.23	0.12	22.71
	(0.97)	(0.88)	(0.87)	(0.37)	(0.74)	(0.73)	(0.76)	
Chic	−0.01	−0.05	0.07	0.52	0.27	−0.22	0.12	22.60
	(0.97)	(0.88)	(0.85)	(0.35)	(0.74)	(0.75)	(0.77)	
CConf	−0.01	−0.05	0.07	0.51	0.28	−0.23	0.12	22.65
	(0.97)	(0.88)	(0.86)	(0.36)	(0.74)	(0.74)	(0.77)	
CPI	−0.01	−0.05	0.08	0.53	0.27	−0.20	0.12	22.46
	(0.96)	(0.89)	(0.82)	(0.34)	(0.73)	(0.77)	(0.78)	
Durab	−0.01	−0.05	0.07	0.51	0.28	−0.22	0.12	22.63
	(0.97)	(0.88)	(0.85)	(0.36)	(0.74)	(0.75)	(0.77)	
ECI	−0.01	−0.05	0.08	0.52	0.27	−0.21	0.12	22.54
	(0.97)	(0.88)	(0.83)	(0.35)	(0.74)	(0.76)	(0.77)	
EHS	0.00	0.00	−0.13	0.33	0.22	−0.45	0.21	22.65
	(0.99)	(1.00)	(0.73)	(0.61)	(0.82)	(0.58)	(0.65)	
FOMC	0.01	−0.06	−0.04	0.38	0.28	−0.39	0.16	23.13
	(0.99)	(0.86)	(0.91)	(0.53)	(0.75)	(0.60)	(0.71)	
GDP	−0.01	−0.05	0.07	0.51	0.28	−0.22	0.12	22.61
	(0.97)	(0.88)	(0.85)	(0.36)	(0.74)	(0.75)	(0.77)	
Defla	−0.02	−0.04	0.15	0.60	0.26	−0.08	0.09	21.37
	(0.95)	(0.90)	(0.67)	(0.25)	(0.73)	(0.90)	(0.82)	
Hst	−0.01	−0.05	0.07	0.51	0.28	−0.22	0.12	22.64
	(0.97)	(0.88)	(0.85)	(0.36)	(0.74)	(0.75)	(0.77)	
IP	−0.01	−0.05	0.07	0.51	0.27	−0.22	0.12	22.63
	(0.97)	(0.88)	(0.85)	(0.36)	(0.74)	(0.75)	(0.77)	
Ijob	0.01	0.05	−0.07	−0.51	−0.28	0.22	−0.12	22.64
	(0.97)	(0.88)	(0.86)	(0.36)	(0.74)	(0.75)	(0.77)	
Lind	−0.01	−0.05	0.07	0.52	0.27	−0.21	0.12	22.58
	(0.97)	(0.88)	(0.84)	(0.35)	(0.74)	(0.75)	(0.77)	
ISM	−0.01	−0.05	0.07	0.52	0.27	−0.21	0.12	22.58
	(0.97)	(0.88)	(0.84)	(0.35)	(0.74)	(0.75)	(0.77)	
NewH	−0.01	−0.05	0.07	0.52	0.27	−0.22	0.12	22.59
	(0.97)	(0.88)	(0.84)	(0.35)	(0.74)	(0.75)	(0.77)	
Phil	−0.01	−0.05	0.06	0.50	0.28	−0.24	0.12	22.72
	(0.97)	(0.88)	(0.87)	(0.37)	(0.74)	(0.73)	(0.76)	
PPI	−0.01	−0.05	0.08	0.52	0.27	−0.20	0.12	22.51
	(0.97)	(0.88)	(0.83)	(0.35)	(0.74)	(0.76)	(0.78)	
Unemp	0.01	0.05	−0.07	−0.51	−0.28	0.22	−0.12	22.62
	(0.97)	(0.88)	(0.85)	(0.36)	(0.74)	(0.75)	(0.77)	

Panel C: Using non-announcement-window returns

	Int	PC1	PC2	PC3	PC4	PC5	MF	Rbar
RetS	−0.71	−0.79	0.39	0.05	−0.24	−0.01	0.92	50.86
	(0.03)	(0.02)	(0.22)	(0.94)	(0.80)	(0.99)	(0.03)	
Nfarm	−0.72	−0.79	0.39	0.05	−0.24	−0.01	0.93	50.86
	(0.03)	(0.02)	(0.22)	(0.93)	(0.80)	(0.99)	(0.03)	
Chic	−0.70	−0.80	0.39	0.05	−0.24	−0.01	0.91	50.87
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	
CConf	−0.71	−0.79	0.39	0.05	−0.24	−0.01	0.92	50.86
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	
CPI	−0.68	−0.80	0.38	0.04	−0.23	−0.00	0.89	50.88
	(0.03)	(0.02)	(0.24)	(0.95)	(0.81)	(1.00)	(0.03)	
Durab	−0.71	−0.79	0.39	0.05	−0.24	−0.01	0.92	50.87
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	
ECI	−0.70	−0.80	0.38	0.04	−0.23	−0.00	0.91	50.88
	(0.03)	(0.02)	(0.23)	(0.94)	(0.81)	(1.00)	(0.03)	
EHS	−1.06	−0.66	0.43	0.01	−0.16	0.02	1.35	46.17
	(0.00)	(0.08)	(0.26)	(0.99)	(0.90)	(0.98)	(0.01)	
FOMC	−0.87	−0.73	0.44	0.10	−0.29	−0.06	1.06	50.31
	(0.01)	(0.03)	(0.18)	(0.88)	(0.77)	(0.95)	(0.01)	
GDP	−0.71	−0.79	0.39	0.05	−0.24	−0.01	0.91	50.87
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	
Defla	−0.57	−0.81	0.33	0.01	−0.18	0.03	0.80	50.69
	(0.08)	(0.02)	(0.30)	(0.99)	(0.85)	(0.97)	(0.05)	
Hst	−0.71	−0.79	0.39	0.05	−0.24	−0.01	0.92	50.87
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	
IP	−0.71	−0.79	0.39	0.05	−0.24	−0.01	0.92	50.87
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	
Ijob	0.71	0.79	−0.39	−0.05	0.24	0.01	−0.92	50.87
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	
Lind	−0.70	−0.80	0.39	0.05	−0.24	−0.01	0.91	50.87
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	
ISM	−0.70	−0.80	0.39	0.05	−0.24	−0.01	0.91	50.87
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	
NewH	−0.70	−0.80	0.39	0.05	−0.24	−0.01	0.91	50.87
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	
Phil	−0.72	−0.79	0.39	0.05	−0.24	−0.01	0.93	50.86
	(0.02)	(0.02)	(0.22)	(0.93)	(0.80)	(0.99)	(0.03)	
PPI	−0.69	−0.80	0.38	0.04	−0.23	−0.00	0.90	50.88
	(0.03)	(0.02)	(0.24)	(0.94)	(0.81)	(1.00)	(0.03)	
Unemp	0.71	0.79	−0.39	−0.05	0.24	0.01	−0.92	50.87
	(0.03)	(0.02)	(0.23)	(0.94)	(0.80)	(0.99)	(0.03)	

Panel D: Using non-announcement-day returns

	Int	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**MF**	**Rbar**
RetS	−0.34	0.54	−0.93	0.34	0.04	−0.02	0.19	24.53
	(0.43)	(0.21)	(0.04)	(0.58)	(0.96)	(0.98)	(0.73)	
Nfarm	−0.34	0.54	−0.93	0.35	0.05	−0.02	0.19	24.46
	(0.43)	(0.21)	(0.04)	(0.57)	(0.95)	(0.98)	(0.73)	
Chic	−0.34	0.54	−0.93	0.32	0.03	−0.01	0.18	24.63
	(0.44)	(0.21)	(0.04)	(0.60)	(0.97)	(0.99)	(0.74)	
CConf	−0.34	0.54	−0.93	0.33	0.04	−0.02	0.18	24.55
	(0.43)	(0.21)	(0.04)	(0.59)	(0.96)	(0.98)	(0.74)	
CPI	−0.34	0.53	−0.93	0.29	0.01	−0.00	0.17	24.84
	(0.43)	(0.21)	(0.04)	(0.63)	(0.99)	(1.00)	(0.76)	
Durab	−0.34	0.54	−0.93	0.33	0.04	−0.01	0.18	24.59
	(0.43)	(0.21)	(0.04)	(0.59)	(0.96)	(0.98)	(0.74)	
ECI	−0.34	0.53	−0.93	0.31	0.03	−0.01	0.18	24.71
	(0.44)	(0.21)	(0.04)	(0.62)	(0.97)	(0.99)	(0.75)	
EHS	−0.05	0.22	−0.87	0.66	0.55	−0.19	0.48	19.72
	(0.90)	(0.63)	(0.07)	(0.36)	(0.56)	(0.82)	(0.42)	
FOMC	−0.32	0.56	−0.91	0.58	0.24	−0.11	0.28	22.88
	(0.46)	(0.19)	(0.05)	(0.33)	(0.76)	(0.87)	(0.60)	
GDP	−0.34	0.54	−0.93	0.33	0.04	−0.01	0.18	24.61
	(0.43)	(0.21)	(0.04)	(0.59)	(0.96)	(0.99)	(0.74)	
Defla	−0.33	0.49	−0.92	0.14	−0.07	0.05	0.11	25.88
	(0.45)	(0.25)	(0.05)	(0.82)	(0.93)	(0.94)	(0.84)	
Hst	−0.34	0.54	−0.93	0.33	0.04	−0.01	0.18	24.57
	(0.44)	(0.21)	(0.04)	(0.59)	(0.96)	(0.98)	(0.74)	
IP	−0.34	0.54	−0.93	0.33	0.04	−0.01	0.18	24.60
	(0.44)	(0.21)	(0.04)	(0.60)	(0.96)	(0.99)	(0.74)	
Ijob	0.34	−0.54	0.93	−0.33	−0.04	0.02	−0.18	24.57
	(0.43)	(0.21)	(0.04)	(0.59)	(0.96)	(0.98)	(0.74)	
Lind	−0.34	0.54	−0.93	0.32	0.03	−0.01	0.18	24.67
	(0.43)	(0.21)	(0.04)	(0.60)	(0.97)	(0.99)	(0.74)	
ISM	−0.34	0.54	−0.93	0.32	0.03	−0.01	0.18	24.66
	(0.43)	(0.21)	(0.04)	(0.60)	(0.97)	(0.99)	(0.74)	
NewH	−0.34	0.54	−0.93	0.32	0.03	−0.01	0.18	24.65
	(0.43)	(0.21)	(0.04)	(0.60)	(0.97)	(0.99)	(0.74)	
Phil	−0.34	0.54	−0.93	0.35	0.06	−0.02	0.19	24.44
	(0.44)	(0.21)	(0.04)	(0.57)	(0.94)	(0.98)	(0.73)	
PPI	−0.34	0.53	−0.93	0.31	0.03	−0.01	0.17	24.75
	(0.43)	(0.21)	(0.04)	(0.62)	(0.97)	(0.99)	(0.75)	
Unemp	0.34	−0.54	0.93	−0.33	−0.04	0.01	−0.18	24.58
	(0.44)	(0.21)	(0.04)	(0.59)	(0.96)	(0.98)	(0.74)	