

Forecasting Bond Returns Using Jumps in Intraday Prices

Author:

Siawash Safavi Nic

Student Number:

769219

Master Program:

QFAS, Tilburg University

Supervisor Tilburg University:

Prof. Dr. Bas Werker

Supervisors Robeco:

Drs. Johan Duyvesteyn, CFA

Dr. Ir. Martin Martens

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Preface

With writing this Master thesis comes an end to my life as a lazy student. At the same time it marks the start of a new life. Studying has been sometimes exiting and enlightening, sometimes boring. My graduation internship has been fun all the way. This thesis can be seen (at least the way I like to see it) as the crown on my work so far.

My special thanks go out to both my supervisors at Robeco Asset Management for giving me the once in a life time opportunity to become a super quant. First of all I would like to thank Dr. Ir. Martin Martens, co-head Quantitative Strategies, for his valuable ideas and insights. I would like to thank Drs. Johan Duyvesteyn, CFA. I could not have written this thesis without his daily feedback and sharp eye on my work. He always kept me on track whenever I was in danger of loosing control. In addition I would like to thank my supervisor at the university, Prof. Dr. Bas Werker, for his critical view on my work. The monthly meetings always encouraged me to work harder. Of course I would like to thank my parents for their encouragement and support in (almost) every decision I made during my life so far. My final thanks go out to my friends and colleagues for giving me the needed distraction during the last half year.

Siawash Safavi Nic
Rotterdam, March 29th 2010

1. Abstract

In 2005 Cochrane and Piazzesi published their paper Bond Risk Premia in the American Economic Review. In this paper the authors show that one to five year forward rates are able to forecast US bond returns with R^2 's up to 36%.

This paper has generated a number of other papers including the paper Bond Risk Premia and Realized Jump Risk of Wright and Zhou (2009). They show that augmenting the regression of excess bond returns on the term structure of forward rates (Cochrane and Piazzesi (2005)) with an estimate of the mean realized jump size almost doubles the R^2 to 60%. This variable is constructed by estimating jumps in intraday prices using high frequency data and subsequently taking the rolling average of all the jumps over the last two years.

In this paper we replicate the findings of Wright and Zhou (2009) and present a refinement of their jump mean variable, namely return jump mean. We show that this variable performs better in the regression models: An R^2 of 67% in the regression together with the forward rates compared to 48% for the jump mean variable of Wright and Zhou (2009). The return jump mean variable also performs well in investment strategies. We show that using a revised version of this variable we achieve an information ratio of 0.64 for our in-sample period and 0.52 for the out-of-sample period.

We show that the jump mean and return jump mean have a low correlation with mean reversion, indicating that these variables are related but not the same. This indicates that there is added value in these variables above mean reversion. In our final regression model we achieve an R^2 of 72% using the forward rates, return jump mean and mean reversion as explanatory variables.

In addition we study the relation between macro-economic news announcements and jumps in bond future prices and show that announcements with the largest impact on bond future prices are related to employment, inflation and confidence announcements. This confirms the findings of Balduzzi (1997). About 44% of all the jumps are caused by macro-economic announcements.

2. Related Literature

In recent years much academic research has been done in the field of bond forecasting literature. The authors have found significant forecastable variation in US excess bond returns. First we refer to some key research (that forms the basis of new results), and then we will continue with some new ideas presented in recent literature.

2.1. *Classics*

Fama and Bliss (1987) find that the spread between the n -year forward rate and the one-year yield predicts (one year) excess returns of the n -year bond ($n=2,3,4$ and 5). The R^2 reported is 18%. Campbell and Shiller (1991) use yield spreads to forecast excess returns. Ilmanen (1995) uses a small set of global instruments to predict bond excess returns in six different countries. Cochrane and Piazzesi (2005) recently showed a large amount of predictability of US excess bond returns (with an R^2 of 35%) with maturities ranging from two to five years using a linear combination of forward rates. The Cochrane and Piazzesi (CP) paper has become a benchmark in the literature. It is cited to by a number of other papers.

Robeco has already analysed these papers and uses the most relevant ideas from these in quantitative investment strategies. For this internship we focus more on the recent research.

2.2. *Recent literature*

Ludvigson and Ng (2009) investigate the predictable power of macro factors to forecast one-year excess returns. They find predictable variation in one year excess bond returns that is associated with macroeconomic activity, even after controlling for the CP forecasting factor, with R^2 's up to 45%.

Greenwood and Vayanos (2008) find that a larger proportion of long term debts predict positive bond excess returns, on top of the CP factor and the slope of the yield curve. The proportion of long term debt is positively related to the steepness of the yield curve. A steeper curve is known to predict positive bond returns because of time varying risk premia. This is known as a carry strategy where you borrow against a low rate and invest at a high rate in the longer maturity bonds.

Faust and Wright (2009) find that using the CP factors is most significant when estimation is based on 15 minutes around 10 important macro-economic news announcements. They show a strategy based on estimated coefficients for these 15 minutes applied to monthly positions improves over using the more noisy coefficients obtained from monthly return data, with a Sharpe ratio of 0.52 versus -0.18 for the 10-year future.

Almeida et al (2008) use arbitrage-free affine term structure models to explain bond and interest rate options (caps) simultaneously. The output contains factors with predictive power for bond markets. They argue that interest rate options may contain information about the risk premium because their prices are sensitive to the volatility and market prices of the risk factors that drive interest rates.

2.3. *Wright and Zhou (2009)*

Wright and Zhou (2009) augment the regression model of CP with measures of Implied Volatility, Realized Volatility, Jump Intensity, Jump Mean and Jump Volatility. The authors use high-frequency Treasury bond futures data to construct realized volatility and jump risk measures. Assuming that the price of an asset (a bond in this paper) follows a jump-diffusion process, the authors take a direct approach to identify realized jumps based on Barndorff-Nielsen and Shephard (2004, 2006). This approach uses high-frequency data to decompose realized volatility into separate continuous and jump components (see Huang and Tauchen (2005) and Andersen, Bollerslev, and Diebold (2007) as well) and hence to detect days on which jumps occur and to estimate the magnitude of these jumps. The jump mean variable in this paper has power to forecast future US bond returns with an R^2 of 15%. Including the forward rate variables of Cochrane and Piazzesi (2005) into the model, the R^2 increases to 60%.

We choose this paper for further research. It shows promising results and uses a new source of data: high frequency (Intraday). This is not used within Robeco yet. A plus is that the data is easy to update from Bloomberg. Intraday data are available for the last 50 days for different countries. After a meeting with the portfolio managers we have agreed to further investigate the idea in this paper. First we want to replicate and check the results in the paper. Furthermore we want to get more intuition into the data and the results.

Our second preference for further research was the paper of Ludvigson and Ng (2005), Macro Factors in Bond Risk Premia. This paper shows good empirical results, however the technique used in the paper (summarize macro-economic data using principal component analysis) is already analyzed within Robeco (with promising results) and shows therefore overlap with previous research done on macro data.

The same holds for the paper of Faust and Wright (2009), Risk Premia in the 8:30 Economy. The idea presented in the paper is interesting, but it leans towards Cochrane and Piazzesi (2005) which is already extensively studied within Robeco.

The results of Greenwood and Vayanos (2008) are less promising. The debt maturity is a very slow variable (high autocorrelation) and the results are not robust over subintervals. The authors split the sample in two and find predictability only in the second part of the sample. Also the intuition is not clear.

The model of Almeida et al (2008) is complex and not transparent. Moreover, the result is not consistent with the disappointing results for implied volatility of Wright and Zhou (2009). In their paper the implied volatility variable is highly insignificant with an R^2 of less than 1%.

3. Data

3.1. Source

For constructing excess returns, yields and forward rates, we used end-of-month data on zero-coupon bonds from the CRSP Fama-Bliss dataset. The CRSP data consists of end-of-month prices of one to five-year US zero coupon bonds. The data are available for students and employees of Tilburg University at the WRDS.com (Wharton Research Data Services).

We also use bond data from Datastream and JP Morgan (market standard for bonds) to compare it to the CRSP data. The latter is mostly used in academic research.

We obtained the intraday data (US 10-year futures) from Tickdata.com. Complete futures & index data by symbol costs 650 USD. Wright and Zhou (2009) consider 30-year futures, but we choose for the 10-year future, since the latter is more liquid (higher volume, lower bid-ask spread). Intraday 10-year futures data is available from January 1983 till October 2009, but before 1989 data is available only from 8:00 AM Chicago time. For our research however it is crucial to also consider data around 7:30 Chicago time, since around this time there are often macro-economic data releases in the US, which usually cause extreme price movements. Therefore we start our analysis from January 1989.

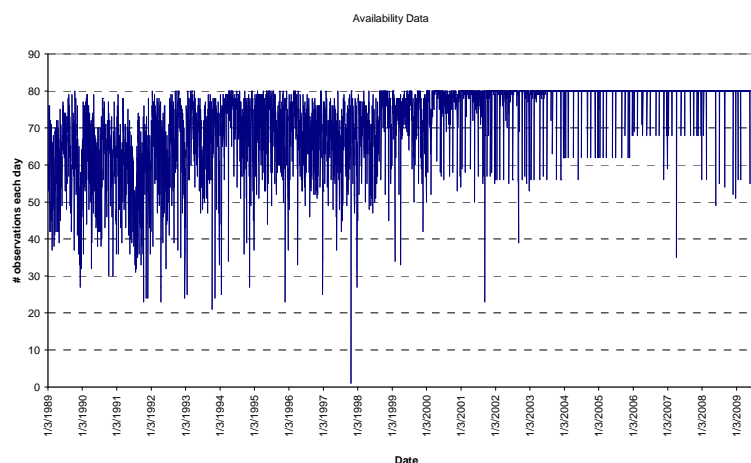
With each order Tickdata includes a database management software, TickWrite, which enables users to create ASCII files custom-tailored to their needs. TickWrite can construct time intervals of any granularity, generate continuous futures files, and adjust for rollover gaps.

We look at five-minute frequency from January 1989 till October 2009. The five-minute frequency is the standard in the literature for high frequency data. Data at higher frequencies are subject to market microstructure noises like the bid and ask bounce. For each day we look at the period from 7:20 till 14:00 Chicago time. This means we have a total of 80 observations for each day. Our in-sample set is from January 1989 till December 2002 and our out-of-sample analysis is based on the period January 2003-October 2009. By explicitly choosing an out-of-sample period, we try to avoid data mining.

3.2. Quality and availability

The data availability (10 year US future from Tickdata) is better for the second part of the sample than the first part as follows from the figure below.

Figure 1: # of observations each day



We (ideally) should have 80 observations for each day, but for the first part of the sample there are a lot of 'holes' in the data as follows from Figure 1. Missing observations are because of no trade within that five-minute interval or because of shorter trading days like 24 and 31 December.

We have in total for 41% of all trading days 80 observations. In case of no data for a specific time, we fill the empty interval with the price of the previous observation. Therefore, for our analysis we do have 80 data points for each day.

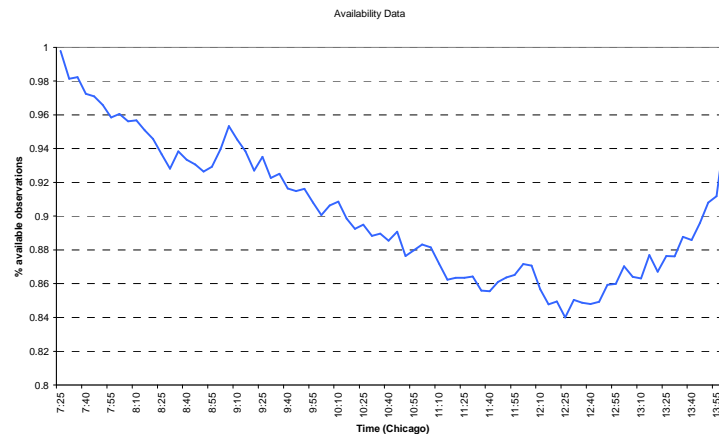
The same pattern follows from the table below. For the first 7 years of our sample only for 2% of the days we have a total of 80 observations. For the periods 1996-2002 and 2003-2009 the percentage increases to respectively 27% and 94%. The 2% for the first 7 years is not much, but the average number of observations for each day for the same period is 65, which is still considerable. For the periods 1996-2002 and 2003-2009 the average number of observations increases to 73 and 79.

Table 1: Data availability for different sub periods

period	# days with 80 obs.	# total days	% days with 80 obs.	average # obs.
1989-1995	43	1763	2%	65
1996-2002	475	1753	27%	73
2003-2009	1619	1724	94%	79

Another interesting feature is to look at the data availability for different time points. As follows from the figure below at 7:20 AM there is always data available. The availability declines till noon and increases after that. Lower availability coincides with lower volume. This pattern is common within high frequency data. Around lunch time there is less data available and also the traded volume is less.

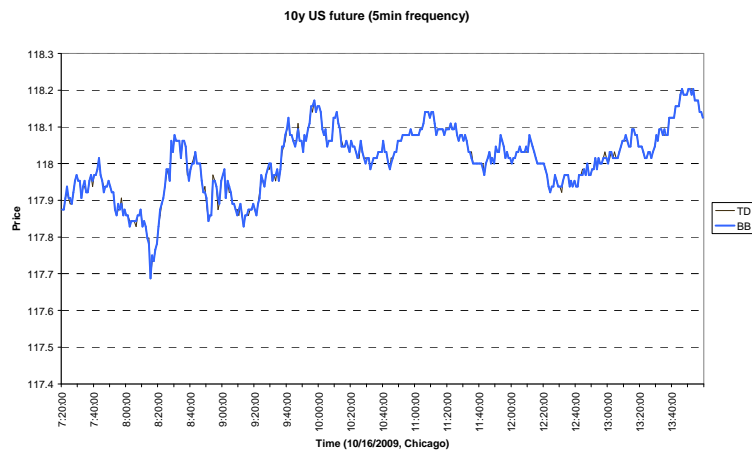
Figure 2: % available observations for each time point



Intraday data is also available from Bloomberg, but only for the last 50 days. To check the quality of our source we compared data from Tickdata to Bloomberg. See the figure below for 16 October 2009.

The two lines are very close (we see similar patterns for other days) and when there is a difference it is either $1/64$ or $1/32$. This could be caused by rounding errors, since future prices (in the US) are always noted in fractions instead of decimals or timing and source differences. In general however the quality of the data looks good.

Figure 3: Comparison intraday data from Bloomberg and Tickdata



We use Bloomberg also as our source for updating the data.

4. Method

In this section we give an outline of the technique used to determine jumps in the time series of future (or more generally asset) prices. A jump is informally defined as an extreme change in the price in a short time window. We illustrate the method with a theoretical example. Next we continue with the formal procedure and after that we give an example using real data. At the end of this chapter we present the definitions of the variables used in the forecast regressions.

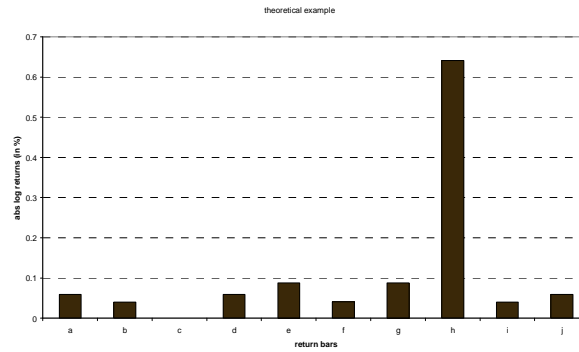
4.1. Theoretical example jump statistic

In this section we give an example to illustrate the method presented in this paper to detect jumps in intraday prices. In the next section we give the formal definitions of the variables.

The method is based on the difference between realized volatility (RV) and bi-power variation (BV). Assuming that the volatility of an asset consists of two parts, a continuous and a jump component, the RV measures both parts, while BV measures only the continuous part. The difference between the two denotes the jump. Based on this idea you can derive various test statistics to derive whether the difference is significant or not.

In the figure below the intraday log returns of a fictional day is shown. The letters denote absolute five-minute returns.

Figure 4: Intraday absolute log returns of an asset



The figure above graphs the (theoretical) intraday absolute log returns of an asset. The return corresponding to the 'h' bar is much larger compared to the rest.

Looking at the graph one would expect a jump, since one of the returns (h) dominates the other ones in size. The RV and BV for this day are equal to:

$$RV = a^2 + b^2 + \dots + j^2$$

$$BV = \frac{\pi}{2} \frac{10}{9} (ab + bc + \dots + ij)$$

RV measures the total price variance (both continuous part and the jump component) during a trading day, while the BV measures only the continuous part of the variance. A large difference between these two indicates a jump. The RV here gets dominated by the h^2 part. In the BV the h -return appears twice: gh and hi . These two products are much smaller than h^2 and this is what causes the RV to be larger than the BV. The example provided here gives the essence of the method to determine jumps in asset prices. To formally test for a jump, we use the test statistic presented in the next section.

4.2. Realized volatility and Bi-power variation

To identify jumps we use high-frequency Treasury bond futures data to construct realized volatility and jump risk measures. Assuming that the price of an asset (a bond future in this paper) follows a jump-diffusion process, we take (following Wright and Zhou (2009)) a direct approach to identify realized jumps based on Barndorff-Nielsen and Shephard (2004, 2006). This approach uses high-frequency data to decompose realized volatility into separate continuous and jump components (see Huang and Tauchen (2005) and Andersen, Bollerslev, and Diebold (2007) as well) and hence to detect days on which jumps occur and to estimate the magnitude of these jumps. We use intraday (high frequency) 10-year Treasury bond future data to construct realized variance and jump measures. We follow the same approach and notation as Wright and Zhou (2009).

Let s_t denote the logarithmic asset price at time t . It is assumed that this quantity evolves as a continuous-time jump diffusion process. It is expressed in stochastic differential equation as:

$$ds_t = \mu_t dt + \sigma_t dW_t + J_t dq_t$$

where μ_t and σ_t are the drift and the strictly positive (stochastic) volatility functions. W_t is a standard Wiener process and q_t is a counting process with intensity J_t (possibly time varying), and J_t is the corresponding (log) jump size with mean JM_t and variance JV_t^2 . Also the jump mean and variance are allowed to be time varying in a completely unrestricted way. Time t is measured in daily units and the intraday returns are defined as:

$$r_{t,j}^s \equiv s_{t,j \cdot \Delta} - s_{t,(j-1) \cdot \Delta}$$

Here, $r_{t,j}^s$ denotes the j -th intraday return on day t and Δ is the sampling frequency within a day. This means that there are a total of $1/\Delta$ observations every trading day. In the literature it is common to use five-minute intervals rather than more frequent observations. This is because more frequent observations may be subject to distortion from market microstructure noise like the bid-ask bounce (See Ait-Sahalia et-al. (2005) and Bandi and Russell (2006)).

The quadratic variation process over day t of the cumulative return process, r_t^s , is then:

$$(r, r)_t = \int_{t-1}^t \sigma_u^2 du + \int_{t-1}^t J_u^2 dq_u \quad (1)$$

where the second part of the summation in the RHS of (1) is equal to the squared jumps occurred at day t . Of course, in the absence of jumps, it is equal to zero and the quadratic variation process becomes the integrated volatility of the continuous sample path component.

Barndorff-Nielsen and Shephard (2004) propose in their paper two general measures for the quadratic variation process, namely realized variance (RV) and realized bi-power variation (BV). These two measures converge (uniformly as the sampling frequency $\Delta \rightarrow 0$ or equivalently the number of observations $m = 1/\Delta \rightarrow \infty$) to different functionals of the underlying jump-diffusion process:

$$RV_t \equiv \sum_{j=1}^m |r_{t,j}^s|^2 \rightarrow \int_{t-1}^t \sigma_u^2 du + \int_{t-1}^t J_u^2 dq_u = (r, r)_t \quad (2)$$

$$BV_t \equiv \frac{\pi}{2} \frac{m}{m-1} \sum_{j=2}^m |r_{t,j}^s| |r_{t,j-1}^s| \rightarrow \int_{t-1}^t \sigma_u^2 du \quad (3)$$

As follows from (2) and (3) realized variance and bi-power variation coincide (in the limit) in case of no jump and the difference is strictly positive when there is a jump. This is the basis of the method to identify jumps.

4.3. Test statistics

A number of jump detection techniques are proposed by Barndorff-Nielsen and Shephard (2004). Wright and Zhou (2009) use in their paper the ratio statistic favored by Huang and Tauchen (2005) and Andersen et al. (2007). We apply the same measure which is defined as:

$$RJ_t \equiv \frac{RV_t - BV_t}{RV_t}$$

RJ_t is a measure of the relative jump. The test statistic based on it is:

$$ZJ_t \equiv \frac{RV_t - BV_t}{\sqrt{[(\frac{\pi}{2})^2 + \pi - 5] \frac{1}{m} TP_t}} \xrightarrow{d} N(0, 1) \quad (4)$$

This test statistic ¹ has in the limit (as the number of observations $m \rightarrow \infty$) under null a standard normal distribution. However Huang and Tauchen (2005) report based on their simulations that ZJ_t in (4) tends to over-reject the null hypothesis of no jump. Huang and Tauchen (2005) find that the ratio-statistic,

$$ZJ_t \equiv \frac{RJ_t}{\sqrt{[(\frac{\pi}{2})^2 + \pi - 5] \frac{1}{m} \max(1, \frac{TP_t}{BV_t^2})}} \xrightarrow{d} N(0, 1) \quad (5)$$

is very closely approximated under the null by a standard normal distribution. Moreover, they find that this test statistic in (5) has great power (small type II error). We follow Andersen et al. (2007) and Wright and Zhou (2009) and use (5) as our test statistic. Huang and Tauchen (2005) showed that this test is quite accurate in detecting jumps in Monte Carlo simulations.

Following Tauchen and Zhou (2010) and Wright and Zhou (2009) we assume that there is at most one jump each day and that when a jump in the future price occurs the jump dominates the return on that day. Using these assumptions, we can filter out the realized jumps in future prices as:

$$\hat{J}_t = \text{sign}(r_t^s) * \sqrt{(RV_t - BV_t) * I_{(ZJ_t \geq \Phi_\alpha^{-1})}} \quad (6)$$

The Φ in (6) is the cumulative distribution function (CDF) of a standard normal random variable. $I_{(ZJ_t \geq \Phi_\alpha^{-1})}$ is the indicator function which takes the value 1 if the test statistic exceeds the critical value and α is the corresponding significance level. Here we choose α equal to 0.0001 (corresponding to a critical value of 3.719). The small significance level is justified since we are interested only in extreme market movements. Andersen et

¹ TP_t is the tri-power quarticity, and as show by Barndorff-Nielsen and Shephard (2004) is holds:

$$TP_t \equiv m \mu_{4/3}^{-3} \frac{m}{m-2} \sum_{j=3}^m |r_{t,j-2}^s|^{4/3} |r_{t,j-1}^s|^{4/3} |r_{t,j}^s|^{4/3} \rightarrow \int_{t-1}^t \sigma_u^4 du$$

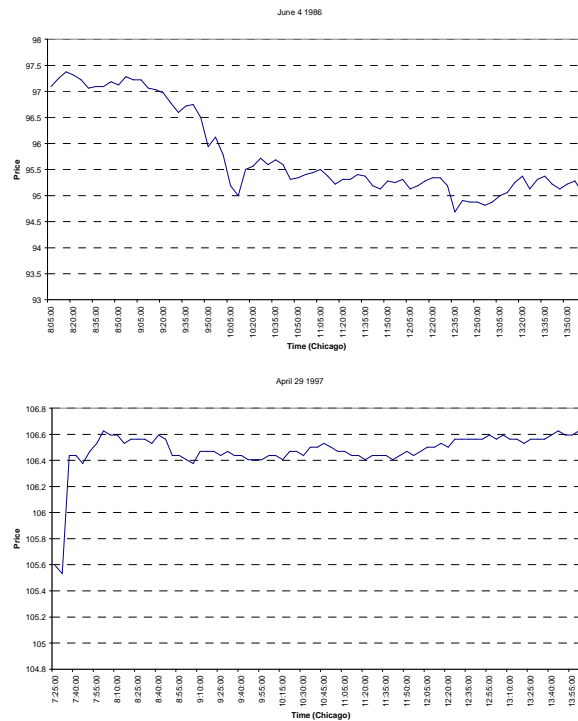
with $\mu_k \equiv 2^{k/2} \Gamma((k+1)/2) / \Gamma(1/2)$ for $k > 0$

al. (2007) document that for their sample (1990-2002 30-year T-bond) taking a significance level of 0.0001 produces jumps at 7.6% of the days. Wright and Zhou (2009) do not mention their significance level, but they also find jumps at 8% of the days for their sample (1982-2006 30-year T-bond).

4.4. Example jump statistics using real data

Below in Figure 5 two graphs are shown. The first one denotes a continuous price movement, while the second shows a 'jump'. This example is meant to show that the method used to filter jumps from intraday data is able to discriminate between large continuous price movements and jump components.

Figure 5: Two examples of large intraday price changes



The two figures above graph the intraday price movements of the 10 year US bond future at five minutes frequency. The first figure graphs a day with large return but continuous movements and the second figure denotes a 'jump' in the intraday price movements.

As explained in the text the RV measures the total price variance (both continuous part and the jump component) during a trading day, while the BV measures only the continuous part of the variance. To look for jumps, determine whether the difference between the two is significant.

Since both RV and BV are variance measures and therefore not in the same dimension as the price and the returns we will denote here the square root of the two to have more feeling for the numbers.

The first graph in Figure 5 follows from the price movement at June 4 1986. The square root of the RV and the BV statistics are for this day equal to:

$$\sqrt{RV} = 1.60\%$$

$$\sqrt{BV} = 1.62\%$$

The square root difference between RV and BV (if significant) denotes the jump size, but the two values are close to each other and the difference is not significant (therefore no jump at this day) as follows formally from the test:

$$ZJ = -0.28 < 3.72 \text{ (= critical value corresponding to } \alpha = 0.0001 \text{)}.$$

As you can see, the BV is slightly larger than the RV (this corresponds to a negative value of ZJ). This might seem strange since RV measures the total price variance and BV measures only the continuous part of the variance,

but in the absence of jump the two statistics measure the same parameter and in a finite sample it can happen that BV becomes (slightly) larger.

The second graph in Figure 5 follows from the price movement at April 29 1997. From the figure you can see an extreme price movement around 7:30 (Chicago time). Around this time there often are macro-economic data releases in the US (for example unemployment, CPI, PPI). One would expect a jump from a formal test. The RV and BV statistics are for this day equal to:

$$\sqrt{RV} = 0.91\%$$

$$\sqrt{BV} = 0.40\%$$

Unlike the previous example there is a big difference here between RV and BV. The question is, is it significant? The null hypothesis of no jump is rejected with great confidence:

$$ZJ = 9.21 > 3.72 \text{ (= critical value corresponding to } \alpha = 0.0001 \text{)}.$$

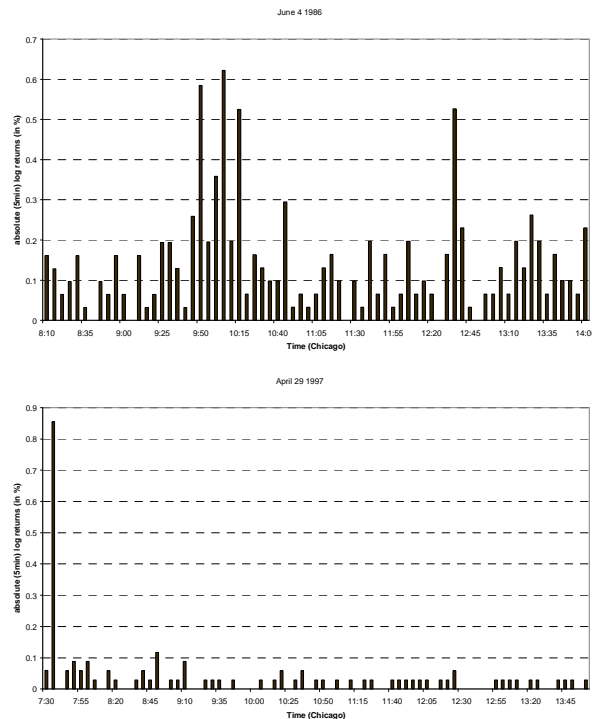
The (log) jump size equals the square root difference between RV and BV:

$$\text{Sqrt}(0.91\%^2 - 0.40\%^2) = 0.82\%.$$

Looking at the graph, you can see that there is a jump between 7:30 AM and 7:35 AM. The closing prices at 7:30 and 7:35 were 105.53 respectively 106.44. The log difference of the two prices is: $\log(106.44) - \log(105.53) = 0.86\%$, which is very close to the estimated jump size.

The same pattern is visible if you look at the five-minute returns at the same days. The first graph in Figure 6 follows from the returns at June 4 1986, the second from April 29 1997.

Figure 6: Intraday five-minute absolute log returns



The two figures above graph the intraday five-minute absolute log returns of the 10 year US bond future for the same days as in Figure 5. Again the first figure graphs a day with large return but continuous movements and the second figure denotes a 'jump' in the intraday price movements.

For June 4 1986 there are different large return bars corresponding to large but continuous price movements, while for April 29 1997 there is clearly one bar extremely larger than the rest, corresponding to a jump in the future price.

4.5. Variable definitions

After identifying the jumps we can then, like Wright and Zhou (2009), estimate the jump mean, volatility and intensity as:

$$JI_t = \frac{\text{Number of realized Jump Days}}{\text{Number of Total Trading Days}}$$

$$JM_t = \text{Mean of realized Jumps}$$

$$JV_t = \text{St.Deviation of realized Jumps}$$

The next step is to investigate the forecast power of these jump measures for bond excess returns. Wright and Zhou (2009) already showed that an estimate of the jump mean has great power to forecast one year bond excess returns.

We want to replicate the results of Wright and Zhou (2009) and check whether we can get similar results. Our estimates of bond future realized volatility, jump mean, jump volatility and jump intensity are based on 10-year Treasury bond futures. We look at data at five-minute frequency from January 1989 till October 2009, obtained from tickdata.com. For each day we look at the period from 7:20 till 14:00 Chicago time (corresponding to 8:20 till 15:00 New York time). This means we have a total of 80 observations for each day. We use the data to calculate (continuously compounded) returns as the log difference in the future quotes, as explained in the section method. We continue to calculate realized volatility and bi-power variation at daily frequency, test for jumps on each day, and estimate the magnitude of the jumps on those days when jumps are detected. Again using the technique explained in the section method.

Let D_{t-j}^{DAILY} denote the dummy variable, which takes the value 1 when a jump is detected at day t and is 0

otherwise, and \hat{J}_t denotes the corresponding jump size at day t .

For our empirical work, let the h -month rolling average realized volatility, jump mean, jump volatility and jump intensity be defined as (in the formulas below 22 refers to the # of trading days each month):

$$RV_t^h = \frac{1}{h*22} \sum_{j=0}^{h*22-1} RV_{t-j}$$

$$JM_t^h = \frac{\sum_{j=0}^{h*22-1} \hat{J}_{t-j} D_{t-j}^{DAILY}}{\sum_{j=0}^{h*22-1} D_{t-j}^{DAILY}}$$

$$JV_t^h = \sqrt{\frac{\sum_{j=0}^{h*22-1} (\hat{J}_{t-j} - JM_t^h)^2 D_{t-j}^{DAILY}}{\sum_{j=0}^{h*22-1} D_{t-j}^{DAILY}}}$$

$$JI_t^h = \frac{1}{h*22} \sum_{j=0}^{h*22-1} D_{t-j}^{DAILY}$$

The jump mean and volatilities are calculated only over days where a jump is detected. Wright and Zhou (2009) take one-month rolling window for realized volatility, since it can be estimated accurately with a fixed span of

sufficiently high-frequency data. Also for realized volatility you have one observation for every day. This is certainly not the case for jumps; given the presumption that jumps in asset prices are both rare and large. Wright and Zhou (2009) therefore argue that you need much longer rolling window for calculating the jump mean, jump volatility and jump intensity. They take the parameter h equal to 24 months or 12 months. The tradeoff in choosing h is that a shorter window gives a noisier but also timelier measure of agents' perceptions of jump risk.

5. Replication Wright and Zhou

In this section we replicate the results of Wright and Zhou (2009). The first objective is to see whether we get similar results. Notice that we can not exactly replicate their findings, since we have a different sample period and our analysis is based on the 10-year US future while Wright and Zhou (2009) use the 30 year future.

5.1. Bond return regression models

Wright and Zhou (2009) use in their paper realized volatility and jump risk measures (as constructed in the previous section) to forecast excess bond returns. We use end-of-month data on zero-coupon bonds from the CRSP Fama-Bliss data to construct excess returns. We use the following notation for log bond prices:

$$p_t^{(n)} = \log \text{ price of the } n\text{-year discount bond at time } t.$$

The log yield is denoted by:

$$y_t^{(n)} = -\frac{1}{n} p_t^{(n)}.$$

Following Cochrane and Piazzesi (2005) we write the log forward rate at time t for loans between time $t + n - 1$ and $t + n$ as:

$$f_t^{(n)} = p_t^{(n-1)} - p_t^{(n)}.$$

We denote the log return from buying an n -year bond at time t and selling it as an $n-1$ year bond at time $t + 1$ as:

$$r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)}.$$

We write one-year log excess returns by:

$$ex_{t+1}^{(n)} = r_{t+1}^{(n)} - y_t^{(1)}.$$

We use over bars to denote averages across maturity:

$$\overline{ex}_{t+1} = \frac{1}{4} \sum_{n=2}^5 ex_{t+1}^{(n)}$$

All the regressions for excess bond returns that we consider in this section are nested within the specification:

$$\overline{ex}_{t+1} = \beta_0 + \beta_1 f_t^1 + \beta_2 f_t^3 + \beta_3 f_t^5 + \beta_4 RV_t^1 + \beta_5 JM_t^h + \beta_6 JI_t^h + \beta_7 JV_t^h + \varepsilon_{t+1} \quad (7)$$

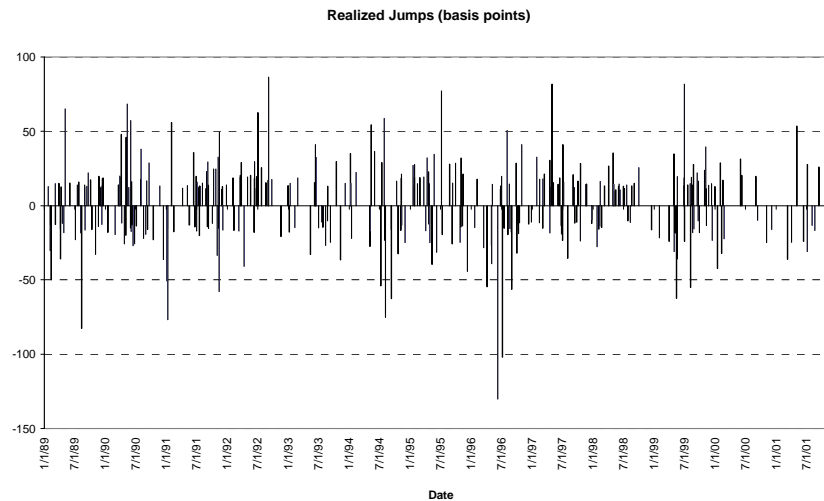
In this section we copy the settings of Wright and Zhou (2009), using their variables and also a one-year holding period. The next sections will include other (our own) variables and we will also consider shorter holding periods (3 months).

Using just the forward rates in the regression you get Cochrane and Piazzesi (2005), except that, following Wright and Zhou (2009) we use three forward rates instead of five, to minimize the near-perfect collinearity problem. Also the R^2 of the CP regression with three forward rates is nearly the same as the regression using all the five forward rates (the difference is less than 1 percentage point).

5.2. Graphs and summary statistics forecast variables

The figure below graphs the realized jumps for our in-sample period (1989-2002). For the first part of the analysis we will only look at excess returns until end of 2002 (jump variables until end of 2001 because of one-year holding period). We do this to minimize the risks of data mining. In the next sections we will perform (again for our in-sample period) some robustness checks and after choosing our optimal model, we perform an out-of-sample analysis until end of 2009.

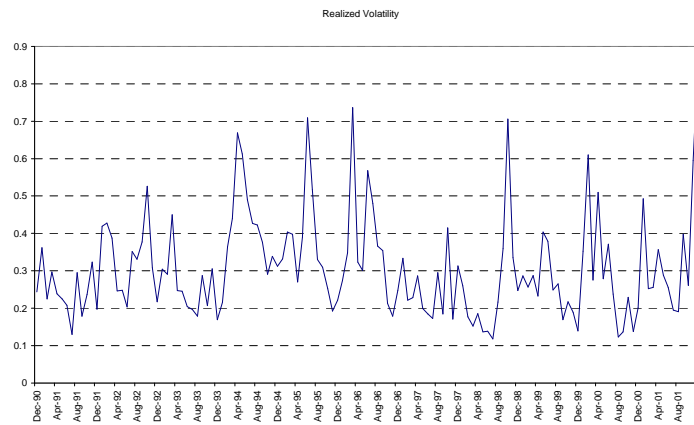
Figure 7: Estimated daily jumps for the 10-year US bond future (in basis points), constructed as described in the text.



Using the realized jumps graphed in Figure 7 we can construct our jump variables described previously. For our complete sample jumps occur on about 8% of the days, which is similar to Wright and Zhou (2009) and Andersen et al (2007). We use 24-month rolling windows for the construction of the jump intensity, jump mean and jump volatility. This seems a long rolling window, but since jumps are rare (on average 2 jumps a month), we need a long rolling window to have enough observations to construct our variables. In the robustness section we will also look at a one-year rolling window. For Realized Volatility however we take a rolling window of one-month, since in contrast with the jump variables we have for the RV an observation for each day and we do not need a long horizon to get an accurate estimate of the mean.

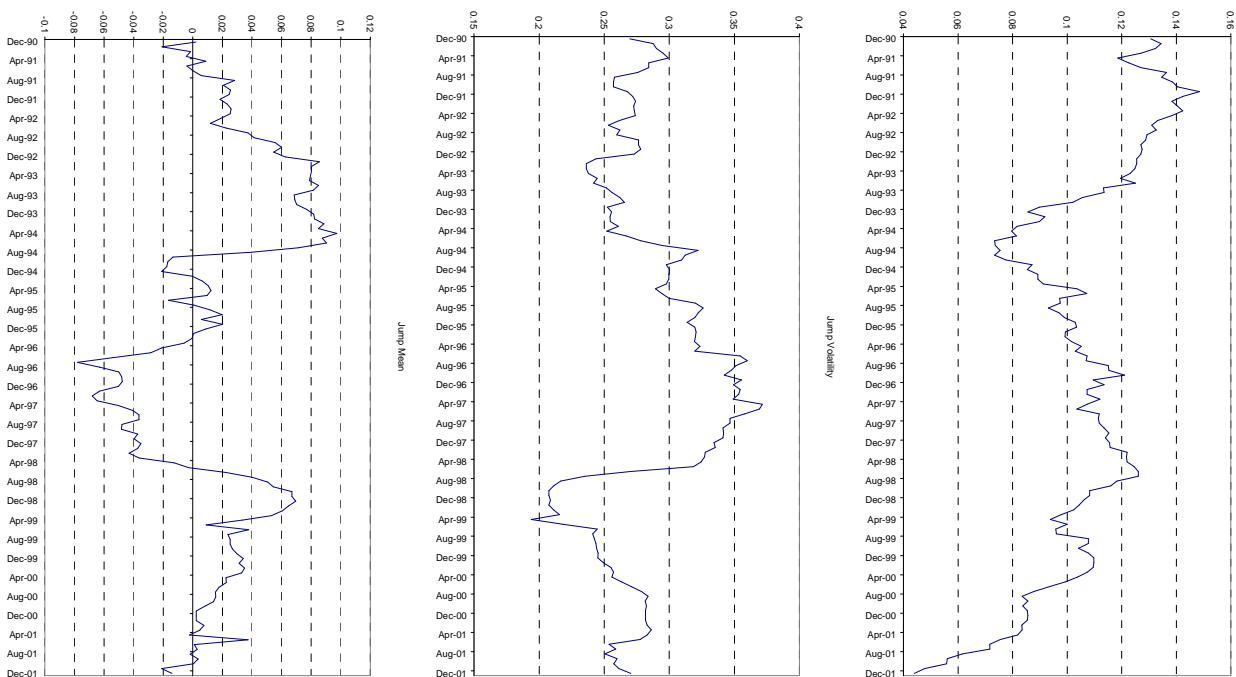
The figure below plots the one-month rolling window of the realized volatility:

Figure 8: Realized volatility for the 10-year US bond future (in annualized percentage points) using a one-month rolling window, constructed as described in the text.



Below you can see the graphs of the jump variables. The RV is less smooth (because of the shorter rolling window) compared to the jump mean, jump intensity and the jump volatility. The jump mean will appear to be a significant forecast variable of the one-year bond excess returns.

Figure 9: Realized jump risk measures. 24-month rolling estimates of the jump mean, jump intensity and jump volatility, constructed as described in the text.



Some summary statistics for the key variables are given in Table 2. The averages of the jump intensity, jump mean and jump volatility for this sample are respectively 11%, 2 basis points and 28 basis points. The average of the jump mean does not seem to be large, but remember that we take the average over positive and negative jumps. Turning to the correlation matrix, you can see that the excess returns are highly correlated. Also the forward rates are positively correlated. The jump mean variable is fairly negatively correlated with the excess returns.

	ex 2	ex 3	ex 4	ex 5	f1	f3	f5	RV	JI	JM	JV
mean	1.05	1.82	2.43	2.67	5.03	6.14	6.36	0.31	0.11	0.02	0.28
std	1.46	2.82	3.95	4.91	1.10	0.89	1.04	0.14	0.02	0.04	0.04
corr matrix											
	ex 2	ex 3	ex 4	ex 5	f1	f3	f5	RV	JI	JM	JV
ex 2	100%	98%	96%	93%	32%	57%	45%	0%	7%	-38%	22%
ex 3		100%	99%	97%	29%	57%	46%	3%	4%	-39%	22%
ex 4			100%	99%	27%	60%	52%	5%	7%	-38%	23%
ex 5				100%	27%	62%	54%	6%	5%	-38%	25%
f1					100%	62%	31%	-12%	14%	-44%	41%
f3						100%	90%	8%	33%	-25%	32%
f5							100%	7%	38%	2%	13%
RV								100%	-28%	8%	-3%
JI									100%	1%	2%
JM										100%	-78%
JV											100%

Table 2: Summary statistics and correlation matrix for excess returns, forward rates, and jump measures for the sample 1991-2002. All the variables are in percentages except jump intensity (raw value).

All the variables in Table 2 are in percentages except the jump intensity. The average excess returns increase with maturity: 1.05% for the two year bond versus 2.67% for the five year bond. This higher return comes with greater risk: 1.46% standard deviation for the two year bond versus 4.91% for the five year bond.

Since the 2, 3, 4 and 5 year US bond excess returns are strongly positively correlated we take, following Wright and Zhou (2009), the average of these variables in the regression analysis. So the y-variable is equal to:

$$\overline{ex}_{t+1} = \frac{1}{4} \sum_{n=2}^5 ex_{t+1}^{(n)}$$

5.3. Main results replication Wright and Zhou (2009)

In this section we present the regression model estimates of the jump variables as presented in Wright and Zhou (2009). Table 3 shows the coefficient estimates, the corresponding t-values and R^2 's for different specifications of (7). The settings are as follows: one-year holding period, two-year rolling window for the jump variables (one-month for RV), the y-variable in the regression is the excess returns on a bond (average 2 to 5 year) over those on a one-year bond. In this table the forward rates are not included in the regressions. The jump mean variable is on its own a significant negative predictor of bond excess returns as follows from the t-value and the R^2 . This implies that positive jumps are followed by negative excess returns and visa versa. The R^2 of the jump mean is comparable with using one single forward rate with a matching maturity, Fama-Bliss (1987). This is in contrast with the other variables.

For the jump volatility you get an R^2 of 6%, however the variable is not significant. The RV and JI show no predictive power at all. These results coincide with the findings of Wright and Zhou (2009).

We look here only at our in-sample period: 1991-2002. We use intraday data of the 10-year US future starting from 1989, but we use two-year rolling window and therefore our first estimate of the jump variables is from the beginning of 1991. We use a one-year holding period, therefore the last estimate of the jump variables is at December 2001 (for the excess returns it is December 2002).

From Table 2 we observe that the standard deviation of both jump mean and jump intensity is 4 basis points. So an increase of one standard deviation of the jump mean variable means ceteris paribus a decrease of 1.2% in the average excess return ($-30.20 * 0.0004$). An increase of one standard deviation of the jump volatility variable means (again ceteris paribus) an increase of 0.76% in the average excess return ($19.02 * 0.0004$). However one has to be careful with the interpretation of this last example, since the jump volatility is not significant.

	Intercept	t-value	variable	t-value	R2
JI	0.01	0.26	0.09	0.24	0%
JM	0.02	3.03	-30.20	-2.15	15%
JV	-0.03	-0.66	19.02	1.13	6%
RV	0.02	1.36	0.16	0.44	0%
sample	1991:2002				

Table 3: This table reports coefficient estimates in a regression of the excess returns on a bond (average 2 to 5 year) over those on a one-year bond, with a holding period of 12 months, an one-month rolling window of realized volatility, and 24-month rolling windows of the bond jump mean, jump intensity and jump volatility. Observations are at the monthly frequency (end-of-month). The t-values are based on Newey-West standard errors.

Table 4 shows the results from other specifications of (7), but now with the forward rates included. The coefficients of the forward rates show more or less the well-known tent pattern. However the pattern is not as strong as in Cochrane and Piazzesi (2005), but this is also an other sample. Running the regression of the excess returns using the forward rates alone gives an R^2 of 41%, which is a lot and similar to the findings in Cochrane and Piazzesi (2005). Including the jump mean variable into the regression the R^2 increases to 48%, however the jump mean loses a bit of its significance (significant at 5%, but not at 2.5%) compared to the case with no forward rates included in the regression. This is a bit different than the results of Wright and Zhou (2009). For their sample (1982-2006) the jump mean remains strongly significant with t-values and R^2 's around respectively -6 and 60%. However in the next chapter we will present a refinement of the jump mean variable, which will perform much better than the jump mean even after including the forward rates in the regression.

Meanwhile, the realized volatility, jump volatility and jump intensity show no predictive power, also after including the CP variables in the regression.

The coefficient of the jump mean variable in the multivariate regression of Table 4 is not much changed compared to the univariate regression, suggesting that the forward rates and the jump mean variable measure different components of the bond risk premium. This also suggests that the interpretation of the jump mean variable as presented in this section does not change much.

	Intercept	t-value	f1	t-value	f3	t-value	f5	t-value	variable	t-value	R2
CP	-0.11	-2.48	-1.16	-1.44	5.08	3.17	-1.92	-1.44			41%
CP + JI	-0.10	-1.82	-1.11	-1.54	4.93	3.23	-1.67	-1.32	-0.20	-0.62	43%
CP + JM	-0.09	-2.33	-1.14	-1.46	3.55	2.93	-0.73	-0.77	-24.16	-1.71	48%
CP + JV	-0.12	-2.00	-1.17	-1.42	4.95	2.93	-1.83	-1.28	3.22	0.24	42%
CP + RV	-0.11	-2.33	-1.28	-1.47	5.34	3.07	-2.06	-1.45	-0.28	-1.01	42%
sample	1991:2002										

Table 4: This table reports coefficient estimates in a regression of the excess returns on a bond (average 2 to 5 year) over those on a one-year bond, with a holding period of 12 months, an one-month rolling window for realized volatility, and 24-month rolling window for the bond jump mean, jump intensity and jump volatility. Observations are at the monthly frequency (end-of-month). In these regressions also the 1-, 3- and 5-year forward rates (CP variables) are included. The t-values are based on Newey-West standard errors.

In this section we replicated the results presented in Wright and Zhou (2009). In the next section, Chapter 6, we present a refinement of the jump mean variable and introduce a mean reversion variable, which we relate to the jump mean. The reason for this is that the jump mean ‘feels’ like mean reversion, since the coefficient estimate in the regression model is negative: Upward jumps forecast negative excess returns. In Chapter 6 we show that these two variables are correlated to some extend, but they are definitely not the same. In Chapter 7 we present different robustness checks (shorter holding period, shorter rolling window and lower threshold value for identifying jumps) and continue to find important role for the jump mean in forecasting excess returns.

6. Refinements

In this chapter we present a refinement of the jump mean variable which performs better in the regression model and we also introduce a mean reversion variable to relate it to the jump mean.

6.1. Definition variables

The jump mean variable is a (two-year) rolling average of the jumps in 10-year US future prices. You can ask the question whether all the jumps are of equal importance in forecasting excess returns. For example it can happen that after a small jump the future price will move back towards its previous level before the jump. This indicates that the jump was of little significance (or not immediately rightly understood by the market). On the other hand, it is possible that after a big jump the price will continue to move towards the same direction. The jump mean variable is not able to capture such features, because we measure the jump size only. It might be more useful to look at the total return occurred on a jump day, instead at the jump size itself. It will indeed turn out that this variable, which we call return jump mean (RJM), will perform better than the jump mean variable. The RJM variable is thus the (two-year) rolling average of the log returns occurred at days where a jump is detected. In formula we get:

$$RJM_t^h = \frac{\sum_{j=0}^{h*22-1} R_{t-j} D_{t-j}^{DAILY}}{\sum_{j=0}^{h*22-1} D_{t-j}^{DAILY}}$$

Again the h denotes the rolling window, D_{t-j}^{DAILY} is the dummy variable which takes the value 1 when a jump is detected at day t and is 0 otherwise and R_t is the log return at day t .

The intuition behind the jump mean variable in Wright and Zhou (2009) is weak. The jump mean variable is strongly significant and the results presented in the paper are great, but it is not presented with a good explanation (we need to improve the intuition in order to have confidence in the results). One of our first ideas was to compare the jump mean to the mean reversion (MR) variable presented in Fama (2006). The jump mean feels like mean reversion since the coefficient in the regression is negative. Our mean reversion variable is the cumulative (log) return of the past two years (same rolling window as the jump mean). We calculate the MR not as the difference between today's log future price and the price two years before, since these denote different future contracts. Instead we calculate for each day the log return and add that up. In formula you get:

$$MR_t^h = \sum_{j=0}^{h*22-1} R_{t-j}$$

Table 5 presents the correlation between the jump mean, return jump mean and mean reversion. JM and RJM are as expected strongly correlated. You would expect that a jump would dominate the return at that day and that indeed follows from the high correlation between JM and RJM. JM and MR show a correlation of 9% but MR is more correlated with RJM. Denote the difference between these two variables. MR is the cumulative return over every day for the past two days, where RJM is the average return only over days where a jump is detected.

	JM	RJM	MR
mean	0.02	0.03	0.03
std	0.04	0.07	0.05
corr matrix			
	JM	RJM	MR
JM	100%	80%	9%
RJM		100%	35%
MR			100%

Table 5: Summary statistics and correlation matrix for JM, RJM and MR for the sample 1991-2002. JM and RJM are in percentages.

These correlations show that the jump variables JM and RJM are related to mean reversion, but they are definitely not the same and thus there is added value in the jump mean variable above mean reversion. Figure 10 graphs the JM together with RJM and MR. JM and RJM show similar patterns as follows from the high correlation. The sign of both variables usually coincides except for the end of the sample (from April 99). The JM remains positive while RJM falls below zero.

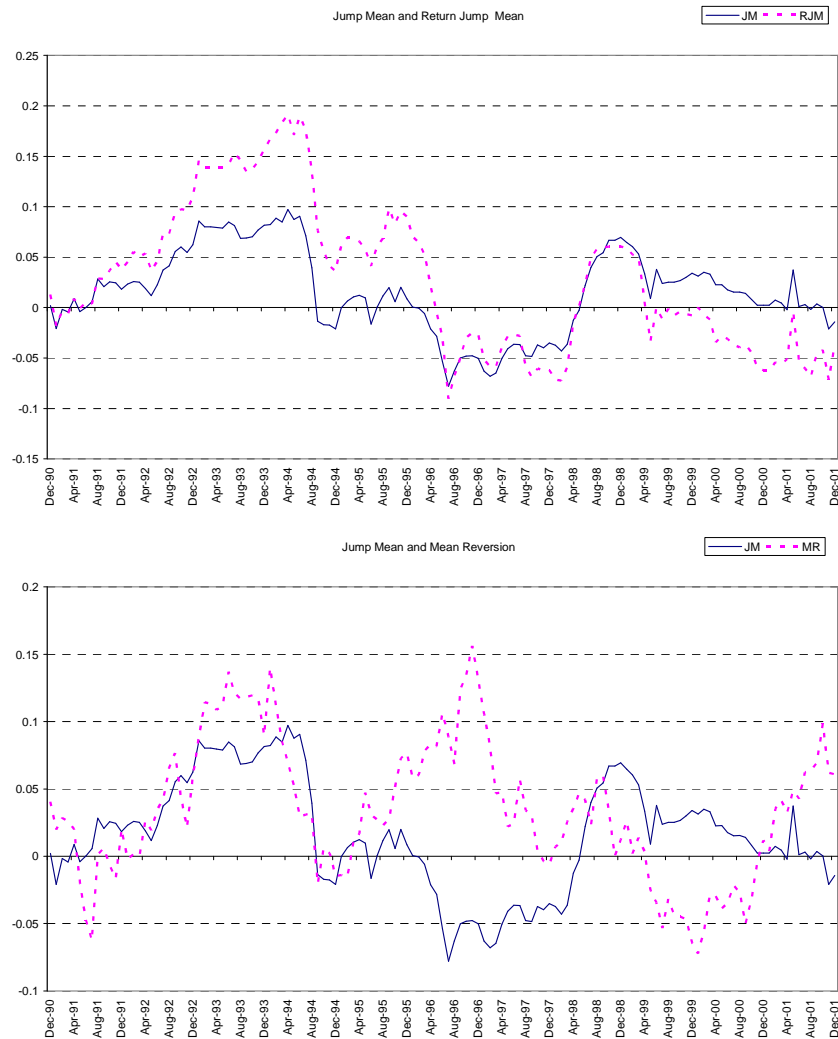


Figure 10: Two year rolling window estimates of the jump mean together with return jump mean (first panel) and mean reversion (second panel). The variables are constructed as described in the text.

Looking at the second graph in Figure 10, you can see that in the first half of the sample JM and MR show the same pattern, but this is not longer the case from 95 onwards. For the period 96-97 the MR is positive while the JM is negative. This means that around that period (remember that the variables are constructed by taking a rolling window of two-year) the returns were positive while the jumps were mostly downwards. In the next section we will estimate regression models including these new two variables (RJM and MR).

6.2. Results regression

Table 6 shows coefficient estimates and corresponding t-statistics and R^2 's taking the jump mean, return jump mean and mean reversion as forecast variables. The dependent variable is the average excess return of the two to five year US bond. The results for the jump mean were already shown in Table 3, but we will also include it here

for the sake of completeness. The RJM shows a higher R^2 compared to JM (18% against 15%) and the coefficient is also estimated more precisely (the t-value is larger in absolute value). The mean reversion variable is also strongly significant. The sign of MR is negative and therefore it is indeed appropriate to call the variable mean reversion: positive returns occurred over the last two years are a negative predictor for returns of the coming year.

Look at Table 5 again for the interpretation of the coefficients. The standard deviation of RJM and MR is respectively 7 basis points and 5%. So an increase of one standard deviation of the RJM variable means ceteris paribus a decrease of 1.3% in the average excess return ($-19.15 * 0.0007$), which is very similar to the jump mean variable. An increase of one standard deviation of the MR variable means (again ceteris paribus) a decrease of 1.45% in the average excess return ($-0.29 * 0.05$).

	Intercept	t-value	variable	t-value	R2
JM	0.02	3.03	-30.20	-2.15	15%
RJM	0.03	3.46	-19.15	-4.04	18%
MR	0.03	3.13	-0.29	-2.40	20%

Sample
1991:2002

Table 6: This table reports coefficient estimates in a regression of the excess returns on a bond (average 2 to 5 year) over those on a one-year bond, with a holding period of 12 months and 24-month rolling window of the bond jump mean, return jump mean and mean reversion. Observations are at the monthly frequency (end-of-month). The t-values are based on Newey-West standard errors.

Table 7 shows the results of the regression but now with the forward rates included. Running the regression of the excess returns using the forward rates alone gives an R^2 of 41%, as we already noted in the previous section. Including the jump mean variable into the regression the R^2 increases to 48%, however the jump mean loses a bit of its significance (significant at 5%, but not at 2.5%) compared to the case with no forward rates included in the regression. The RJM performs again better than the JM. The difference here is huge. The RJM variable is strongly significant (t-value of -4.76) and the R^2 increases to 67%. The information contained in the RJM variable seems to complement that of the forward rates, since the R^2 in the regression of the combined variables (RJM and the forward rates) is larger than the sum of the R^2 's of the separate regressions. It is interesting to notice that the three year forward rate, f_3 , is always significant, while f_1 and f_5 are not significant at conventional significance levels. Most information in forecasting excess returns seems to be hidden in the three year forward rate.

Also the MR variable remains significant after including the Cochrane-Piazzesi variables. Controlling for mean reversion does not change the coefficient of the forward rates greatly, suggesting that the term structure of the forward rates and the mean reversion variable are measuring different components of the bond risk premia.

	Intercept	t-value	f1	t-value	f3	t-value	f5	t-value	variable	t-value	R2
CP	-0.11	-2.48	-1.16	-1.44	5.08	3.17	-1.92	-1.44			41%
CP + JM	-0.09	-2.33	-1.14	-1.46	3.55	2.93	-0.73	-0.77	-24.16	-1.71	48%
CP + RJM	-0.11	-3.95	-1.29	-2.71	2.95	2.83	0.27	0.46	-27.14	-4.76	67%
CP + MR	-0.07	-1.36	-1.70	-2.67	4.72	4.51	-1.64	-1.74	-0.26	-2.51	53%

sample
1991:2002

Table 7: This table reports coefficient estimates in a regression of the excess returns on a bond (average 2 to 5 year) over those on a one-year bond, with a holding period of 12 months and 24-month rolling window of the bond jump mean, return jump mean and mean reversion. Observations are at the monthly frequency (end-of-month). In these regressions also the 1-, 3- and 5-year forward rates (CP variables) are included. The t-values are based on Newey-West standard errors.

From the fact that both MR and RJM remain significant after including the forward rates in the regression and the fact that the two are not highly correlated, it seems straightforward to estimate a regression model taking the forward rates, MR and RJM as regressors. It follows that both variables are again significant and keep their sign (both negative). The R^2 increases further to 72%. You can argue that including variables into a regression model always increases the R^2 . Therefore it is also useful to look at the adjusted R^2 , where you get a

'punishment' for every new variable added to the model. For our last named model the adjusted R^2 is slightly lower than the ordinary R^2 , namely 71%, meaning that it is still an improvement compared to the regressions of Table 7.

Figure 11 graphs the in-sample fit of the Cochrane-Piazzesi model and our model to the excess returns. In the CP model we take the three forward rates as regressors, while for our model we include besides the CP variables, MR and RJM.

The ex-post excess returns were negative during the economic boom at the end of the nineties, in 1994 when the Federal Open Market Committee was tightening the monetary policy, and around the end of the IT bubble in 1999, while positive during and after the recessions of 1990-1991 and 2001. The in-sample fit using only the forward rates (top panel Figure 11) shows some of these counter cyclical movements. However this model overpredicts the bond returns in 1994, while underpredicting it during the 2001 recession. Our model, where besides the forward rates also MR and RJM are included, is better able to fit these movements. The only weak period is around the millennium change, where our model moves too soon towards positive excess returns. Interesting to notice is that the CP model predicts in 77% of the cases the right sign of the excess returns, including our variables to the model this increases to 93%.

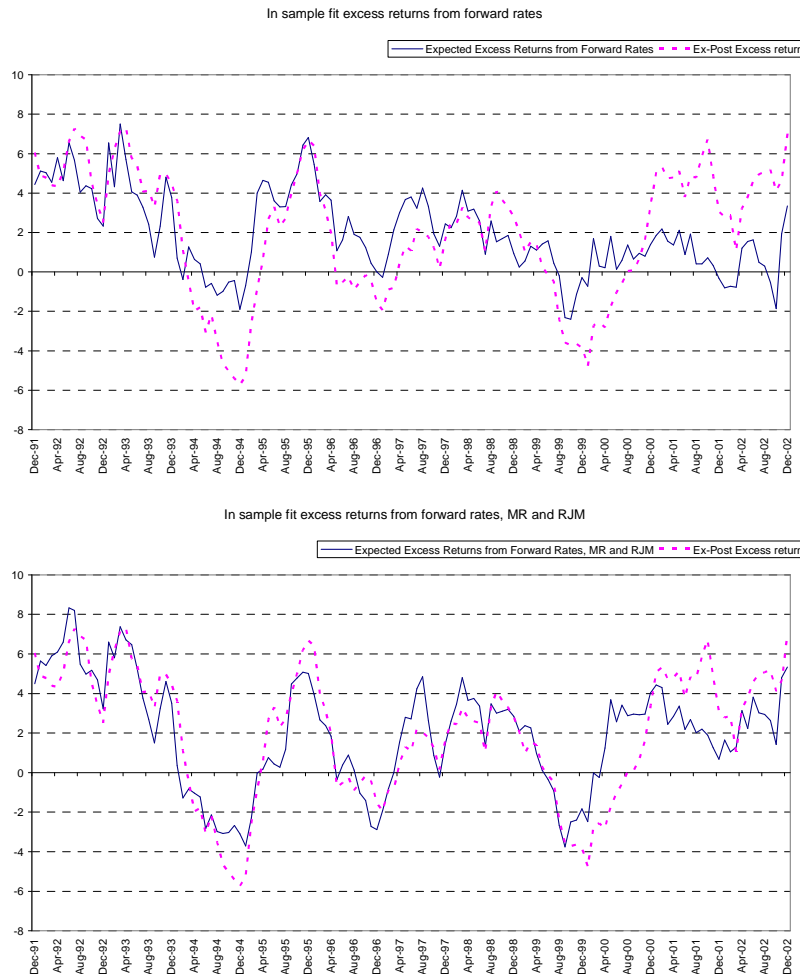


Figure 11: The excess bond returns (average 2 to 5 year) over those on a one-year bond for a one-year holding period. The top panel graphs realized ex-post excess returns together with projected ex-ante estimates using the forward rates as regressors. The bottom panel graphs realized ex-post excess returns together with projected ex-ante estimates using the forward rates, RJM and MR as regressors.

7. Robustness checks

In this section we address some robustness checks of our findings that the jump mean, return jump mean and mean reversion help to forecast bond excess returns. First we look at different significance levels for identifying jumps and also investigate other rolling windows. We also investigate shorter holding periods (3 months instead of one year).

7.1. Changing the significance level and rolling window

Table 8 presents the robustness checks for different significance levels for identifying jumps. Remember that the test to filter jumps from high frequency data is based on the difference between realized volatility and bi-power variation. Assuming that the volatility of an asset prices consists of two parts, a continuous part and a jump component, the realized volatility measures both parts while the bi-power variation measures only the continuous part. A big difference between the two indicates a jump. Based on this idea you can derive various test statistics.

For our main settings we choose the α equal to 0.9999. In the table below we look at other significance levels as well, namely 0.999 and 0.99.

Table 8 shows that JM loses its significance for smaller values of α , while the RJM is robust to changing the α . Remember the difference between JM and RJM. The jump mean variable is the average over all the jumps for the past two years, while the return jump mean is the average of the returns occurred at days where a jump is identified. The intuition can be explained as follows: By taking smaller significance levels and corresponding smaller critical values, you also take into account smaller jumps. These smaller jumps are less important for the RJM variable, since for this variable you look at the total return occurred at a jump day and not at the jump size itself (as for the JM variable).

The mean reversion variable is not taken into account here since the significance level is not of any relevance for the MR variable.

	JM t-value	R2	RJM t-value	R2
alpha = .9999	-2.15	15%	-4.04	18%
alpha = .999	-1.91	8%	-3.89	17%
alpha = .99	-1.15	5%	-3.36	18%

Table 8: This table reports t-values and R^2 's in the regression of excess returns (average 2 to 5 year) over those on a one-year bond, on JM and RJM for different significance levels for identifying jumps. Holding period is equal to 12 months, rolling window for the construction of JM and RJM is equal to 24 months. Observations are at monthly frequency (end-of-month). The t-values are based on Newey-West standard errors. The intercept coefficients, intercept t-values and JM and RJM coefficient estimates are not reported here. Sample 1991-2002.

Table 9 reports the results for shorter rolling windows. For our default analysis we take the rolling window of two years. For our robustness checks we also look at 12-month and 6-month rolling windows. The tradeoff is that a longer rolling window gives more precise and less noisy estimate, while a shorter rolling window gives a timelier estimate of an agents risk preferences.

As follows from the table below, the variables lose their significance for shorter rolling windows (however RJM and MR are borderline significant for a one-year rolling window). We explain this by the fact that for shorter rolling windows you do not have enough jumps to calculate an accurate estimate of the jump mean or return jump mean. For our sample we have on average two jumps a month.

The second (economic) explanation is that to capture the dynamics of a business cycle a 12 or 6 month rolling window is just too short.

For the MR variable it holds that for a shorter rolling window (12 and 6 month) trend and mean reversion will work against each other².

	JM t-value	R2	RJM t-value	R2	MR t-value	R2
Rol. Win. = 24m	-2.15	15%	-4.04	18%	-2.40	20%
Rol. Win. = 12m	-1.24	3%	-1.75	4%	-1.88	10%
Rol. Win. = 6m	0.36	0%	-0.08	0%	-0.64	1%

Table 9: This table reports t-values and R^2 's in the regression of excess returns (average 2 to 5 year) over those on a one-year bond, on JM, RJM and MR for different rolling windows. Holding period is equal to 12 months. Observations are at the monthly frequency (end-of-month). The t-values are based on Newey-West standard errors. The intercept coefficients, intercept t-values and JM, RJM and MR coefficient estimates are not reported here. Sample: 1991-2002.

7.2. Three- months holding period

Until now we have looked at one-year holding periods. The idea is that you borrow against the (risk-free) government one-year interest rate and invest in longer term bonds (in this paper the average of a two to five year bond). Although this is the academic standard, this is not the case in practice since it is not possible to borrow against the one-year interest rate. Therefore, in this section, we look at a three month holding period, where you borrow against the three month LIBOR rate and invest in longer term bonds.

Table 10 reports the regression results for a three-month holding period³. The R^2 's reported are lower than for a one-year holding period, which is in line with the results of Wright and Zhou (2009). In Chapter 10, where we discuss investment strategies, we show that the most predictability, within a one-year holding period, is between four to ten months.

The RJM and MR variables are however again significant, even after controlling for the forward rates, while JM is only borderline significant.

Intercept	t-value	f1	t-value	f3	t-value	f5	t-value	JM	t-value	RJM	t-value	MR	t-value	R2
-0.11	-2.52	-0.86	-1.26	3.35	2.47	-1.23	-1.24							20%
-0.12	-1.76	-0.92	-1.33	3.40	2.27	-1.81	-1.71	-19.11	-1.90					27%
-0.13	-2.18	-1.02	-1.46	4.29	2.14	-0.90	-0.43			-23.34	-3.26			33%
-0.07	-2.21	-1.06	-1.70	4.01	2.92	-3.58	-0.91					-0.18	-2.19	30%

Table 10: This table reports the coefficient estimates in a regression of the excess returns on holding a bond (average two to five year) for a holding period of three months. We used the three-months LIBOR rate for constructing the excess returns. We regress the excess returns on the term structure of the forward rates, the jump mean, return jump mean and mean reversion (variables constructed as described in the text). Sample: 1991-2002.

² Trend is a short-term property, while mean reversion is a long-term property of bond markets.

³ The CRSP Fama-Bliss dataset consists of 1-, 2-, 3-, 4- and 5-year zero coupon bonds only. To construct three months excess returns, we need some bonds that are not available, like the 4.75 year bond. We use here the approximation 4.75 year bond = 5.00 year bond. We use the same approximation for the 1.75, 2.75, and 3.75 year bond.

8. Insight in Jumps

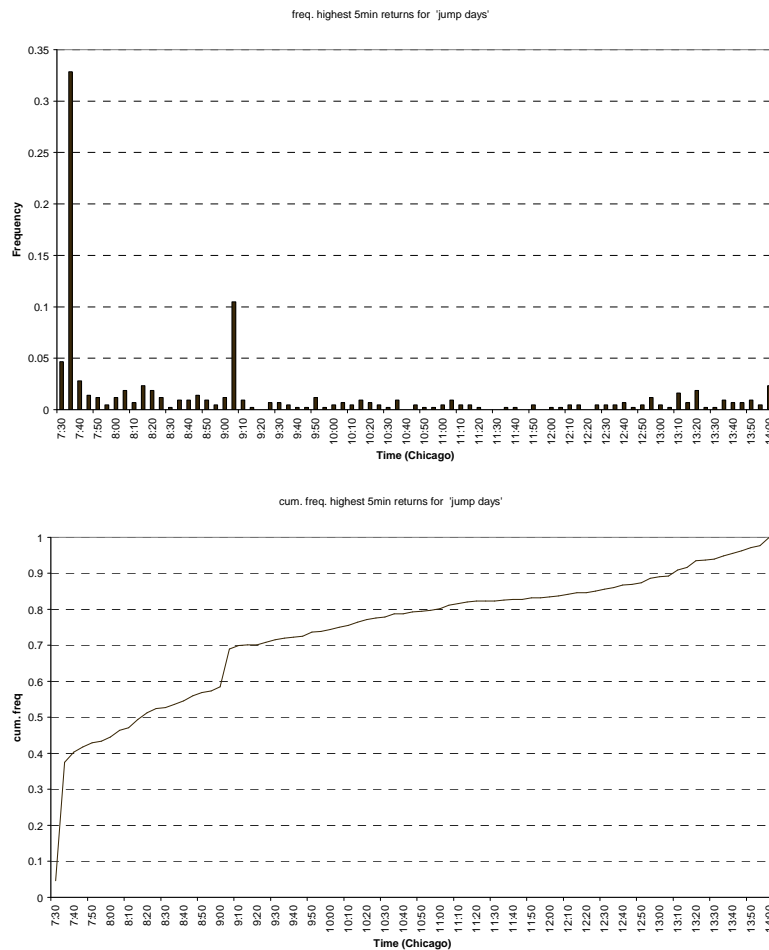
Although the purpose of this thesis is to investigate the power of our jump variables in forecasting US bond excess returns, in this chapter we would like to give more insight in jumps occurred in the 10-year US future. Interesting features are for example: During which time of the day is the most jump activity? What kind of 'news' causes jumps in intraday prices and is there a clear pattern over time?

Johannes (2004) argues that "there are three major sources of jump" in treasury prices. First, official macro-economic news announcements regarding the current state of the economy like unemployment or inflation announcements. Second, announcements by the FED regarding the monetary policy; and third, exogenous political events in the US or other important countries in the world. Das (2000) argues that "the two-day FED Open Market Committee meetings have a substantially greater impact on the short rate than the one-day meetings".

8.1. Moment of Jumps

In this section we present the distribution of jumps during a day for our sample (January 1989 – October 2009). To determine the moment of a jump we look at the largest (in absolute value) five-minute return on a jump-day.

Figure 12: Distribution of the time of jumps during a day.



The two figures above graph the distribution (above panel) and cumulative distribution (bottom panel) of the time of jumps during a day.

Figure 12 shows that one-third of all the intraday jumps occurred are around 7:30 AM Chicago time and 11% around 9:00 AM Chicago time. Around these times there are macro-economic news announcements in the US, which in case of a surprise can cause a jump in the bond future prices. Around noon there is almost no jump activity and 70% of all jumps occur before 9:00 AM. This is an interesting finding and it raises the question whether an (successful) investment strategy can be build by taking a position directly after a jump in the same direction. We will come back to this in the next chapter.

Next question is to link the jumps at 7:30 AM and 9:00 AM to macro-economic announcements to see which variables have the largest impact on interest rates and to see whether themes change over time. This is the topic of the next section.

An interesting sidestep here is to investigate the challenges that rise up in modeling interest rates movements in the presence of jumps. These models are used for pricing and hedging interest rate derivatives (like interest rate swaps, swaptions and bond options). Diffusion models rule out extreme market movements which are observed in the market. These models are approximately normal over short time intervals while the increments in actual data can be very non-normal. This makes it difficult for diffusion models to fit the actual data. However this topic is beyond the scope of our research.

8.2. Jumps and macro-economic news announcements

Here we will present which macro variables are important in explaining intraday jumps in future prices. For this analysis we only consider 7:30 and 9:00 jumps, since around these times there are a number of announcements. From Figure 12 it follows that 44% of the jumps are at these two times. For every 7:30 and 9:00 jump we looked at which news came out at that time using Bloomberg. For the 7:30 jumps we could go back until 2000 and for the 9:00 jumps until 1997.

Table 11 shows the results for 7:30 jumps. In total 60 jumps occurred at 7:30 AM in the period 2000-2009. Exactly 50% of the jumps are caused by unemployment announcements (nonfarm payrolls and initial jobless claims) and a quarter by inflation (CPI and PPI). Other important macro variables are retail sales, GDP and durable good orders. These results coincide with Balduzzi et al (1997)⁴.

Table 11: Macro-economic news releases at 7:30 AM causing jumps in the 10-year US bond future for the period 2000-2009.

	total	Nonfarm Payrolls	Claims	CPI	PPI	Retail Sales	GDP	Durable Goods	others
absolute:	60	18	12	8	6	4	3	4	5
%:	100%	30%	20%	13%	10%	7%	5%	7%	8%

Table 12 shows the results for 9:00 jumps. In total 29 jumps occurred at 9:00 AM in the period 1997-2009. The announcement at 9:00 with the largest impact for future prices is the ISM index, which causes almost half of all the 9:00 jumps. Also important is consumer confidence with 5 jumps in total. Again these results are in line with Balduzzi et al (1997).

Table 12: Macro-economic news releases at 9:00 AM causing jumps in the 10-year US bond future for the period 1997-2009.

	total	ISM	CC	House sales	others
absolute:	29	13	5	3	8
%:	100%	45%	17%	10%	28%

Below in Figure 13 you can see the graphical representation of Table 11 and Table 12. We divided the 7:30 jumps into the categories employment (nonfarm payrolls, initial jobless claims), inflation (CPI, PPI), others (retail sales, GDP and durable goods among others) and two unidentified jumps (we could not link the jump with a macro-economic news announcement). For the 9:00 jumps there are three unidentified jumps. Other categories are ISM, consumer confidence and others (existing house sales and new house sales among others).

⁴ For some days in our sample there was more than one announcement at the same time. For these days we attributed the jump to the "most important" variable (the variable which causes the most jumps in our sample).

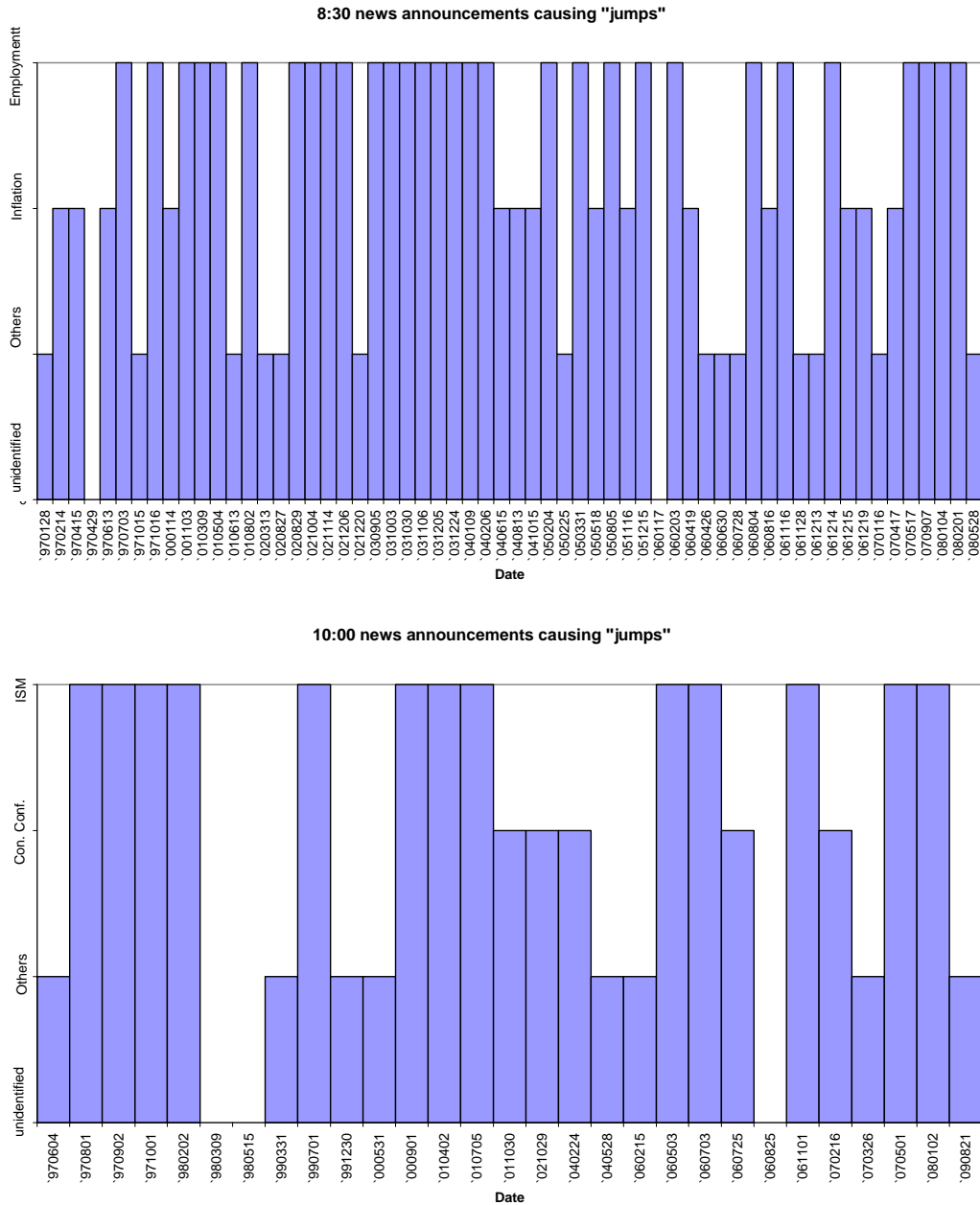


Figure 13: Graphical representation of the relation between macro-economic data releases and 7:30 (above panel) and 9:00 (bottom panel) jumps during time.

The number of jumps is too limited to make clear statements about patterns over time, but from the first panel of Figure 13 it follows that when the first signs of economic slowdown arrive (2000, 2007), the employment variables (especially nonfarm payrolls) are causing a number of jumps. This means that the announcements are considered as a surprise to market participants. However, there are no clear patterns visible over time. We conclude that announcements with the largest impact on bond future prices are related to employment (Nonfarm Payrolls, Initial Jobless Claims), inflation (CPI, PPI) and confidence (ISM, Consumer Confidence).

8.3. Intuition

In this section we intend to improve the intuition of the empirical findings in this paper and also link the results to other findings in the literature. Generally, predictive regressions with excess returns on the LHS and significant forecast variables on the RHS (like the JM, RJM and MR in this paper) imply that bond risk premia are time varying and predictable to some degree. A central topic in asset pricing is the premium that investors require for holding a risky asset, the so-called risk premium. Furthermore, classical financial theory argues that time varying risk premium of an asset are caused by either a change in the price of risk (λ) or by a change in the exposure of an asset to the risk factor (β).

Recently much progress has been made in using intraday (high frequency) data to estimate realized volatility measures. Furthermore, if we observe intraday data, we can detect days on which jumps occur and estimate the magnitude of the jumps. Wright and Zhou (2009) argue that then "it seems natural to relate realized volatility and the distribution of jumps to bond risk premia". In their paper the jump mean variable is highly significant with an R^2 of 15%, including the forward rates in the regression the R^2 increases to 62%.

Wright and Zhou (2009) continue that "the bond jump mean appears to be procyclical, peaking around the 1990 and especially the 2001 recessions, and thus predicts well the countercyclical bond excess returns, which is not fully captured by the forward term structure". This is an argument to use the JM variable as a business cycle indicator.

In their last chapter Wright and Zhou (2009) introduce an illustrative model in which jump risk is useful for term structure forecasting. In the model assuming that the bond price follows a jump-diffusion process, they show that instantaneous return is a function of jump risk and so jump risk measures should have forecast power for excess bond returns. The purpose of their model is to theoretically illustrate the empirical findings in the paper.

Faust and Wright (2009) decompose bond returns into the sum of those occurring in 15-minute windows around major news announcements at 7:30 and those occurring at other times. They first replicate the CP regressions for total returns and then run the regressions separately for the two additive components. They argue that "the statistically significant predictability in bond returns appears to occur only around news announcements, were it not for the effects of news announcements, we could not reject the expectations hypothesis". This can be interpreted as direct evidence for a time-varying price of jump risk. In this paper we show that besides 7:30 jumps also 9:00 jumps play an important role in explaining bond risk premia (33% of all the jumps are "7:30 jumps" against 11% for the 9:00 jumps).

Johannes et al (2007) argue that using a stochastic volatility-jump (SVJ) model, the mean price jump risk premia is 3% to 6% (depending on the volatility of price jump risk premium), which is considerable. This paper is however about jumps in equity markets instead of jumps in bond markets as studied in this paper. However they argue that "price jump risk premia contribute about 3% per year to an overall equity premium of 8%".

Todorov (2009) argues that investors generally dislike the randomness of the future variance (variance of the variance) and in equilibrium ask a premium for accepting the risk, the so-called variance risk premium. In the literature already much is known about the existence of this risk premium in contrast to the dynamic dependencies of it. This is the main topic of his paper. He continues by stating that the reasons for changes in the variance risk are twofold. First, because of expected stochastic volatility (ex-ante) changes over time. Second, variance risk is also caused by unanticipated market jumps.

He argues that "the results suggest that jumps play a very important role in explaining the variance risk premium" and "the differential impact of jumps on the risk premium suggests that investors attitude towards jumps is time-varying". Again as with Johannes et al (2009) also this paper is about jumps in equity markets.

However, unfortunately, not much has been published about the link between jumps in bond futures and time varying (jump) risk premium.

9. Event Plots

In this chapter we analyze short-term investment strategies. A position is taken in the direction of a jump directly after a jump. We perform this analysis for the 7:30 and 9:00 jumps separately.

9.1. Event Plot 7:30 jumps

Here we consider short term investment strategies, where you take a position in the direction of the jump immediately after a jump (you go long in case of an upward jump, and short in case of a downward jump). We again only consider the 7:30 and 9:00 jumps, because these jumps are as explained in the previous chapter caused by macro-economic data releases and these announcements always arrive at deterministic (fixed) times during the month and you can construct investment strategies based on this. The idea is to examine whether markets continue to move in the same direction after a jump.

Table 13: Returns earned (in basis points) after taking a position immediately after a 7:30 jump for the period 1989-2009.

# jumps: 144				
	same day	next 3 days	together	
sum:	790	891	1681	bp
average:	5	6	12	bp
st. dev:	34	48	62	bp
# positive jumps: 89				
	same day	next 3 days	together	
sum:	383	851	1234	bp
average:	4	10	14	bp
st. dev:	36	51	66	bp
# negative jumps: 55				
	same day	next 3 days	together	
sum:	406	40	447	bp
average:	7	1	8	bp
st. dev:	31	45	54	bp

Table 13 reports the earned returns for the 7:30 jump strategy of our sample (January 1989-October 2009) consisting of 144 jumps (89 positive and 55 negative⁵). We look at returns at the same day *after* a jump plus the cumulative return for the next three days. The total earned return based on this strategy (for all jumps) is almost 17%, which is quite considerable⁶. That is on average 12 basis points (bp) per jump. This value is significantly larger than zero, as follows from a simple t-test: $\sqrt{144} * 12 / 62 = 2.26$.

Looking at positive and negative jumps separately, the first strategy shows a better performance with on average a return of 14 bp per jump (borderline significant with a t-value of 1.98 ($= \sqrt{89} * 14 / 66$)) versus 8 bp for the negative jump strategy (not significant). However, statistical significance is of course influenced by splitting the number of estimates (144) between positive (89) and negative (55) jumps.

In Figure 14 you can see the event plot corresponding to the results in Table 13. Again the first figure denotes the event plot for all the 7:30 jumps, while the second and third denote respectively the event plots for the positive and negative jumps. There are however some limitations to this analysis. Overnight returns are for example not

⁵ With a positive jump we mean an upward jump in the futures price. This corresponds to a downward jump in the yield.

⁶ We did not take transaction costs into account here.

taken into account here (because of rolling into a new contract issues). Also in some cases there are two jumps shortly after each other (within 3 days). This means that you can be two times long (or two times short) or long and short (so neutral) at the same time in that case. In general we can say that after a jump, there is a momentum (3 days here) in the same direction of a jump.

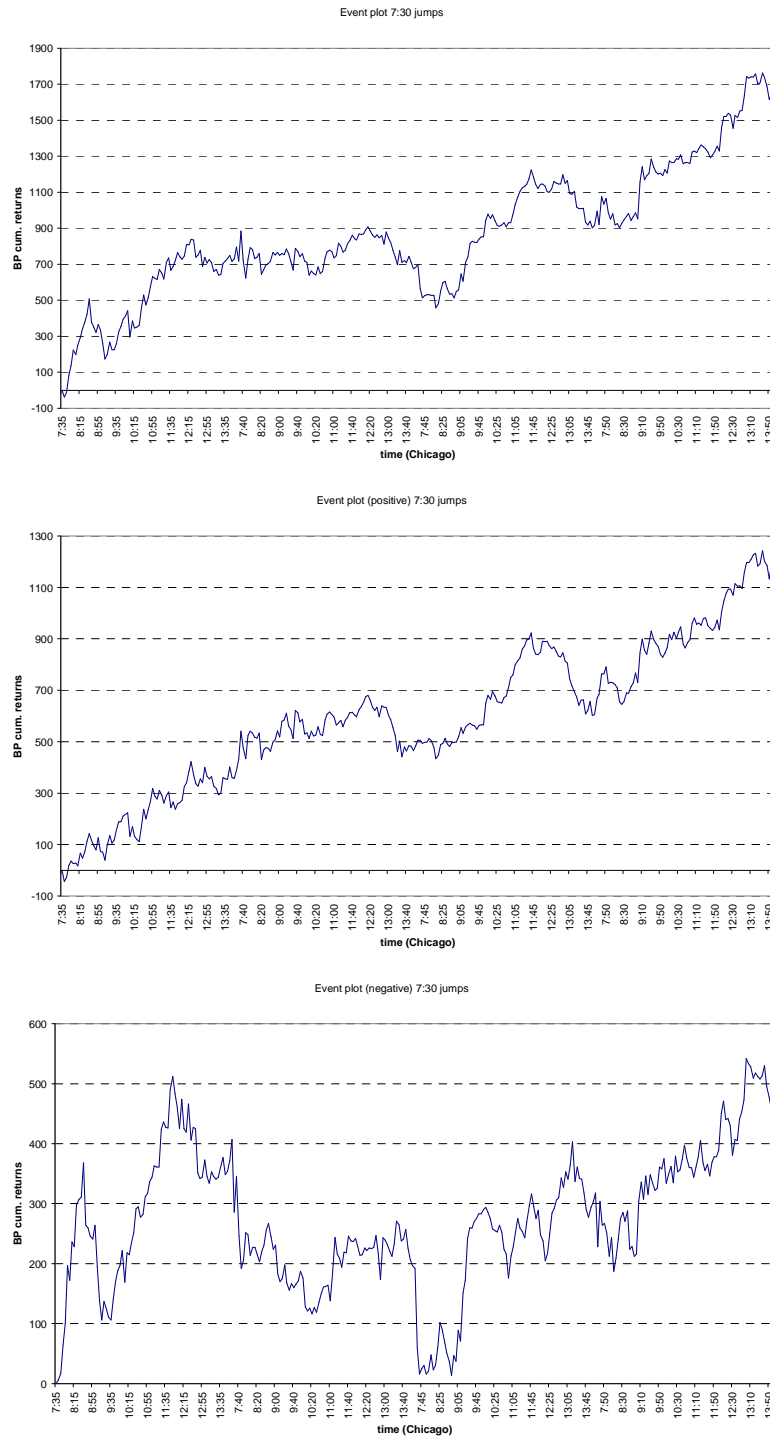


Figure 14: Event plot of the investment strategy where you take a position in the same direction of a jump (7:30) for the same day plus the following three days.

9.2. Event Plot 9:00 jumps

Here we repeat the same analysis as in the previous section, but now for the 9:00 jumps. Again a position is taken in the direction of the jump immediately after a jump (you go long in case of an upward jump, and short in case of a downward jump). Table 14 denotes the results of this strategy for the three categories (all, positive and negative jumps). The overall strategy is not successful here: the total return is almost -1%. However as with the 7:30 jumps the positive jump strategy performs better than the negative one and the difference is big (243 bp versus -341 bp). However the number of jumps is too limited to make hard statements about: The average returns earned after each jump for the three strategies are not significant.

Table 14: Returns earned (in basis points) after taking a position immediately after a 9:00 jump for the period 1989-2009.

# jumps: 47				
	same day	next 3 days	together	
sum:	24	-122	-98	bp
average:	1	-3	-2	bp
st. dev:	23	60	68	bp
# positive jumps: 24				
	same day	next 3 days	together	
sum:	114	129	243	bp
average:	5	5	10	bp
st. dev:	19	58	69	bp
# negative jumps: 23				
	same day	next 3 days	together	
sum:	-90	-252	-341	bp
average:	-4	-11	-15	bp
st. dev:	26	62	66	bp

In Figure 14 you can see the event plots corresponding to the results in Table 14. Again the first figure denotes the event plot for all the 9:00 jumps, while the second and third denote respectively the event plots for the positive and negative jumps. The large sudden increases in the cumulative return in the graphs below are caused by 7:30 jumps the day after the 9:00 jumps. This is as mentioned in the previous section a limitation of this method, because what happens after such a 7:30 jump cannot be attributed to the original 9:00 jump. Below in Table 15 you can see the success ratio of the investment strategies presented in this and the previous section⁷. The overall success ratios for the 7:30 and 9:00 jumps are respectively 60% and 45%.

7:30	same day	next 3 days	together
All jumps	55%	54%	60%
positive jumps	56%	57%	63%
negative jumps	53%	49%	56%

9:00	same day	next 3 days	together
All jumps	57%	43%	45%
positive jumps	71%	58%	54%
negative jumps	43%	26%	35%

Table 15: The success ratios of the investment strategies of Table 13 and Table 14.

⁷ A success ratio is defined as the percentage positive returns after each bet.

As in line with the results in Table 13 and Table 14 the performance is better for the positive jumps: 63% versus 56% for the 7:30 jumps and 54% versus 35% for the 9:00 jumps.

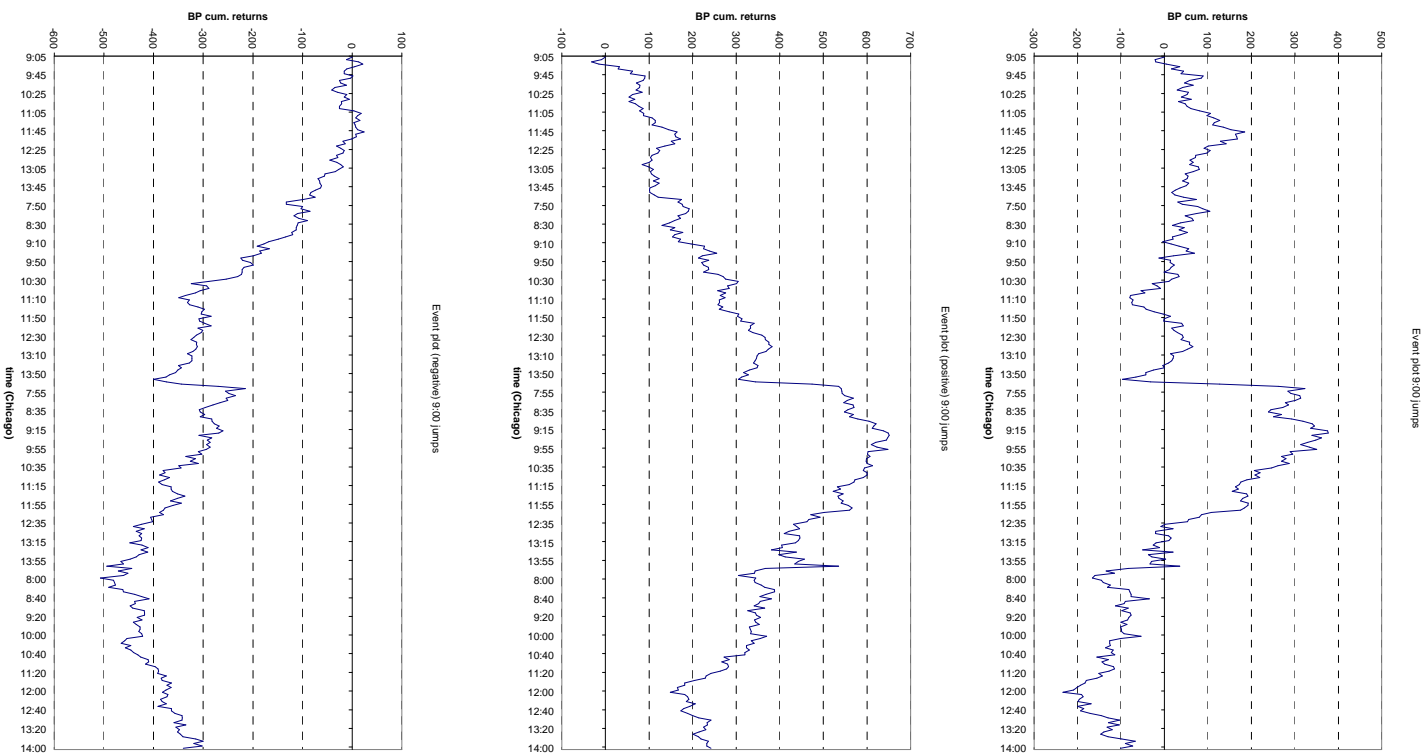


Figure 15: Event plot of the investment strategy where you take a position in the same direction of a jump (9:00) after the jump for the same day plus the following three days.

10. Long Term Investment Strategies

In this chapter we study investment strategies using the jump variables (JM and RJM) and the mean reversion variable (MR) of the regression models. Here we first analyze different models for our in-sample period and choose our optimal model for an out-of-sample exercise.

10.1. Investment strategies for the in-sample period

Here we present the results for the different variables for our in-sample period. To investigate investment strategies we calculate demeaned z-scores for our variables, meaning that for each value we first subtract the previous five-year average and then divide by the standard deviation of the same period⁸. In formula you get for RJM:

$$Zscore RJM_t = \frac{RJM_t - (\frac{1}{60} \sum_{j=t-59}^t RJM_j)}{\frac{1}{60} \sqrt{\sum_{j=t-59}^t (RJM_j - (\frac{1}{60} \sum_{j=t-59}^t RJM_j))^2}}$$

The data we use here (the asset in which we invest) is the JP Morgan US Bond Index (per entity duration)⁹. We use monthly z-scores to invest for the coming month, but in the regression models we look at an one-year holding period. To match this setting we use a z-score not just to invest for the coming month, but we use it 12 times (one for each month). With this analysis we can check when the most predictability in excess returns occurs (in which month). To make this strategy clear, take for example the z-score of January. For the first strategy, we use it for a position in the next month (February). For the second strategy, we use the January z-score for a position in March etc. By repeating this analysis we get 12 different strategies. For our final strategy we take the average of these 12 strategies and look which one performs the best in a risk and return trade-off framework for the different variables. Equivalently you can explain this by saying that for each month, the earned return is based on the previous 12 z-scores. This is comparable with the regression analysis where we looked at an one-year holding period at monthly frequency (12 overlapping periods).

Below in Table 16 you can see the results of the investment strategies for JM, RJM and MR for our in-sample period. The bet-size is here equal to the (negative) value of the z-score. Notice that the coefficient estimates in the regression models of these three variables are all negative, which means that in case of a negative z-score you go long and visa versa. Table 16 reports the annualized average returns and annualized standard deviations together with the information ratios (IR)¹⁰ of the different strategies. For each variable we report 13 strategies. The first one is when you use a z-score to invest directly for the next month (January z-score to invest for February). The second one is when you use a z-score to invest for the month after the next month (January z-score to invest for March), etc. In the final column we present a strategy, which is the average of the first 12 strategy. For this strategy the bet-size is equal to the (negative) sum of the previous 12 z-scores.

All the reported IR's in Table 16 are positive. As with the regression results the RJM performs better than JM. For both of the variables the IR is relatively low for the first strategy (0.22 for JM and 0.31 for RJM) and it increases after that. The highest IR's are obtained by using a z-score after 6 to 8 months. The strategy which is a combination of the first 12 also shows a good performance for this in-sample period (IR of 0.55 for JM and 0.61 for RJM). The high IR of the final strategy is mostly caused by the relatively low standard deviation, which is a bit lower than for the first 12 strategies.

The results are worse for MR. This variable shows a good performance in the regression models, but the results are less promising in this analysis. The IR of the final strategy is 0.31, which is considerable lower than for the first two variables. Especially the IR's of the first 6 strategies are low, ranging between 0.08 and 0.21.

⁸ For the first five-year of our sample we use forward looking to calculate the z-scores.

⁹ The index is based on all outstanding US government bonds.

¹⁰ IR is equal to the quotient of annualized average return and annualized standard deviation of a strategy.

sample: 1992-2002													
demeaned, z-score:													
JM	1	2	3	4	5	6	7	8	9	10	11	12	strategy
mean:	0.20%	0.39%	0.48%	0.54%	0.55%	0.56%	0.52%	0.44%	0.39%	0.37%	0.28%	0.30%	0.42%
stdev:	0.88%	0.89%	0.90%	0.93%	0.97%	0.91%	0.92%	0.94%	0.87%	0.88%	0.95%	0.99%	0.77%
IR:	0.22	0.44	0.53	0.58	0.57	0.61	0.57	0.47	0.45	0.42	0.29	0.31	0.55
												skew:	0.41
										success ratio:	53%	kurt:	2.54

RJM	1	2	3	4	5	6	7	8	9	10	11	12	strategy
mean:	0.29%	0.43%	0.51%	0.48%	0.48%	0.59%	0.60%	0.58%	0.55%	0.57%	0.46%	0.52%	0.50%
stdev:	0.93%	0.93%	0.96%	0.98%	1.02%	0.97%	0.98%	0.99%	0.98%	1.02%	1.08%	1.10%	0.83%
IR:	0.31	0.46	0.53	0.49	0.47	0.61	0.61	0.58	0.56	0.56	0.43	0.47	0.61
												skew:	0.49
										success ratio:	55%	kurt:	2.67

MR	1	2	3	4	5	6	7	8	9	10	11	12	strategy
mean:	0.14%	0.17%	0.09%	0.18%	0.28%	0.21%	0.21%	0.44%	0.52%	0.38%	0.34%	0.26%	0.27%
stdev:	1.07%	1.09%	1.04%	1.00%	1.07%	1.03%	1.00%	1.02%	0.91%	0.94%	0.91%	0.93%	0.86%
IR:	0.13	0.15	0.08	0.18	0.26	0.21	0.21	0.43	0.57	0.41	0.38	0.28	0.31
												skew:	-0.03
										success ratio:	52%	kurt:	1.83

Table 16: The results (mean annualized returns, annualized standard deviation and information ratio) for the investment strategies for JM, RJM and MR based on demeaned z-scores. The bet-size is equal to the z-score.

The success ratios denoted in Table 16 are based on the final strategy (mentioned in last column). The success ratio is defined as the percentage of positive monthly returns after each bet. The success ratio is highest for the RJM variable: 55%.

Now we will introduce a new variable, related to RJM. The RJM variable is the average return occurred on "jump days" over the last two years. For this new variable, which we call sign RJM, we do not look at the magnitude of a jump, but just the sign. We denote a one in case of a positive jump and zero for a negative jump. The sign RJM variable is then the average of these ones and zeros over the last two year. The reason behind this new variable is to eliminate the effects of extreme jumps and z-scores, since the bet-size is equal to (minus) the z-score. With JM or RJM, one extreme jump has already a big effect on the variable and the z-score. In the table below, you can see that sign RJM shows better performance for the first three months compared to JM and RJM. Therefore you can also see this variable as a more robust version of RJM.

signRJM	1	2	3	4	5	6	7	8	9	10	11	12	strategy
mean:	0.37%	0.49%	0.50%	0.59%	0.69%	0.68%	0.59%	0.56%	0.52%	0.38%	0.34%	0.32%	0.50%
stdev:	0.93%	0.93%	0.90%	0.91%	0.94%	0.90%	0.90%	0.91%	0.87%	0.87%	0.90%	0.93%	0.78%
IR:	0.40	0.52	0.55	0.65	0.73	0.76	0.66	0.62	0.59	0.44	0.38	0.34	0.64
												skew:	0.20
										success ratio:	56%	kurt:	0.83

Table 17: The results (mean annualized returns, annualized standard deviation and information ratio) for the investment strategies for sign RJM based on demeaned z-scores. The bet-size is equal to the z-score. The sample is again 1992-2002.

Table 17 show the results for the investment strategy based on the new variable sign RJM. The overall strategy is comparable to RJM (IR's: 0.64 versus 0.61). Also with this strategy we see that the performance is best after a few months, however the difference is less compared to RJM. This strategy (with an IR of 0.64) is our favorite to perform an out-of-sample test, because of the reason presented above.

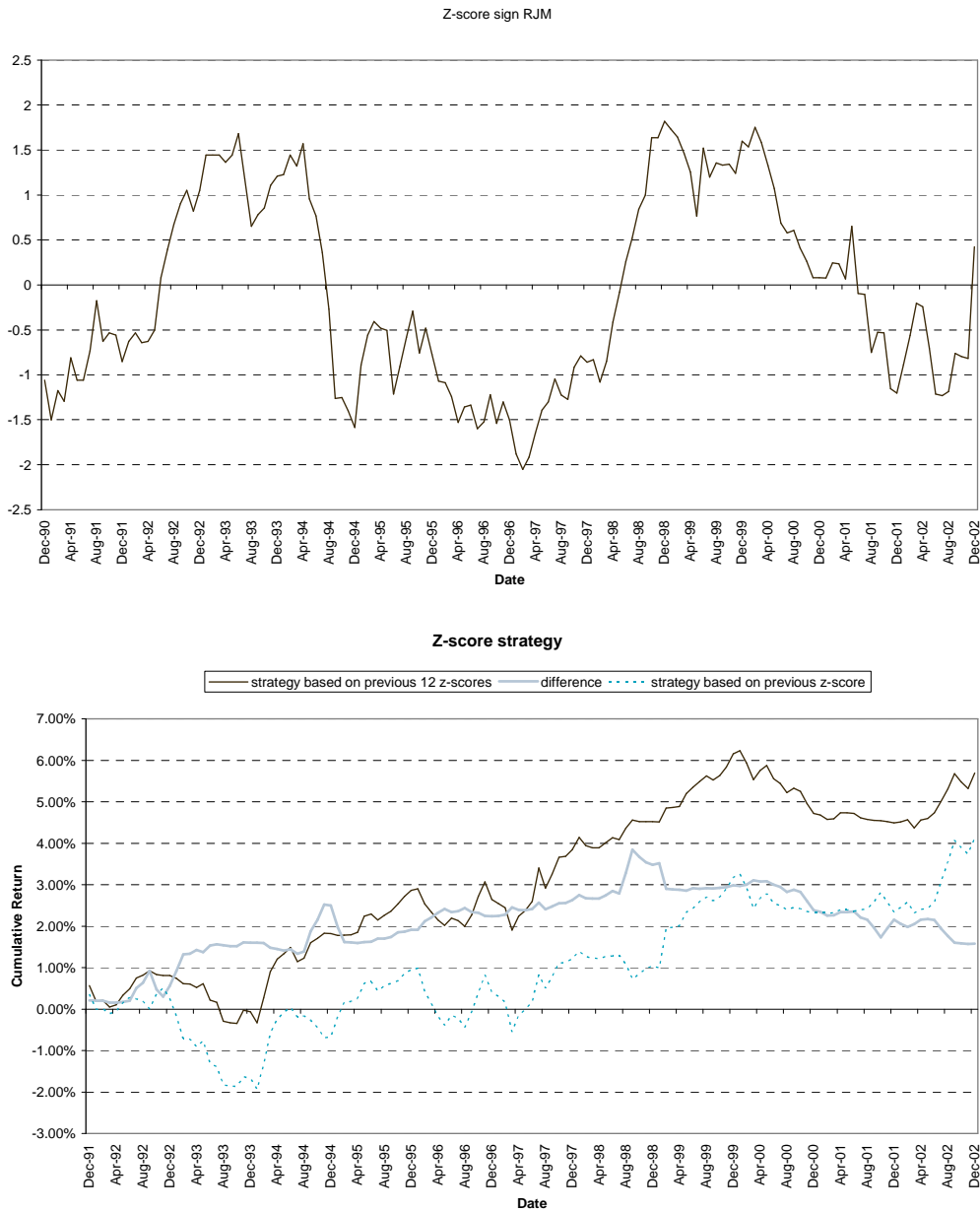


Figure 16: The cumulative returns of the variable sign RJM based on the final investment strategy (IR 0.64), investment strategy where you use a z-score to invest for the coming month (IR 0.40) and the difference of the two.

Above, Figure 16 shows the cumulative returns of the first strategy of the sign RJM variable in Table 17 with an IR of 0.40 and the final strategy with an IR of 0.64 plus the difference of the two strategies. As follows from Table 17, the final strategy generates higher returns against lower risk. This shows that using the past 12 z-scores produces higher and more stable returns than just using the last z-score. For some periods the final strategy performs much better and the final difference at the end of 2002 is 1.6%. This suggests that there is a delayed, lagged effect in the market, which is best exploited by using not just the last z-score.

10.2. Out-of-sample model

In this section we present the out-of-sample test. Our in-sample period is 1992-2002, while the out-of-sample period is from 2003 until October 2009. We take the final strategy of the sign RJM variable (Table 17, IR 0.64) for the out of sample test. By explicitly choosing an out-of-sample period and doing an out-of-sample test for one model, we try to avoid data mining.

In the figure below, you can see that also after 2002, this strategy performs well in general. For the first two years of the out-of-sample period there is no excess return, but this strategy shows very high returns in 2007 and during the crisis of 2008.

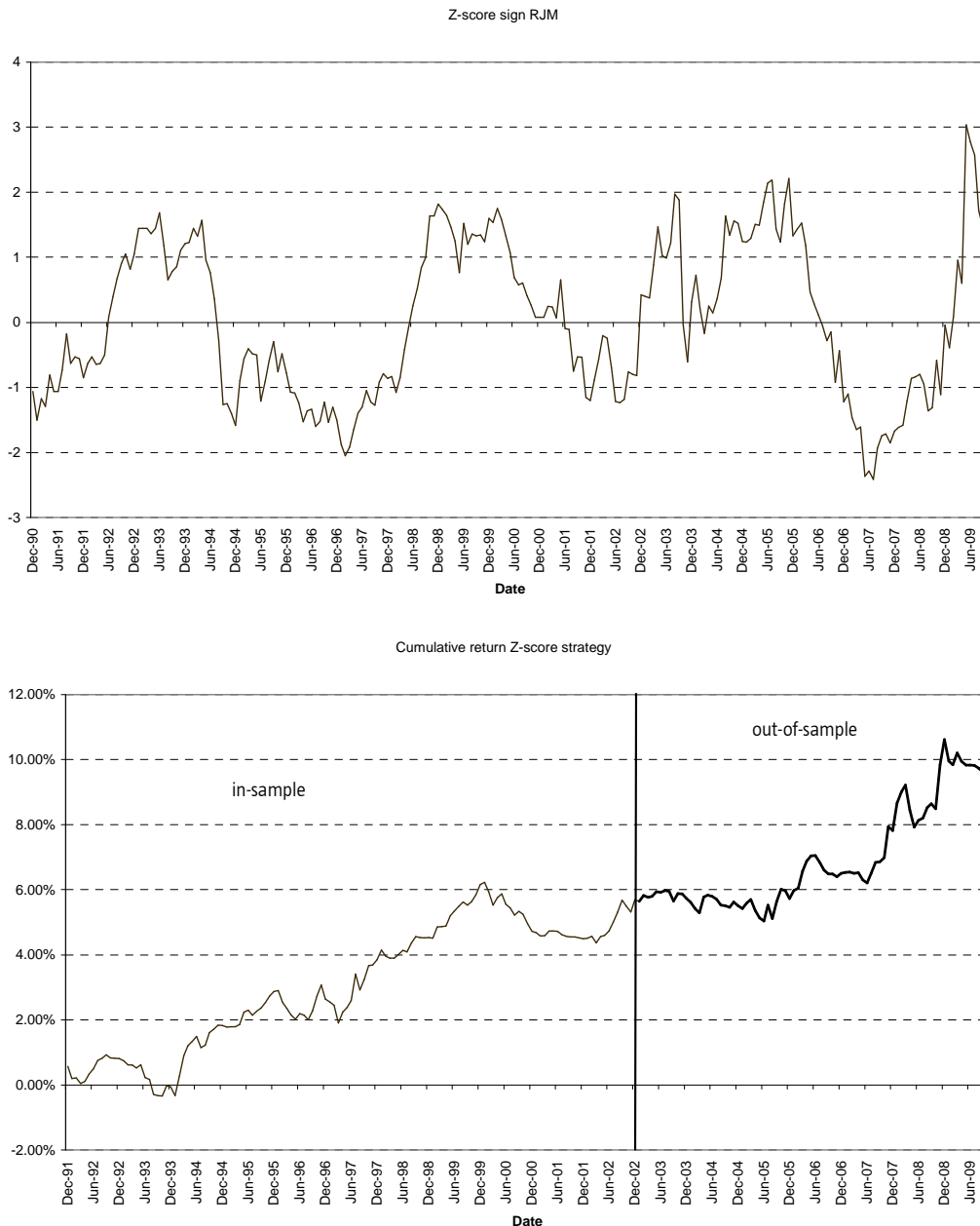


Figure 17: The cumulative return of the variable sign RJM based on the final investment strategy for our complete sample (bottom panel), 1992-2009, and the corresponding z-scores (above panel).

Over the whole sample (1992-2009), we have an excess return of almost 10%. Remember that this return is per entity duration. For the 10-year future, with a duration of approximately 7, the excess return for this period is 70% ($=7 \times 10\%$).

Below in Table 18 you can see the results of the investment strategies for sign RJM, but now for both the in-sample and the out-of-sample period. The IR of the final strategy for the in-sample period is equal to 0.64. This is the same as in Table 17 of course, but in Table 18 you can see that the IR for the same strategy for the out-of-sample period is equal to 0.52, which is still considerable.

in-sample:		1992-2002												strategy
signRJM		1	2	3	4	5	6	7	8	9	10	11	12	
mean:	0.37%	0.49%	0.50%	0.59%	0.69%	0.68%	0.59%	0.56%	0.52%	0.38%	0.34%	0.32%		0.50%
stdev:	0.93%	0.93%	0.90%	0.91%	0.94%	0.90%	0.90%	0.91%	0.87%	0.87%	0.90%	0.93%		0.78%
IR:	0.40	0.52	0.55	0.65	0.73	0.76	0.66	0.62	0.59	0.44	0.38	0.34		0.64

out-of-sample:		2003-2009												strategy
signRJM		1	2	3	4	5	6	7	8	9	10	11	12	
mean:	0.42%	0.55%	0.81%	0.66%	0.20%	0.53%	0.66%	0.55%	0.60%	0.68%	0.46%	0.37%		0.54%
stdev:	1.16%	1.22%	1.25%	1.18%	1.14%	1.12%	1.11%	1.21%	1.22%	1.23%	1.33%	1.34%		1.04%
IR:	0.36	0.45	0.65	0.56	0.18	0.47	0.60	0.45	0.49	0.55	0.34	0.28		0.52

Table 18: The results (mean annualized returns, annualized standard deviation and information ratio) for the investment strategies for sign RJM based on demeaned z-scores for in-sample and out-of-sample period. The bet-size is equal to the z-score.

11. Recommendation for further research

The analysis in this paper is based on the US market. An extension could be to look at other countries as well (for example UK, Germany and Japan) and see whether the results are robust over different countries.

In this paper we presented already some robustness checks. There are more checks possible. For example, the y-variable presented here was the average excess return of the 2, 3, 4 and 5 year US bond. You could also take the return of the 10-year future as the y-variable. For the regression models, we looked at one-year holding period at monthly frequency. This means that there are 12 overlapping periods, which can cause statistical problems¹¹. To avoid this, you can run a regression using only non-overlapping data.

In the event plots presented in chapter 9 we did not take into account overnight returns, which could be important for the overall results. You can expand our analysis here by also considering this feature. However, with future data you have always to be careful with overnight returns because of rolling effects¹². Therefore, in case of big overnight returns you have to investigate whether this was caused by changing market circumstances or because of the effects of rolling into a new contract.

Again for the event plots we looked at all the 7:30 and 9:00 jumps. A next step could be to differentiate between jump event plots by considering which macro-economic news announcement caused a jump. For example have inflation and employment announcements different effects in the future markets? A difficulty here is the fact that the number of jumps is limited, even for a large (1989-2009) sample period. A practical solution is to take a lower threshold value for identifying jumps. In this paper we took the significance level equal to 0.0001 (corresponding to a critical value of 3.719). By taking a bigger significance level (smaller critical value) more jumps will be filtered out. Of course this comes with more type II errors.

An extension of the standard (in-sample) regression analysis is to perform an out-of-sample analysis by looking at the mean squared prediction error (mspe). Starting half-way the sample, you can run a regression using only data available at that time and then make a 12-month ahead forecast of the excess bond returns. You can then repeat this for each subsequent month through the end of the sample. You can do this analysis for the model with only the forward rates as regressors and for the model with besides the forward rates also the RJM and MR and look at the ratio of the mspe of the two models (to see the improvement over using only the forward rates).

In Chapter 8 we considered the relation between macro-economic news announcements and jumps in intraday data. Data releases cause jumps if the announcement is a surprise to the market. To test this hypothesis you can look at actual releases versus what the analysts expected. You can perform this analysis for days with and without jumps and look whether there is a bigger difference between actual releases and analyst expectations for jump days.

The method of identifying jumps in intraday prices is based on the difference of the realized volatility and bi-power variation. A very simple alternative for identifying jumps would be to look at the historical average of the volatility of the five-minute intervals and denote every five-minute return larger than three times the standard deviation as a jump. You can compare this simple method to the method used in this paper (which is favored by the findings of Huang and Tauchen (2005)).

In the Chapter 8 we put effort to improve the intuition, but the question why a jump mean variable has information about future bond returns remains partly unanswered. A drawback here is that in contrast to the equity market, there is not much known in the literature about the relation between bond returns and jump risk. An idea is to link the jump mean variable to the ISM index and see whether there is a relation with the business cycle as it is briefly mentioned in Wright and Zhou (2009).

These questions pose interesting research challenges for the future.

¹¹ For discussions of some of the difficulties associated with the use of overlapping data see Boudoukh et al. (2008) and Valkanov (2003).

¹² US 10-year future contracts last for three months. After three months the positions are closed and you enter into a new contract. The prices of the new and old contract can be different.

12. Conclusion

In this paper we have replicated the results of Wright and Zhou (2009), with similar results, and showed that the jump mean variable, constructed from five-minute returns on the 10-year US future, is able to forecast US bond returns. In a univariate regression the R^2 is equal to 15% for our in-sample period 1991-2002. Augmenting regressions of excess bond returns on the term structure of forward rates (Cochrane and Piazzesi (2005)) with the jump mean the R^2 increases to 48%. Using just the forward rates we achieve an R^2 of 41% for our in-sample period.

The sign of the coefficient estimate of the jump mean variable in the regressions is negative, which means that upward jumps are a negative predictor of bond returns and visa versa.

Next in Chapter 6 we presented two new variables, namely return jump mean (RJM) and mean reversion (MR). The RJM is our refinement of the jump mean. The jump mean is the average of estimated jump sizes over the last two year, while the RJM is the average return over the last two year occurred on jump days, instead of the jump size itself.

We showed that the RJM performed better than the JM in the regression models. The R^2 of the multivariate regression, with the forward rates and the RJM as explanatory variables, increases to 67%. We explain this by the fact that not all jumps are of equal importance. For example it can happen that after a small jump the future price will move back towards its previous level before the jump. On the other hand, it is possible that after a big jump the price will continue to move towards the same direction. The jump mean variable is not able to capture such features, because it measures the jump size only.

We discussed the MR variable, which is a revised version of the mean reversion of Fama (2006), to relate it to the jump mean, since this variable “feels” like mean reversion. The sign of the coefficient estimate in the regression is as already mentioned negative (upward jumps forecast low excess returns and visa versa).

The correlation between JM and MR is 9% for our sample. RJM and MR are a bit more correlated, namely 35%. From this we can conclude that the jump variables JM and RJM are related to the MR, but they are definitely not the same. Remember the difference between RJM and MR. MR is the return over all days over the last two year, while the RJM is the average return over only the jump days.

The MR variable is also significant in the regression models (both univariate and multivariate) and the sign of the coefficient estimate is negative as would be expected from a mean reversion variable.

A next step was to estimate a regression model using the forward rates, RJM and MR as explanatory variables, since both RJM and MR remain significant even after controlling for the forward rates and the fact that the two variables are not highly correlated. It follows that both variables are again significant and keep their sign (both negative). The R^2 increases further to 72%.

We looked at the relation between jumps in bond future prices and macro-economic new announcements. 33% of the jumps occurred around 7:30 AM Chicago time, while 11% around 9:00 AM. Around these times there are macro news announcements in the US. We found that announcements with the largest impact on bond future prices are related to employment (Nonfarm Payrolls, Initial Jobless Claims), inflation (CPI, PPI) and confidence (ISM, Consumer Confidence).

We investigated short term investment strategies, where a position is taken in the direction of a jump directly after a 7:30 or 9:00 jump. This position is then closed after three days. We showed that this strategy works well specially for the 7:30 jumps. Also positive jump strategies perform better than the negative jump strategies.

In Chapter 10 we tested JM, RJM and MR in an investment strategy. We used the variables to calculate z-scores. These z-scores determine our bet-sizes. The strategies based on RJM and JM performed well, with an IR for the in-sample period of 0.61 respectively 0.55, while the results were less for MR (IR of 0.31).

In that chapter we also introduced a new variable: sign RJM. For this new variable, we do not look at the magnitude of a jump, but just the sign. We denote a one in case of a positive jump and zero for a negative jump. The sign RJM variable is then the average of these ones and zeros over the last two year. The reason behind this new variable is to eliminate the effects of extreme jumps and z-scores, since the bet-size is equal to (minus) the z-score. The strategy based on this variable has an IR of 0.64 for the in-sample period and we choose this model for an out-of-sample test and showed that we also gain positive excess returns for the period 2003-2009.

Finally, we can conclude that the jump variables are able to forecast US bond returns, both in regression models as in investment strategies.

13. Appendix

13.1. Distribution of Jumps

Figure 18 shows the distribution of the jumps for our sample. The jumps are estimated as described in the text. The idea is to check whether the distribution is skewed or not and from the figure below it looks to be (close to) symmetric. There are a bit more positive than negative jumps (55% versus 45%).

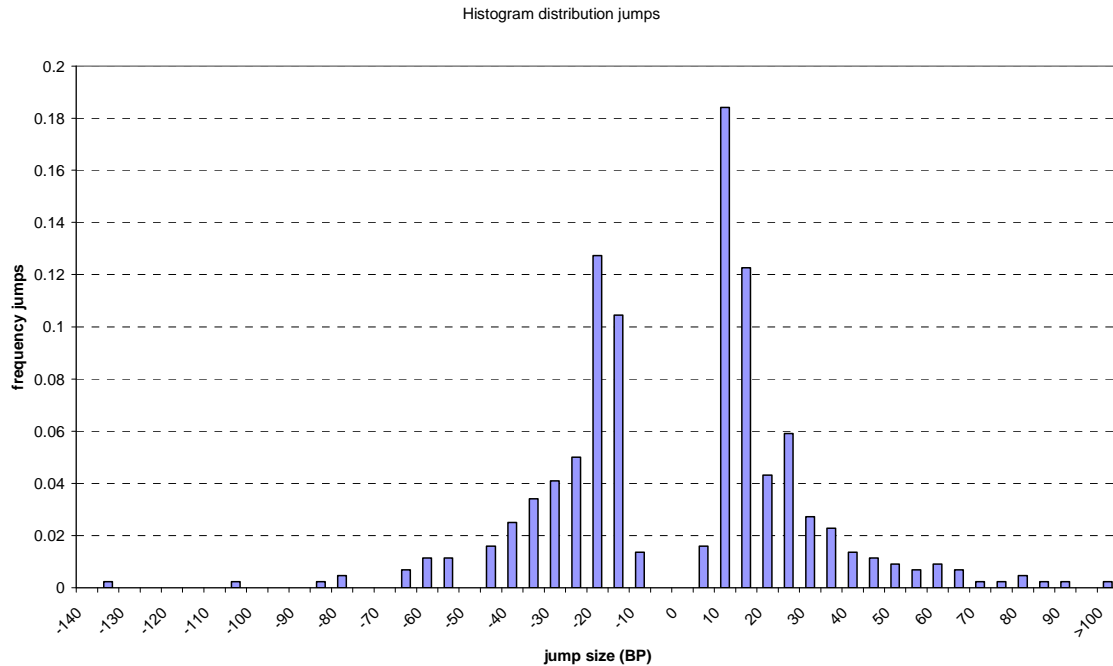


Figure 18: The distribution of the jumps (positive and negative) for the period 1989-2008 in basis points.

13.2. Long/Short investment strategies

In Chapter 10 we presented investment strategies where the bet-size is equal to the (negative) value of the z-score. Here we show long/short strategies, where the bet-size is not the negative value of the z-score, but you just go long or short based on the sign of the z-score. The final strategy is again the average of the first 12 strategies.

This analysis can be seen as a robustness check to investigate whether the results in Chapter 10 are not due to a few extreme bets. By going long/short small z-scores (less than 1 in absolute value) are inflated and large z-scores are capped. The information in size (of the z-score) is not used.

Below, Table 19 shows the results for this strategy for JM, RJM, MR and sign RJM.

The results are a bit worse for JM compared to the results of Chapter 10 (IR of 0.55 versus 0.42 for the final strategy). However for RJM the results are better than in Table 16. For the final strategy the IR is 0.86, which is considerable for just one variable. As with the results displayed in Table 16 the highest IR's are obtained by using a z-score after 6 to 8 months. The final strategy is less risky than the first 12. The standard deviation of this strategy is 0.67% on annualized basis versus around 0.90% for the first 12 strategies.

For MR the results for the first 6 strategies are better than in Table 16, but for the final strategy the results are not much different: an IR of 0.31 versus 0.39. The results for sign RJM are comparable to Chapter 10.

The success ratios of the different variables based on the final strategy are again mentioned in Table 19. For RJM the success ratio is 58%, which is reasonable. For MR it is 53%, which is comparable to Table 16. For the JM variable from the success ratio (50%) it follows again that the results are worse than denoted in Table 16.

sample: 1992-2002													
demeaned, long/short:													
JM	1	2	3	4	5	6	7	8	9	10	11	12	strategy
mean:	0.20%	0.20%	0.30%	0.42%	0.31%	0.48%	0.27%	0.57%	0.25%	0.19%	0.13%	0.21%	0.29%
stdev:	0.90%	0.90%	0.90%	0.90%	0.90%	0.90%	0.90%	0.89%	0.90%	0.90%	0.90%	0.90%	0.70%
IR:	0.22	0.22	0.33	0.47	0.35	0.54	0.30	0.64	0.28	0.21	0.14	0.23	0.42
												skew:	0.19
succes ratio:												kurt:	0.58

RJM	1	2	3	4	5	6	7	8	9	10	11	12	strategy
mean:	0.23%	0.40%	0.52%	0.61%	0.69%	0.74%	0.76%	0.73%	0.56%	0.64%	0.42%	0.58%	0.57%
stdev:	0.90%	0.90%	0.89%	0.89%	0.88%	0.88%	0.88%	0.88%	0.89%	0.89%	0.90%	0.89%	0.67%
IR:	0.25	0.44	0.58	0.69	0.78	0.84	0.86	0.82	0.63	0.72	0.47	0.66	0.86
												skew:	0.14
succes ratio:												kurt:	0.65

MR	1	2	3	4	5	6	7	8	9	10	11	12	strategy
mean:	0.28%	0.43%	0.26%	0.21%	0.20%	0.35%	0.36%	0.29%	0.52%	0.25%	0.18%	0.04%	0.28%
stdev:	0.90%	0.90%	0.90%	0.90%	0.90%	0.90%	0.90%	0.90%	0.89%	0.90%	0.90%	0.91%	0.72%
IR:	0.31	0.48	0.28	0.23	0.23	0.39	0.41	0.32	0.59	0.28	0.19	0.04	0.39
												skew:	0.30
succes ratio:												kurt:	0.83

signRJM	1	2	3	4	5	6	7	8	9	10	11	12	strategy
mean:	0.36%	0.44%	0.54%	0.66%	0.49%	0.47%	0.48%	0.54%	0.45%	0.39%	0.32%	0.27%	0.45%
stdev:	0.90%	0.90%	0.89%	0.89%	0.89%	0.90%	0.89%	0.89%	0.90%	0.90%	0.90%	0.90%	0.74%
IR:	0.40	0.49	0.60	0.74	0.54	0.52	0.54	0.60	0.50	0.44	0.36	0.30	0.61
												skew:	0.11
succes ratio:												kurt:	0.10

Table 19: The results (mean annualized returns, annualized standard deviation and information ratio) for the investment strategies for JM, RJM, MR and sign RJM based on demeaned z-scores. For the first 12 strategies the bet-sizes are long in case of a negative z-score and short in case of a positive z-score.

However, we pay more attention to the results presented in Chapter 10, since here only the sign of the z-score matters, which means that a small and a large z-score of the same sign both result in the same bet.

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