Opposing Seasonalities in Treasury versus Equity Returns*

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Abstract

We demonstrate a novel and striking annual cycle in the US Treasury market, with a variation of over 80 basis points from peak to trough in monthly returns. The Treasury return seasonal pattern is opposite to that evident in equity returns, and the opposing patterns are not due to unconditional negative correlation between Treasury and stock returns. We show that the seasonal Treasury and equity return patterns are unlikely to arise from macroeconomic seasonalities, seasonal variation in risk, cross-hedging between equity and Treasury markets, investor sentiment, seasonalities in the Treasury market auction schedule, seasonalities in the Treasury debt supply, seasonalities in the FOMC cycle, or peculiarities of the sample period considered. The seasonal cycles become more pronounced during periods of high market volatility, consistent with time-varying risk aversion among market participants. The seasonal patterns in equity and Treasury returns are coincident with the incidence of seasonal depression observed clinically in North American populations, and depression has been shown to be associated with reduced risk tolerance. The White (2000) reality test confirms that the correlation between returns and the clinical incidence of seasonal depression cannot be easily dismissed as the simple result of data snooping. Our findings are all the more remarkable given that it is expert traders who dominate the Treasury market.

1 Introduction

In this paper, we establish the presence of a striking anomalous seasonality in US Treasury security returns which has not been previously shown. This seasonal pattern is strongly statistically and economically significant, with holders of Treasuries earning a monthly return which peaks in the early fall, declines monotonically through to the late spring, and is roughly 80 basis points higher in October than it is in April (implying holders of Treasury earn roughly 30 billion dollars more income in October than in April on the more than 3 trillion dollars of outstanding Treasury bonds and notes). We find, further, that the seasonality in riskfree returns is the reverse of the seasonal pattern in equity returns previously shown by Kamstra, Kramer and Levi (2003), despite the empirical positive correlation between stock and Treasury returns and in contrast to the theoretical implications of standard asset pricing models.

A large literature has explored return patterns of risky assets and the factors that explain them (see Cochrane, 2005, for a comprehensive review of the asset pricing literature), however, much less attention has been devoted to the movement over time in the riskfree rate of return. Several papers have shown seasonalities in returns of various classes and maturities of bonds, including Schneeweis and Woolridge (1979) who demonstrate the presence of autocorrelation in bond index returns; Jordan and Jordan (1991) who find there is no evidence of a day-of-the-week effect in corporate bonds over the past few decades but there is evidence of a January seasonal, a week-of-the-month effect, and a turn-of-the-year effect; and Chang and Huang (1990) and Wilson and Jones (1990) who demonstrate the presence of a January seasonal in various US bond returns. Other papers have attempted to explain time-varying bond returns based on time-varying risk. For example, Boudoukh (1993) considers macroeconomic factors like consumption growth and inflation. Connolly, Stivers, and Sun (2005) find that Treasury and stock markets can move in opposite directions for short periods, perhaps due to cross-market hedging. They control for this possibility using a volatility measure and a turnover measure. De Bondt and Bange (1992) and Brandt and Wang (2003) suggest that predictable, time-varying term premia on government bonds could arise due to unexpected inflation. Still other studies have explored the possibility of time-varying risk aversion having an influence on government bond returns. For instance, Ilmanen (1995) examines long-term government bond returns in six countries and finds evidence of risk premia that depend on aggregate relative wealth measures. There is a closely related literature on bond yields that demonstrates time-varying risk premiums on nominal bonds. See, for instance, Ang and Piazzesi (2003) and Cochrane and Piazzesi (2005) for some recent evidence, and the classic work of Fama and Bliss (1987) and Campbell and Shiller (1991). Work on yields strongly supports bond return predictability based on yield spreads and macroeconomic factors. Collectively, these studies suggest possible sources for the seasonality in returns that we present, and each is explored in turn below.

There are also behavioral explanations that potentially underlie the seasonality we demonstrate, for instance investor sentiment. Baker and Wurgler (2005) predict that investors will shift into speculative, higher growth equities when sentiment is high, and that when sentiment is low investors will shift into bond-like equities and government bonds. They suggest this could account for "flights to quality" in times of market turbulence. Thus investor sentiment ought to lead to opposing seasonal patterns in equities versus Treasuries, and sentiment is therefore a natural explanation to consider for the seasonal patterns we illustrate.

Our primary focus is to attempt to determine the exact source of the seasonal pattern we show in bond returns, a pattern that has the striking characteristic of being the reverse of a previously demonstrated seasonal cycle in equity returns. While we find support for a great many of the existing hypotheses and previously described empirical regularities in bond and equity returns, we demonstrate that none can explain these particular patterns in bond and equity returns, except for one.

We investigate the behavioral time-varying risk aversion hypothesis of Kamstra, Kramer and Levi (2003) and find the opposing seasonal cycles appear to be consistent with their hypothesis. Specifically, the opposing seasonal cycles in bond and equity returns are significantly correlated with the clinical incidence of seasonal depression in North American populations. The underpinnings of this correlation could be a previously shown association between depression and reduced risk tolerance, a possibility we explore using a model that allows the opposing seasonal cycles to become more pronounced during periods of high volatility. We find this model fully captures the seasonality. The intensification of the seasonal cycle during high-risk periods is difficult to explain without considering seasonally changing risk aversion.

Our findings contribute to the body of evidence that even the decisions of professional market participants are influenced by behavioral considerations. For example, Goldreich (2006) shows that Treasury market dealers submit bids in price space that are dominated in yield space, suggesting bounded rationality among these professionals. Further, Cici (2005) finds that the trades and performance of mutual fund managers exhibit some evidence of the disposition effect.

The remainder of the paper is organized as follows. We present evidence in Section II of an economically large seasonal cycle in Treasury returns that is opposite to a previously shown seasonal pattern in equity returns. In Section III we describe how we model this seasonality initially, and we conduct preliminary regression analysis. We show in Section IV that the relation between seasonal depression and bond and equity returns is not simply a result of data mining, and we demonstrate in Section V that the relation does not arise simply due to unconditional correlation between the equity and bond returns. We demonstrate in Section VI that the seasonal pattern we demonstrate cannot be explained by a broad range of potentially seasonal macroeconomic factors. In Section VII we show that the seasonality in equity and Treasury returns is not explained by cross-hedging effects, whereby periods of stock market uncertainty may induce opposing effects in stock versus Treasury returns. In Section VIII, we explore the possible impact of a significant change to the Treasury Department's auction announcement policy that was introduced in the late 1970s to facilitate liquidity in the Treasury market, the impact of the supply of Treasury debt on returns, and the influence of the Federal Reserve Board's annual cycle of rate-setting meetings. We conduct sub-period analysis and find evidence of the seasonal cycle both before and after the policy change, and we find no impact on the seasonal cycle from seasonalities in Treasury debt supply or the rate-setting meetings. We demonstrate in Section IX that the seasonal pattern is not induced by investor sentiment. In Section X we show that the opposing cycles in Treasury and equity returns cannot be explained by Fama-French risk factors or momentum. We demonstrate in Section XI that the opposing seasonal patterns in stock and Treasury returns become more pronounced during periods of high market volatility. In Section XII we describe a variety of robustness checks, including a model that finds that the seasonal pattern remains evident even when controlling simultaneously for all the potential sources of seasonalities explored in Sections VI through X, twenty-four separate effects in total. We conclude with section XIII.

II The Treasury Market

We consider monthly returns to holding the medium-to-long end of nominal Treasury market securities, specifically 5-year, 7-year, 10-year, and 20-year Treasury note and bond returns, where the returns include interest and capital gains/losses. We avoid the short end because of the extensively documented impact of monetary policy surprises on shorter maturity Treasuries and the possible return seasonalities this may induce. Urich and Wachtel (2001) demonstrate that the 90-day T-bill rate reacts strongly to target rate changes. Cook and Hahn (1990) and Radecki and Reinhart (1994) examine the response of short-term and long-term rates to changes in a measure of the funds rate target in the days surrounding policy actions, and Dale (1993) measures the short-run response of UK market rates to monetary policy actions by the Bank of England. Although these studies find that policy actions have a significant effect on interest rates of all maturities, the size of effect declines as maturity lengthens. Indeed, the estimated response of long term rates to policy actions in these studies is extremely small. For example, long-term rates increase only four to ten basis points in response to a 100-basis-point increase in the interest rate target in the days surrounding a policy change. Of course long term rates can react very strongly to other macroeconomic announcements. We control for the usual suspects (employment, industrial production, etc.) below using realtime economic data. We also control for the Federal Open Market Committee (FOMC) meeting schedule of the US Federal Reserve.

The Treasury index data are obtained from the Center for Research on Security Prices (CRSP) US Treasury and Inflation Series. The series contain returns from the CRSP US

Treasury Fixed Term Index Series and the CRSP Risk Free Rates File. The monthly holding period returns are calculated as described in the *Data Description Guide for the CRSP US Stock Database and the CRSP US Indices Database* published by CRSP. We also study monthly equity returns on the CRSP US stock index, equal-weighted, including distributions. We include the US stock market index as a point of reference against which the Treasury index results will be compared and contrasted.

In Table I, we present summary statistics on the monthly Treasury index returns and on the monthly stock index returns. We consider data from 1952 onward, consistent with Campbell's (1990) observation that interest rates were almost constant in the United States until 1951, after which an accord between the Federal Reserve Board and the US Treasury permitted interest rates to respond more freely to market forces.

[Table I goes approximately here]

The stock index returns are over one percent per month on average, ranging from a minimum below -26 percent to a maximum over 33 percent. The average monthly Treasury index returns are roughly half a percent. The standard deviations of the Treasury indices are well below that of the equity index, increasing monotonically with maturity, and the minimum and maximum observed for each Treasury series generally spans a smaller range as maturity shortens. All the series are leptokurtotic and skewed; the stock index is skewed toward negative returns and the Treasury series are skewed toward positive returns.

In Figure 1 we plot average monthly percentage Treasury returns to informally demonstrate the prominence of a seasonal cycle; more formal analysis will follow. The black dots in Figure 1 are the monthly average returns across the Treasury security maturities listed in Table I. Omitted plots based on individual monthly Treasury returns, as opposed to the monthly average returns across the series, appear very similar in their seasonal patterns. Monthly average Treasury returns are high and above the annual average (of approximately 0.54%) through most of the fall months. Then in April, the monthly average return plummets to its lowest point of the year. The decline in returns is virtually monotonic from the annual peak in October to the annual trough in April. Further, the difference in the average returns from October to April is striking: the difference is over 80 basis points per month, which is approximately ten percent per annum on an annualized basis. Again, these plotted monthly average Treasury returns are unconditional; conditional analysis is presented later.

[Figure 1 goes approximately here]

III Measuring the Seasonality

To evaluate the conditional manifestation of anomalous seasonal variations in Treasury returns versus equity returns, we must first decide how to model the seasonality. The specification we start with is related to an annual seasonal pattern for equities shown by Kamstra, Kramer, and Levi (2003, henceforth KKL). They claim that seasonal affective disorder (SAD) underlies this seasonality. SAD is a major depressive disorder that affects approximately 5 to 15% of the population to varying degrees. Onset of the condition is in the fall, recovery is in the spring, and incidence is related to the length of the day, increasing as days shorten. KKL postulate that enough people suffer from SAD that aggregate trading patterns may be affected. As SAD is related to the number of hours of daylight, and the impact on returns is hypothesized to be opposite in the fall versus winter, they utilize a length of night variable combined with a fall dummy variable. (See KKL for further details on their rationale for this two-variable specification.) They demonstrate that this specification captures a remarkable cycle in equity returns.

The fall dummy variable and the length of night variable of KKL could be picking up cyclical factors unrelated to SAD, a possibility raised by Kelly and Meschke (2007). A possible remedy to this concern is to consider in place of these variables an alternative linked directly to the clinical incidence of SAD. Thus, in a series of steps we detail below, we define a variable that is based on the empirical incidence of SAD symptoms among individuals who suffer from SAD. As we argue below, use of this variable should be more suitable for studying seasonality potentially induced by SAD.

Young *et al.* (1997) and Lam (1998) document the clinical *onset* of SAD symptoms and *recovery* from SAD symptoms among North Americans known to be affected by SAD. These data indicate that most SAD-sufferers begin experiencing their symptoms in early-to-mid fall and fully recover by early spring, though exact timing varies by individual.[1,2] In several steps, we construct a SAD onset/recovery measure based on the Young *et al.* and Lam data. Details of the construction are as follows. First, we construct a SAD "incidence" variable which reflects the monthly proportion of SAD-sufferers in the two samples who are actively experiencing SAD symptoms in a given month. The incidence variable is calculated by cumulating, monthly, the proportion of subjects who have experienced the *onset* of their SAD symptoms (cumulated starting in late summer, when a small proportion of subjects are first diagnosed with onset) and then deducting the cumulative number of people who have experienced full *recovery* from SAD. The resulting monthly incidence variable takes on values between zero percent, in summer, and close to 100 percent, in winter. It is important to account for the fact that this measure of SAD incidence is based on *estimates* of onset and recovery in the broader population of all North Americans who suffer from SAD. That is, onset and recovery, and hence incidence, are *measured with error*. Direct use of a variable measured with error in a regression model would impart an error-in-variables bias, thus we use an instrumented version of the incidence variable.[3] Finally, the *monthly change* in this

[1]Young *et al.* study 190 Chicago residents with SAD and find that 74 percent of them are first diagnosed with SAD in the weeks between mid-September and early November. Lam studies 454 SAD patients in Vancouver on a monthly basis and finds, like Young *et al.*, that the peak timing of diagnosis is during the early fall. Lam (1998) also studies the timing of clinical remission of SAD and finds it peaks in April, with almost half of all SAD-sufferers first experiencing complete remission in that month. March is the second most common month for subjects to first experience full remission, corresponding to almost 30 percent of subjects. For most sufferers, the initial onset and full recovery are separated by several months over the fall and winter.

[2]The timing of SAD symptoms recorded by Young *et al.* (1997) and Lam (1998) is consistent with the vast majority of thousands of other studies that have examined the timing of SAD symptoms. That is, the Young *et al.* (1997) and Lam (1998) studies reflect the consensus of SAD-researchers' beliefs about the timing of SAD symptoms. We should, however, comment on the fact that Kelly and Meschke (2007) question clinical findings about the timing of SAD symptoms by citing a non-clinical telephone study by Kasper *et al.* (1989) in which roughly 40 percent of randomly selected residents of a Washington D.C. suburb reported "feeling worst in January and/or February". Kasper *et al.* did not seek to determine whether any of their telephone participants actually suffered from the medical condition of SAD. Nor did Kasper *et al.* seek to determine how individuals' feelings (such as "feeling worst" in a particular month) translated into depression or risk tolerance.

[3]To produce the instrumented version of incidence, first we smoothly interpolate the monthly incidence of SAD to daily frequency using a spline function. Next we run a logistic regression of the daily incidence on our chosen instrument, the length of day. (The nonlinear model is $1/(1+e^{\alpha+\beta day_t})$, where day_t is the length of day t in hours in New York and t ranges from 1 to 365. This particular functional form is used to ensure that the fitted values lie on the range zero to 100 percent. The $\hat{\beta}$ coefficient estimate is 1.22 with a standard error of 0.0116, the intercept estimate is -14.58 with a standard error of 0.138, and the regression R^2 is 99.0 percent.) The fitted value from this regression is the instrumented measure of incidence. Employing additional instruments, such as change in the length of the day, makes no substantial difference to the fit of the regression or the subsequent results using this fitted value.

instrumented incidence variable yields the version of onset/recovery used in our model, which we denote $\hat{OR}_t$ (short for onset/recovery, with the hat indicating the variable is the fitted value from a regression). $\hat{OR}_t$ is calculated as the instrumented incidence value for a given month minus the instrumented incidence value for the previous month.[4]

$\hat{OR}_t$ reflects the change in the proportion of SAD-affected individuals actively suffering from SAD. The measure is positive in the summer and fall and negative in the winter and spring. Its value peaks near the fall equinox and reaches a trough near the spring equinox. The opposite signs on $\hat{OR}_t$ across the fall and winter seasons should, in principle, permit it to capture the opposite impact on returns across these seasons shown by KKL, without employing the two (perhaps problematic) variables used by KKL: the simple fall dummy variable and the length-of-day variable, neither of which is necessarily directly related to the incidence of SAD.

In an unreported regression (detailed results available on request), we compare the performance of $\hat{OR}_t$ to the two variables KKL originally employed in their model. We find that adding onset/recovery to the original model for US equity returns reduces the magnitude and significance of the original KKL variables remarkably. For instance, with the introduction of onset/recovery the coefficient on KKL's length of night variable drops by two thirds, the t-test on this variable drops from over 5 to 1.6, and the coefficient on the KKL fall dummy variable flips sign and becomes insignificant. The onset/recovery variable, in contrast, is both statistically and economically significant when added to KKL's original model. Further, the onset/recovery coefficient estimate is similar in magnitude and significance to the case we explore below which excludes the KKL variables. The implication is that onset/recovery does at least as good a job as the two original KKL variables. KKL document extensive robustness checks using different measures of the impact of the onset and recovery from SAD, including the number of hours of night normalized to lie between 0 and 1, the number of hours of night normalized to lie between -1 and +1, and a SAD measure taking on non-zero values through the spring and summer. They document that

[4]The values of $\hat{OR}_t$ by month, rounded to the nearest integer and starting with July, are: 3, 16, 40, 29, 7, 0, -5, -20, -43, -22, -5, 0. These values represent the instrumented *change* in incidence of symptoms.

the economical magnitude, sign and statistical significance of the effect is very similar across all measures explored.

Some additional features of our onset/recovery variable are also important to mention. First, our onset/recovery variable is based directly on the clinical incidence of SAD in humans, unlike KKL's variables. Second, our onset/recovery variable spans the entire year, whereas KKL's length of night and fall dummy variables take on non-zero values during the fall and winter months only (and therefore do not account for the small number of SAD-sufferers who experience symptoms earlier than fall or later than winter). In light of these points, the remainder of our analysis is conducted using the onset/recovery variable. We turn now to estimating the opposing seasonal patterns in Treasury and equity returns in a variety of contexts.

A Baseline Regression Analysis

Our first goal is to determine whether $\hat{OR}_t$ is able to capture the annual seasonality we seek to study. We jointly estimate a set of regressions for the Treasuries and equity return indices, starting with a simple model controlling only for well-known market seasonals and the onset/recovery variable:[5]

$$\begin{aligned} r_{i,t} &= \mu_i + \mu_{i,OR}\hat{OR}_t \\ &\quad + \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5}\rho_{i,j}r_{i,t-j} + \epsilon_{i,t}. \end{aligned} \tag{1}$$

Variables are defined as follows: $r_{i,t}$ is the month t return for a given index i, D_t^{Jan} equals one for the month of January and equals zero otherwise, and $\hat{OR}_t$ is defined as above. We include five lags of the dependent variable to control for autocorrelation.[6]

The various index return series form a panel-time-series data set. Estimating Equation (1) jointly across the indices, we can exploit the covariance of the series to provide more precise

[5]See Schneeweis and Woolridge (1979) for evidence of autocorrelation in bond index returns, and Schneeweis and Woolridge (1979), Chang and Huang (1990), and Wilson and Jones (1990) for evidence of a January seasonal in bond returns. Regarding equity returns, see KKL for extensive references on well-known seasonalities such as the tax-year-end effect and autocorrelation.

[6]Our results are very similar if we pre-whiten the returns data, removing evidence of autocorrelation prior to estimating the seasonality.

estimates of the regression coefficients.[7] Table II contains estimation results. In Panel A we provide parameter estimates and t-statistics based on system estimation with Hansen's (1982) GMM and Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.[8] At the bottom of Panel A we provide the value of R^2 for each index, and χ^2 tests for the presence of up to 12 lags, i.e. a year, of residual autocorrelation or ARCH.

[Table II goes approximately here]

The January seasonal is significant for only the equity index, and all the series show evidence of ARCH but no statistically significant evidence of residual autocorrelation. These results are typical of empirical investigations that consider equity and bond return series. The seasonality variable, $\hat{OR}_t$, is strongly statistically significant in both the equity and bond series, with the sign positive in the Treasury return series and negative in equity return series. As the onset/recovery variable is itself positive in the fall and negative in the winter, this implies an annual cycle of above average returns in the fall (winter) for Treasuries (equities) and below average returns in the fall (winter) for equities (Treasuries). In considering the onset/recovery variable it is also informative to consider the joint significance *across* all the indices, not just within each of the individual indices. The Wald χ^2 test statistic in Panel B, based on the HAC covariance estimates, tests the joint significance of $\hat{OR}_t$ across the equity and Treasury series. We strongly reject the null of no seasonal effect.

B Economic Significance of the Seasonal Effect

We turn now to the economic significance of the seasonal effect: How much influence does this seasonal have on actual returns? Also, is the seasonal pattern we capture in Treasuries the same one that is apparent in Figure 1? (A monotonic decline in returns from the October

[7]Estimating Equation (1) separately for *each* index, as opposed to jointly, yields very similar results, though the significance of some coefficient estimates is reduced. Ignoring the covariance structure of errors across the return indices will typically result in larger standard errors and a loss in power.

[8]Estimation of this system with full information maximum likelihood rather than GMM leads to very similar results, as do small changes in the number of instruments used to identify model parameters and window width smoothing parameters employed in GMM estimation. In general, the more instruments used to identify model parameters, the more significant (the sharper are) the parameter estimates, consistent with the intuition that the more over-identifying information used, the better able we are to estimate parameters of the system.

peak to the April trough, approximately a one percent decline over this period.) Figures 2 and 3 help us answer these questions. We consider Figure 2 first, the case of Treasury returns.

[Figure 2 goes approximately here]

The solid black dots represent the unconditional monthly Treasury returns, averaged across the 5-year, 7-year, 10-year, and 20-year Treasury series. The mean return for the month of January has been adjusted to remove the January seasonal in bond returns documented by Schneeweis and Woolridge (1979) and others, an adjustment that involves subtracting less than 6 basis points. The asterisks in Figure 2 represent the estimated monthly conditional Treasury returns due to the onset/recovery seasonality, computed as follows. First, the average effect on Treasury returns due to onset/recovery in each month is calculated by taking the value of $\hat{OR}_t$ for each month and each index and multiplying by the $\hat{OR}_t$ coefficient estimate for that index, then averaging across indices. Next we add the unconditional average Treasury return, which is just over 0.5 percent, to generate the series plotted with asterisks in Figure 2. (We add the unconditional mean return to the net return to make the two lines in Figure 2 easily comparable.) This series represents the net monthly average Treasury return movements which can be directly attributed to the onset/recovery variable, centered about the mean return.

Examining month-by-month the conditional Treasury returns due to seasonality (again, marked with asterisks), we see that the effect of onset/recovery tracks the unconditional seasonal pattern in monthly Treasury returns remarkably well. Both the peak (October) and trough (April) are within a month of matching, and the long decline from October to mid-spring and subsequent rise from mid-spring to June are captured by the onset/recovery seasonality. Conditional (and unconditional) returns are well above the average annual Treasury return throughout the fall, and drop well below the average in the winter months following January.[9]

When the amount of outstanding US Treasury debt is taken into consideration, it becomes

[9] In terms of the statistical significance of the raw unconditional monthly returns, however, only the extreme mean monthly returns are different from each other at conventional levels of significance. What is remarkable about the raw monthly mean returns is the *pattern* over the year – the conditional results in Section III A demonstrate that this pattern is strongly statistically significant and White Reality tests, presented below, validate the significance of this pattern against possible data-snooping issues.

clear that the conditional seasonal fluctuation in Treasury returns is very large in financial terms. The current amount of US Treasury debt outstanding that falls into the range of the mid- to long-term maturities (that is, excluding bills and TIPS) we consider is over 3 trillion dollars.[10] Based on that amount outstanding, the values plotted in Figure 2 imply that holders of these Treasuries are collectively earning about 30 billion dollars per month more in the early fall than they are in the late winter, conditional on our measure of seasonality.[11]

Turning to the case of the equal-weighted stock returns, we see opposite seasonals relative to Treasury returns. In Figure 3, the line indicated with solid black dots represents monthly average stock returns for the CRSP equal-weighted stock index. The mean return for the month of January has been adjusted to remove the well-known tax-loss selling effect, a calculation that involves subtracting roughly 4 percent. While the plot is unconditional in nature, Figure 3 suggests stock returns follow a remarkable seasonal pattern, consistent with the findings of KKL. (See KKL's Figures 1-5 for a larger set of plots demonstrating that unconditional returns for a broad collection of US and foreign indices follow a similar seasonal pattern.) The conditional equity returns are calculated analogously to the conditional Treasury returns: the effect due to onset/recovery in each month is calculated by taking the value of $\hat{OR}_t$ for each month and multiplying by the $\hat{OR}_t$ coefficient estimate for the stock index. Adding that conditional return to the average unconditional mean stock return of about 1.2 percent yields the series plotted with asterisks in Figure 3. The series marked with asterisks represents the net monthly stock return movements that can be attributed to the onset/recovery variable, centered around the mean of 1.2 percent.

[Figure 3 goes approximately here]

In contrast to Treasuries, the minimum unconditional stock return occurs in October (when the maximum for Treasury returns occurs), within a month of the *conditional* minimum. The conditional peak stock return occurs in March (when the conditional minimum

[10] See the Monthly Statement of Treasury Securities of the United States, issued by the US Treasury.

[11] We exclude from our analysis bills, notes, and bonds maturing in less than 5 years, whereas the 3 trillion dollar debt figure includes notes and bonds maturing in less than 5 years (but does not include bills). A reasonable question, therefore, is whether the difference between early fall and late winter returns is really as large as 30 billion dollars. Robustness checks we performed, available on request, indicate that all of the shorter-term Treasury securities (*i.e.*, those maturing in less than 5 years) demonstrate a seasonal pattern very similar to the one we have shown in the medium-to-long term maturities. Thus our 30 billion dollar estimate is, if anything, conservative as it excludes the impact of bills.

Treasury return occurs), with March exhibiting the second highest *unconditional* mean stock return. One remarkable feature of the annual equity return cycle apparent in Figure 3 that our model of seasonality is unable to explain is the November peak. This particular feature is, however, somewhat sensitive to the sample period used to calculate averages.

C Discussion

Overall, the results in Table II and Figures 2 and 3 are strongly supportive of large seasonal influences on both risky and relatively risk-free asset returns. As described above, the coefficient estimate on $\hat{OR}_t$ is significantly positive for the Treasury indices we consider, opposite to the sign for equities. The impact of the seasonality on Treasury and stock returns is economically significant, causing substantial seasonal variation in Treasury and stock returns over much of the year. Perhaps most remarkably, the seasonal patterns in Treasury returns are approximately opposite to what we observe in stock returns. Treasury returns are (roughly) shifted from the winter into the fall, which is opposite to the pattern in stock markets shown by KKL.

IV Is This Just Data Snooping? The White Reality Test

When conducting inference with such frequently studied data as those we employ, there is a legitimate concern that significant results may arise due to data snooping, rather than due to any truly significant underlying economic phenomenon. To test for this possibility, we employ the data-snooping test developed by White (2000) which was designed to account for the fact that researchers tend to report only those results that are statistically significant. To implement the procedure, a benchmark set of models must first be defined, in our case, an alternative set of patterns that would have been as remarkable to find to be correlated with our returns data as the onset/recovery pattern. Once the benchmark models have been defined, bootstrap resampling techniques are used to determine the data-snooping-adjusted significance of the original pattern.[12] Specifically, for each simulated dataset, the

[12] In implementing the reality test, we follow White (2000) and use block bootstrapping to allow for return dependence.

most significant pattern (across all the benchmark models being considered) is determined. Across all the simulations, this yields a distribution of the test statistic for the model which happens to be the most correlated with returns. (In the actual US data we employ, the onset/recovery pattern is the one which is the most correlated with returns.) We can then compare our original model's test statistic with the bootstrap distribution, yielding a data-snooping adjusted p-value.

We now define the alternative/benchmark models we consider. Since the result for which we are conducting the data-snooping test is a positive correlation with onset/recovery, we consider a *negative* correlation with onset/recovery as our first benchmark model. Next, we consider positive or negative correlations with *lagged* versions of our onset/recovery variable (lagged by 1 to 11 months), yielding 22 additional benchmark patterns. Additionally, we consider a monthly oscillation in average monthly returns (higher, then lower, then higher, then lower, *etc.*, throughout the year) starting any month of the year, yielding two more benchmark patterns. Our next benchmark models consist of quarterly oscillations in average monthly returns (higher for three months, then lower for three months, repeated throughout the year) starting any month of the year, yielding six more patterns. Another set of benchmarks consist of average monthly returns that oscillate every four months (higher for four months, then lower for four months, repeated over the course of two years) starting any month of the year, yielding sixteen additional patterns. We also consider a simple sine wave pattern of returns (similar to but not identical to onset/recovery) starting in any month of the year, yielding twelve further benchmarks, and a squared-sine-wave pattern of returns starting in any month of the year, yielding six more. We explored enlarging the pool with even more patterns, but found that the reality test-adjusted p-value changes very little with the addition of models once a large collection of models such as we have specified is incorporated.[13]

The results of the data-snooping test are as follows. The bootstrapped probability of finding equity returns as strongly correlated with the onset/recovery variable as we find in the data is 2.53%. The bootstrapped probability of finding bond returns as strongly

[13]White (2000) conjectures that as the number of alternative models is increased, the test statistic is bounded in probability, basically that the set of all possible models is spanned in probability.

positively correlated with the onset/recovery variable that we find in the data is 5.33%. In addition to conducting these two data-snooping tests, we conducted another. We examined the probability of observing a run of six months of near-consecutive declining monthly mean bond returns, as shown in Figure 2.[14] The bootstrapped probability of observing a run of six months of positive (or negative) returns such as we see in Figure 2 is 0.38%.

The *joint* significance of all three data-snooping-adjusted test statistics (the onset/recovery effect in bonds, the onset/recovery effect in equities, and the six-month run of consecutively declining average monthly returns) is 0.55%. While it is impossible to prove that mere chance did not generate the bond and stock return patterns we demonstrate in this paper, application of the White reality test suggests that simple data-mining is very unlikely to be responsible for our results.

V Are Opposing Seasonals in Treasuries and Equities Surprising?

Since we are comparing and contrasting seasonals in Treasury returns and stock returns, it is helpful to consider whether our monthly Treasury index returns are unconditionally correlated with stock returns.[15] If stock returns and Treasury returns are unconditionally highly negatively correlated, then it would not be surprising to find Treasury returns display an opposite seasonal relative to stock returns, even if the seasonal were spurious. If, however, there is unconditional positive correlation or a lack of correlation between stock returns and Treasury returns, then finding opposite seasonals in Treasury returns relative to stock returns would be noteworthy.

Table III contains correlation coefficients based on the covariance between the CRSP monthly equal-weighted total stock market index returns and each of the monthly Treasury index returns for various sample periods. Note that for the full-sample period, shown in the

[14] In Figure 2 there is a flat spot between February and March, where the change in the average return is within 2 basis points of zero. For the purposes of this test, we do not consider that flat spot to be a break in the six-month run. To be conservative in constructing the bootstrapped probability, we do *not* treat any average monthly return within five basis points of the previous month's average return as a reversal in a run.

[15] Some market circumstances, such as bad news about the economy or stock market crashes, can cause the Treasury and stock markets to move in opposite directions. (See Connolly, Stivers, and Sun, 2005, for a discussion of decoupling in the behavior of stock and bond returns over short periods.) There are other events, such as interest rate movements, that can make stock and bond returns move in the same direction.

first row, each of the Treasury return series is significantly positively correlated with stock returns. In the decade sub-periods, stock returns and Treasury returns are insignificantly correlated in the 1960s and the 1990s, strongly positively correlated in the 1970s and 1980s, and negatively correlated only in some instances during the 1950s and the 1990s. Given that the full-sample results and the majority of the sub-sample results indicate Treasury return and stock returns are significantly positively correlated, we assert that the evidence we present below on seasonalities in Treasuries relative to stocks are not unduly biased in favor of finding an opposing seasonal in Treasury returns. Replacing the CRSP equal-weighted stock index returns with either the CRSP value-weighted stock index returns or returns on the S&P 500 stock index leads to very similar results. Considering returns in excess of the 30-day T-bill generates very similar results, both here and in the conditional analysis that follows. Consequently, we largely restrict ourselves to nominal returns.

[Table III goes approximately here]

An important pair of questions that remain are what could be driving this effect, and why is the seasonality opposite in Treasury returns compared to equity returns, particularly when treasury and equity returns are unconditionally positively correlated?

VI Macroeconomic Time-Varying Risk

Several studies have shown that macroeconomic factors significantly affect stock and bond returns. For example, Chen, Roll, and Ross (1986) find the following macroeconomic risks are priced in the stock market: the spread between long and short interest rates, expected and unexpected inflation, industrial production, and the spread between high- and low-grade bonds. Some of these factors might even influence stocks versus Treasuries differently, such as expected inflation. A recent strand of the literature posits that a particular set of macroeconomic news can have a different impact on financial assets depending on the state of the economy. For instance, Boyd, Hu, and Jagannathan (2005) find that unemployment rate surprises impact stock and bond returns symmetrically in an economic expansion but oppositely during a contraction. They find that in an expansion, unexpected rising unemployment is good news for both stocks and bonds, but in a contraction, unexpected rising unemployment is bad news for stocks and irrelevant for bonds.

Since the seasonality we model is cyclical by definition, and since we posit that the seasonality impacts equity and fixed income returns oppositely, it is interesting to explore whether the influence of the seasonal variable we introduce is actually accounted for by other possibly cyclical events in the economy. Thus we control for the influence of various macroeconomic factors on stock and Treasury returns and allow for the opposite influence of some macroeconomic factors during economic expansions versus contractions.

The macroeconomic effects we control for include the surprise in the industrial production growth rate, the expected change in the unemployment rate, the expected growth in industrial production, the monthly change in the spread between Baa and Aaa corporate bond rates, and the monthly spread between 20-year and 30-day Treasury returns. Additionally, studies including De Bondt and Bange (1992) and Brandt and Wang (2003) suggest inflation surprises may lead to time-varying government bond returns, and thus we control for inflation surprises. As described in Appendix A, we consider two different measures of surprises, one using real-time data and the other using the most recently available data (which includes corrections). We report results only for the inflation surprise measure based on real-time data, but the findings are virtually identical using either series. We also control for a contraction probability index (the experimental coincident recession index constructed by Stock and Watson, 1989). Further, we interact the probability of a contraction with the surprise in the unemployment rate change, since Boyd, Hu, and Jagannathan find that unemployment rate surprises influence stock and bond returns oppositely across expansionary and contractionary periods. We construct the interactive unemployment surprise variables four different ways, as explained in Appendix A. We report results based on only the first of these four methods, but results pertaining to the seasonality effect are virtually identical using any of the measures we construct. Appendix A also contains details on construction of the industrial production surprise variable, and Appendix B outlines the data sources.

Summary statistics for each of the macroeconomic variables we consider are provided in Panel A of Table IV. (We discuss Panels B, C, and D later in the paper.) Because of data limitations on some of the macroeconomic series, we are restricted to the period

December 1965 through December 2003. Beneath each variable's name is the abbreviation we use in the regressions to be described below. Each observation in all of the listed series in the table has been multiplied by 100, except for the probability of contraction series. The most volatile series are the expected change in unemployment and the change in the spread between Baa and Aaa corporate bonds. Stock and Watson's contraction probability variable ranges from a low of one percent to a high of 99 percent, with a mean near 16 percent, consistent with the empirical fact that the economy is usually in an expansionary state. The interactive unemployment surprise is less volatile in the contraction state than in the expansion state, and negative surprises are more common in the expansion state than they are in the contraction state.

[Table IV goes approximately here]

Now we estimate a version of Equation (1) that has been supplemented with the macroeconomic variables described above:

$$
\begin{aligned}
r_{i,t} = {} & \mu_i + \mu_{i,OR}\hat{OR}_t + \mu_{i,U}U_t \\
& + \mu_{i,IP}IP_t + \mu_{i,IPSurp}IPSurp_t + \mu_{i,Default}Default_t \\
& + \mu_{i,Term}Term_{t-1} + \mu_{i,Inf}Inf_t + \mu_{i,InfSurp}InfSurp_t \\
& + \mu_{i,ProbC}ProbC_t + \mu_{i,USurpC}USurpC_t + \mu_{i,USurpE}USurpE_t \\
& + \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5}\rho_{i,j}r_{i,t-j} + \epsilon_{i,t}
\end{aligned}
\tag{2}
$$

The variables $r_{i,t}$, $\hat{OR}_t$, and D_t^{Jan} are as previously defined. U_t is the expected change in the unemployment rate, IP_t is the expected growth in industrial production, $IPSurp_t$ is the surprise in industrial production growth, $Default_t$ is the change in the spread between Baa and Aaa corporate bond rates from month $t-1$ to month t, $Term_t$ is the difference between the one-month return on 20-year Treasuries and the one-month return on 30-day Treasuries at month t, Inf_t is the expected inflation rate, $InfSurp_t$ is surprise in the inflation rate, $ProbC_t$ is the Stock and Watson (1989) experimental coincident recession index (reflecting the probability of a contraction), $USurpC_t$ is surprise in the change in unemployment interacted with the probability of a contraction, and $USurpE_t$ is surprise in the change in unemployment interacted with the probability of an expansion (which equals 1 minus the probability of a contraction). Our findings with respect to the seasonality variables are virtually identical if we replace $USurpC_t$ and $USurpE_t$ with any of the three other measures of the interactive unemployment surprise variables described in Appendix A, or if we replace $InfSurp_t$ with the other measure of the inflation surprise described in that appendix. As before we include five lags of the dependent variable to account for autocorrelation.

This model includes a large number of macroeconomic variables that other researchers normally study in smaller sets. The exercise of including all of the variables in a single model may lead to counter-intuitive estimates on various macroeconomic variables due, for instance, to multicollinearity. Note that including the macroeconomic variables is intended to capture news that would have been available to market participants at the time prices were being formed. The model is not intended as a predictive model; rather it permits us to isolate possible seasonalities in macroeconomic news in order to investigate whether the seasonality in returns that we consider is simply a function of macroeconomic seasonalities.

Results from estimating the model are reported in Table V. As before, we provide in Panel A parameter estimates and t-statistics based on system estimation with Hansen's (1982) GMM and Newey and West (1987) HAC standard errors. For the stock index, we find that the coefficient estimate on $\hat{OR}_t$ is significantly negative, and for the Treasuries, this coefficient is significantly positive. The coefficient estimate magnitudes are very similar to those that arise for the case where the macroeconomic factors are excluded from the estimation, and as before these estimates are not only statistically significant, but economically large. The onset/recovery estimates are jointly strongly significant across series (as shown in Panel B).

[Table V goes approximately here]

The uniformly maintained magnitude and significance of the onset/recovery variable is striking in light of the fact that several of the macroeconomic variables have an opposite and statistically significant impact on stocks versus Treasuries. For example, the change in the default spread has a positive coefficient for stocks and a negative coefficient for the

Treasuries, the Stock and Watson (1989) experimental coincident recession index ($ProbC$) has a negative impact on equities and a positive impact on Treasuries, and the surprise in the change in unemployment interacted with the probability of an expansion ($USurpE$) has a negative impact on equities and a positive impact on Treasuries.[16]

In short, even after controlling for predicted and surprise contemporaneous macroeconomic events, including some macroeconomic variables which have an opposite impact on stocks and bonds, the $\hat{OR}_t$ variable maintains its sign, magnitude (economic significance), and statistical significance relative to the results presented earlier. This seasonal in stock returns continues to be opposite in sign relative to the seasonal in Treasury returns. It appears that neither simple macroeconomic seasonalities nor macroeconomic risk factors can account for the opposing equity and Treasury return seasonal patterns.

VII Time-Varying Cross-Hedging

Connolly, Stivers, and Sun (2005) find the Treasury and stock markets can move in opposite directions during short periods, such as market crashes, perhaps due to cross-market hedging. They control for this possibility using a volatility measure and a turnover measure. Now we ask the question, could the seasonality we uncover, apparently related to the clinically measured onset of and recovery from SAD in individuals, actually be a result of seasonality in cross-hedging? A disproportionate share of market crashes have occurred in the early fall and have led to large negative swings in equity returns and hedging in Treasuries, exactly the sort of return movements that could lead to the seasonality we demonstrate.

The first variable we control for is stock market volatility, measured using the predicted variance of the S&P 500 index, based only on lagged realized volatility.[17] We denote the

[16] The coefficient on the term structure variable, being based on lagged differences between 20 year and 30-day treasury rates, is strongly correlated with lagged returns to Treasuries, in particular the 20 year Treasury return. This collinearity makes it difficult to interpret the coefficient on the term structure variable (which is positive for the 5, 7 and 10 year Treasuries and negative for the 20 year) and the coefficients on the lagged returns to the Treasury series.

[17] We proxy for the conditional volatility of the US equity market using the predicted volatility of the S&P 500 stock index return, estimated as the fitted value from an ARMA(1,2) model of realized volatility (the monthly sum of squared daily returns). The ARMA(1,2) specification is selected because it is the lowest order ARMA model that removes evidence of autocorrelation from the realized volatility series. For reference to the theoretical justification for and superior properties of the realized volatility measure, see Andersen *et al.* (2003). Robustness checks using the conditional volatility of the CRSP value-weighted or equal-weighted

conditional volatility as $\hat{\sigma}_t^2$. The second variable we control for is stock market turnover. Using the CRSP monthly stock file, we calculate the monthly total volume and total shares outstanding of all stocks, and use this to produce monthly turnover. We define $Turnover_t$ as the deviation of monthly turnover from the (rolling) one-year average turnover. Summary statistics on the volatility and turnover measures (multiplied by 100) appear in Panel B of Table IV.

We estimate a version of Equation (1) which has been supplemented with the stock market uncertainty variables described above. The model is estimated using data spanning January 1952 through to the end of 2004.

$$
\begin{aligned}
r_{i,t} = {} & \mu_i + \mu_{i,OR}\hat{OR}_t \\
& + \mu_{i,\sigma_t^2}\hat{\sigma}_t^2 + \mu_{i,Turnover}Turnover_{t-1} \\
& + \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5}\rho_{i,j}r_{i,t-j} + \epsilon_{i,t}
\end{aligned} \tag{3}
$$

The variables $r_{i,t}$, $\hat{OR}_t$, $\hat{\sigma}_t^2$, $Turnover_t$, and D_t^{Jan} are as previously defined. Note we use the lag of $Turnover_t$. As before we include five lags of the dependent variable to account for autocorrelation. Results are presented in Table VI.

[Table VI goes approximately here]

The impact of controlling for cross-hedging on the seasonality variable $\hat{OR}_t$ is minimal. The economic significance is slightly reduced, and the statistical significance is barely affected, both equation by equation and overall. Volatility has a positive effect on both stock and Treasury returns consistent with market risk being priced. Turnover has a positive impact on equities and a negative impact on Treasuries. It does not appear that cross-hedging explains the strong reverse seasonal in equities versus Treasuries.

return series show that our results are not sensitive to the choice of the S&P 500 volatility measure. These results are available on request.

VIII Seasonalities in the FOMC Meeting Cycle, the Announcement of Treasury Auctions, and the Supply of Treasury Debt

Throughout most of our sample, mid-quarterly Treasury auctions of notes and bonds have been held in February, May, August, and November. In the early part of our sample, however, the maturity and supply of securities offered at these auctions was typically determined by surveying buyers of the Treasury issues then making adjustments in a "tactical" fashion. Thus the selection and quantity of Treasuries offered for sale did not follow a predictable pattern, an occurence that occasionally disrupted the market by catching investors off guard.[18] During the mid-1970s US Treasury officials, concerned about growing financing demands due to fiscal deficits, began to regularize Treasury offerings of notes and bonds. Quarterly and mid-quarterly auction schedules were put in place for most maturities of notes and bonds by 1980, and by 1982 the choice and supply of offered maturities was announced well in advance of auctions. The posted dates are tentative and can change, but changes are rare.[19] The US Treasury currently sells bills, notes, bonds, and TIPS at more than 150 auctions held throughout the year. See Dupont and Sack (1999) for an overview of the operations of the Treasury securities market.

To ensure our results are not driven by features of the data observed prior to the Treasury's effort to stabilize government offerings of notes and bonds, we run regressions on the post-1979 sub-period. We also seek to ensure that the mid-quarterly auction schedule that was a more prominent feature of the pre-1980 period does not in itself induce a seasonal pattern, so as an additional check we add a dummy variable for the auction announcement months. As the supply of debt has been shown to impact the Treasury market,[20] we control for Treasury debt supply changes. We measure the impact of Treasury debt supply several different ways. Following Krishnamurthy and Vissing-Jorgensen (2007), we form the ratio of Treasury debt to GDP as our first measure.[21] For a second measure, we follow Sundaresan

[18] See Garbade (2007) for further details.

[19] See Garbade (2007) for details.

[20] See, for instance, Krishnamurthy (2002) and Krishnamurthy and Vissing-Jorgensen (2007).

[21] The data were collected from the web site of the Federal Reserve Bank of St. Louis, series IDs GFDEBTN and GDP, and as these are quarterly data we linearly interpolated to the monthly frequency.

and Wang (2006) and form the change in the amount of Treasury debt. For a third measure, Cortes (2003) suggests that fiscal balance can impact the Treasuries market, so we employ net federal US government saving in place our other measures of the supply of Treasuries.[22] Finally, for each of these measures we also take the three-month lead, to account for the fact that all of these measures are all based on *quarterly* data and thus the information they contain may have been at least partially anticipated by market participants.

Finally, the Federal Reserve conducts open market operations, the sale or purchase of Treasury debt, as a tool to implement monetary policy. The explicit intent of these efforts is to manage the money supply, short-term interest rates, and seasonal movements of funds. The decision to conduct open market operations is based on directives from the FOMC, which only meets six to eight times a year. Further, the preparation for and follow-up to the FOMC meetings generates a vast amount of microeconomic and macroeconomic economic information, some of it released shortly before the meetings (*e.g.* the Beige book), some of it released on the meeting date (rate changes, statement of bias, *etc.*), and some released shortly after (*e.g.* minutes of the meeting). Long-term rates can react strongly to the FOMC minutes, even if the FOMC announces no immediate rate change and makes no recommendation for open market operations. It is thus interesting to control for FOMC meeting dates, which we accomplish with a dummy variable equal to one in months when the FOMC has a meeting. Recall that in Section VI we controlled for the macroeconomic effects impacted by FOMC open market operations, such as the spread between 20-year and 30-day Treasury returns, inflation surprises, *etc.* We do not replicate that exercise here. In Section XII we estimate a model that incorporates all of these different variables simultaneously.

The model we estimate and present in Table VII uses our first measure, the Treasury-debt-to-US-GDP ratio, and is a version of Equation (1) which incorporates the dummy variable for the quarterly announcement of the auction schedule, the monthly debt-to-GDP ratio, and the dummy variable for FOMC meeting months. The model is estimated using

[22] The net savings data were collected from the web site of the Federal Reserve Bank of St. Louis, series ID FGDEF. Because the data are provided at the quarterly frequency, we linearly interpolated to the monthly frequency.

data spanning January 1980 through to the end of 2004.

$$
\begin{aligned}
r_{i,t} = {} & \mu_i + \mu_{i,OR}\hat{OR}_t \\
& + \mu_{i,Auction} D_t^{Auction} \\
& + \mu_{i,Debt-to-GDP} Debt-to-GDP_t \\
& + \mu_{i,FOMC} D_t^{FOMC} \\
& + \mu_{i,Jan} D_t^{Jan} + \sum_{j=1}^{5} \rho_{i,j} r_{i,t-j} + \epsilon_{i,t}.
\end{aligned} \tag{4}
$$

Variables are as previously defined, plus we include the debt-to-GDP ratio ($Debt-to-GDP_t$) to account for seasonalities in Treasury debt supply, a dummy for the months of February, May, August, and November ($D_t^{Auction}$) to account for a quarterly seasonal possibly induced by the announcement of the Treasury auction schedule, and a dummy for the months during which the FOMC meetings occur (D_t^{FOMC}) to account for a seasonal induced by the FOMC and related activities surrounding it.[23] As before, we include five lags of the dependent variable to control for autocorrelation. Results appear in Table VII.

[Table VII goes approximately here]

We see from Table VII that the coefficient estimates on $\hat{OR}_t$ demonstrate once again the familiar pattern of opposing seasonals in equities and Treasuries. The inclusion of the auction and FOMC dummy variables capture small impacts on Treasury returns, negative and significant for three Treasury series for the auction dummy, and positive but largely insignificant for the FOMC dummy. Both the auction and FOMC dummy coefficients are positive, large, and statistically significant for equities, presumably picking up the large positive November return easily visible in Figure 3, a seasonality that this paper's onset/recovery variable cannot easily account for. The measure of Treasury debt supply, the debt-to-GDP ratio, is strongly statistically significant and negatively correlated with Treasury returns, consistent with Krishnamurthy and Vissing-Jorgensen (2007). The inclusion of these variables, however, does not diminish the economic magnitude or statistical significance of the

[23] There are normally six to eight FOMC meetings per year, typically held during the months of January/February, March, May, June, August, October/November and December, though the schedule varies enough from year to year that every month of the year has held a FOMC meeting one year or another.

onset/recovery effect.

This consideration of the sub-period from 1980 onward reveals that the seasonality captured by $\hat{OR}_t$ is stronger in the last half of our sample, roughly twice that measured for the entire period 1952 through 2004 for the Treasuries, and roughly 25% larger for equities. To be assured that the strengthening of the seasonality we see in Table VII is not simply a function of the high inflation of the 1980s (even though we explicitly control for expected and unexpected inflation with the macro factors models in Section VI and this left our results unaffected), we also estimate this model on returns in excess of the 30-day Treasury bill. These results (unreported, but available on request) show a virtually unchanged seasonal effect relative to nominal returns. In another set of unreported regressions (available on request), we estimate a version of Equation (4) that replaces the debt-to-GDP measure of supply with (sequentially) the change in the amount of Treasury debt, the net federal US government saving, and a three-month lead of *each* of the three measures of Treasury supply. This set of five regressions all produce qualitatively identical results: the economic magnitude and statistical significance of the onset/recovery variable is undiminished.

Overall, the seasonality we demonstrate related to onset/recovery is not explained by the supply of Treasury debt, nor can it be explained by the quarterly auction cycle of the US Treasury or the FOMC meeting cycle. Further, the seasonality does not appear to be weakening over the modern period post-1979, a period that is arguably less liquidity-impacted than in the past due to the efforts of the US Treasury to pre-announce auction schedules. In further robustness checks (unreported, but available on request) we find that the onset/recovery seasonality is also apparent in data pre-1980, being both statistically significant and economically large.

IX Time-Varying Investor Sentiment

Based on consideration of the cross-section of equities, Baker and Wurgler (2006) suggest that waves of investor sentiment can have an impact "on securities whose valuations are highly subjective and difficult to arbitrage." Baker and Wurgler (2005) propose that sentiment should also impact government bonds, predicting that when sentiment is high investors will shift into speculative, high-growth equities, and when sentiment is low investors will shift into bond-like equities and government bonds. Baker and Wurgler (2006) measure investor sentiment as a function of the closed-end fund discount, NYSE share turnover, the number of IPOs and the average first-day IPO return, equity share (defined as gross equity issuance divided by gross equity plus gross long-term debt issuance), and the dividend premium (measured as the log difference of the average market-to-book ratios of dividend payers and nonpayers).

Investor sentiment predicts bond and equity return patterns much like we observe in our equity and Treasury return series – opposing movements in bond and equity returns, under some conditions. Also, investor sentiment is measured as a function of data that are possibly seasonal. It is therefore natural to consider whether the seasonality we illustrate is actually a result of seasonally varying investor sentiment.

We face a challenge in constructing a monthly sentiment index, as Baker and Wurgler (2006) construct measures of sentiment at an annual frequency.[24] Their measures are composite indices, constructed by utilizing principal components to capture the common variation among the variables identified as related to investor sentiment. The common variation of these variables is their measure of investor sentiment. Although not all their input series are available monthly, a number of the constituents of their annual measures as well as variables that should be correlated with the sentiment measure are available monthly. This permits us to form monthly indices based on instrumental variables techniques that exploit their annual sentiment indices.

The procedure we use to produce a monthly index from the annual series is as follows. First we interpolate a smoothed monthly series from the annual series. The interpolated monthly series proxies the true value with error. We then take this monthly proxy and regress it on monthly instruments, including monthly counterparts to annual data used by Baker and Wurgler to form their annual series. The fitted series from this regression yields our instrumented version of the monthly sentiment index.[25] We create monthly instru-

[24] We thank Baker and Wurgler for posting their data on Jeff Wurgler's web site.

[25] The instrumental variables we employ to create our monthly versions of Baker and Wurgler's SF2RAW and SF2 series include the following. First, the US market-wide variables are lagged turnover (calculated as the deviation of the natural logarithm of monthly turnover from its five month average), lagged volume

mented versions of two of Baker and Wurgler's sentiment indices, their raw sentiment index (SF2RAW) and their sentiment index with macroeconomic cycles purged (SF2). Our model is able to achieve an explanatory power (R^2) of 76.5 percent for the SF2RAW index, and 76.4 percent for the SF2 index. Estimating our model on the original annual data produces a very similar model fit.

Figure 4 displays the original annual series from Baker and Wurgler, side-by-side with the monthly fitted values, in order to give the reader a sense for how well our monthly instrumented series compare to the original annual series. In Panels A and C of Figure 4 we present the original SF2 and SF2RAW series, respectively, while in Panels B and D we present our monthly instrumented series. Peaks and troughs are well fitted and monthly variation is apparent, though for both series the peak of the series in the late 1960s as well as the trough in the early 1970s are not quite matched. As well, the peak in the late 1990s is overshot. Overall, however, the time series movements in the two sentiment indices appear well matched by these monthly instrumented values. In Table IV, Panel C, we present summary statistics for these fitted values. Baker and Wurgler produce the indices to have a mean value of 0 and a unit variance. The means of our monthly fitted values are close to 0, and the standard deviations are somewhat less than one, consistent with these being fitted values and thus by construction less volatile than the actual series. These data show little evidence of skewness or kurtosis. Detailed regression results are available on request.

[Figure 4 goes approximately here]

(calculated as the deviation of the natural logarithm of volume from its five month average), lagged dividend yield (constructed by using the CRSP monthly stock file individual firm dividend yields and forming a market value weighted average), lagged price-dividend ratio, number of IPO issues, and lagged first-day IPO return. (The IPO data are the updated version of the Ibbotson, Sindelar, and Ritter, 1994, data, generously made available on Jay Ritter's web site.) We also include as instruments the lagged University of Michigan consumer sentiment index (not seasonally adjusted, series ID UMCSENT), the lagged one-year T-bill yield, the lagged term structure spread (calculated as the difference in yields of the twenty-year Treasury bond and the 30-day T-bill), the lagged default spread (represented by the difference in yields of Aaa and Baa corporate bonds), and the lagged dividend yield spread (calculated as the dividend yield minus the one-year T-bill rate). Finally, to control for autocorrelation, we also include as an instrumental variable the one-month lag of the *predicted* sentiment index. (We do not include a lag of the dependent variable itself, but rather the lagged predicted value, as using the actual value of the lagged dependent variable would reintroduce an errors-in-variables problem.) Of the instrumental variables used, the most significant are the Ritter IPO variables and the turnover variable (with positive coefficients), and the volume and default spread variables (with negative coefficients). For the SF2RAW series the price-dividend ratio, the one-year T-bill rate, and the dividend yield spread were negative and significant, and the Michigan consumer sentiment index was positive and significant. The lag of predicted sentiment was significant for both the SF2 and SF2RAW regressions, with a coefficient of 0.89 for the SF2 regression, and 0.91 for the SF2RAW regression.

The model we estimate to control for investor sentiment is a version of Equation (1) which has the monthly instrumented SF2 index added, denoted $\hat{SF}2_t$. The model is estimated using data spanning January 1952 through to the end of 2004.

$$
\begin{aligned}
r_{i,t} = \mu_i &+ \mu_{i,OR}\hat{OR}_t \\
&+ \mu_{i,SF2}\hat{SF}2_t \\
&+ \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5}\rho_{i,j}r_{i,t-j} + \epsilon_{i,t}.
\end{aligned} \tag{5}
$$

Variables are defined as above. We present results for the sentiment index SF2, appearing in Table VIII. Results, available on request, are very similar if instead we make use of the investor sentiment index SF2RAW.

[Table VIII goes approximately here]

Sentiment does capture opposing movements in equities and Treasuries as expected, and consistent with Baker and Wurgler, we find the sign on sentiment is negative for equities and positive for Treasuries. Of primary concern to us here, the index of investor sentiment does not capture the annual seasonality we identify with the onset/recovery variable; the magnitude and statistical significance of the coefficient estimate on $\hat{OR}_t$ is unaffected by the addition of the investor sentiment index, suggesting investor sentiment captures an effect unrelated to the annual cycle we identify.

X Fama-French Factors

Fama and French (1993) identify common risk factors in the time-series returns to stocks and bonds, finding that there are three equity return factors and two bond return factors. The equity return factors include the excess return on the overall market, SMB (firm size) and HML (book-to-market), and the bond return factors include the term spread (long-term Treasury bond returns minus the 30-day T-bill rate) and the default spread (difference between long-term corporate and government bond returns). Fama and French find that the cross-section of stock returns is well explained with the three equity return factors, and the bond returns are well explained with the term-structure factors. They also find, for the most part, that when all stock and bond factors are included together, bond return factors do not directly influence stock returns and stock return factors tend not to directly influence bond returns. The shared impact of these factors across stock and bond returns – the equity return factor impact on bond returns and the bond return factor impact on stock returns – appears to come in through the excess market return, which is itself influenced by all five factors. As momentum has also been shown to be an influential return factor (see Jegadeesh and Titman, 1993), we include it in our collection of factors. Since bond returns have been shown to be a function of term structure factors as well as the excess market return, itself "a hodgepodge of the common factors in returns" (Fama and French, 1993, p.27), it is interesting to consider if the seasonal we uncover is in fact arising due to seasonalities in these factors.

We estimate a version of Equation (1) that excludes the lags of the dependent variable,[26] uses returns in excess of the 30-day T-bill rate in place of nominal returns, and adds the three Fama-French factors (excess return on the overall market, SMB and HML), the two bond return factors (the term spread measured by the Ibbotson long term bond return minus the 30 day T-bill rate for the corresponding month, and the default spread, measured by the yield difference of BAA and AAA corporate bonds), as well as a momentum factor.[27] As before, we use the equal-weighted CRSP stock return and the 5, 7, 10, and 20-year Treasury return series and estimate this system of equations with GMM and HAC standard errors. To distinguish the roles of the bond and equity factors as well as that of the onset/recovery variable, we follow Fama and French (1993) and orthogonalize the excess market return with respect to these variables, and we use this orthogonalized variable in place of the excess return on the overall market. We call this orthogonalized variable $\hat{R}_{m,t}$. Summary statistics for all of these factors appear in Panel D of Table IV. Data availability limits us to estimate the model using data spanning December 1965 through December 2003.

[26]The inclusion of the excess market return removes most or all autocorrelation from the series so that no lags of the return dependent variable are necessary.

[27]The Fama-French and momentum factors were all retrieved from Ken French's web site. We thank him for making the data available.

$$
\begin{aligned}
r_{i,t} - r_{tb,t} = \mu_i &+ \mu_{i,OR}\hat{OR}_t \\
&+ \mu_{i,R_m}\hat{R}_{m,t} + \mu_{i,HML}HML_t + \mu_{i,SMB}SMB_t + \mu_{i,MOM}MOM_t \\
&+ \mu_{i,FFDefault}FFDefault_t + \mu_{i,FFTerm}FFTerm_t \\
&+ \mu_{i,Jan}D_t^{Jan} + \epsilon_{i,t}. \qquad (6)
\end{aligned}
$$

The variable $r_{tb,t}$ is the 30-day T-bill rate, $\hat{R}_{m,t}$ is the orthogonalized excess return on the market, SMB_t and HML_t are Fama and French's firm size and book-to-market factors, MOM_t is the momentum factor, $FFTerm_t$ is the term spread and $FFDefault_t$ is the default spread. The remaining variables are as previously defined.

[Table IX goes approximately here]

The results we obtain are very similar to those of Fama and French, apart from lower explanatory power of the factors for the Treasuries series. (Unlike the factors Fama and French use, these are not portfolio returns averaged over the term structure but are rather returns to an individual note or bond and are hence noisier and harder to explain.) Like Fama and French we find that the impact of the equity return factors is much stronger in the stock return series. The bond return factors are important in both the equity and the Treasuries series. For our equal-weighted equity index, the coefficient on the orthogonalized excess market return is close to one, and SMB has a stronger impact than HML. For the Treasury return series, the orthogonalized excess market return has a coefficient which is small but positive, the coefficients on SMB and HML are both small, the default spread has a positive and significant coefficient, and the term variable has a large positive and moderately significant coefficient. Momentum has a negative significant coefficient for the equity return series and a positive significant coefficient for the Treasury return series. The return seasonality we have shown to be correlated with the clinical onset of and recovery from SAD, $\hat{OR}_t$, is once again largely unchanged relative to previously reported. It is still both economically and statistically strongly significant, and the pattern in bonds is the reverse of that in stocks. If the opposing seasonality we show in Treasury and equity returns is related to some systematic risk factor, it must be something other than the factors we consider.

XI Seasonality in Risk Aversion

A remaining possible explanation for the opposing seasonal patterns we observe in Treasuries and equities is time-varying risk aversion. KKL claim that the seasonal pattern they find in equity returns is an outcome of SAD-affected investors experiencing higher levels of risk aversion during seasons of the year when daylight is relatively reduced. In this section we evaluate the empirical support for that possibility, considering as well whether the *opposing* seasonals in Treasuries versus equities may be associated with time-varying risk aversion. For the interested reader, we present in Appendix C a simple model in which the opposing seasonal patterns in Treasury and equity returns emerge as a direct consequence of time-varying risk aversion among a subset of investors who are affected by SAD.

If the seasonal cycles in Treasury and equity returns are related to seasonalities in risk aversion, then the importance of our onset/recovery variable should be more pronounced during periods of high market volatility, which are inherently riskier. If the return due to onset/recovery is larger during periods of high conditional market volatility, this suggests rewards for taking on systematic risk are higher during those periods. We test for this possibility by forming a variable that interacts onset/recovery with conditional volatility, measured using the S&P 500 stock index volatility described in Section VII.

We define $\hat{OR}_t \cdot \hat{\sigma}_t^2$ as the onset/recovery variable interacted with the conditional volatility variable. For ease of comparison of its economic impact, we normalize this variable so that it has the same mean value as $\hat{OR}_t$. In Figure 5 we plot the monthly values of $\hat{OR}_t \cdot \hat{\sigma}_t^2$ over the time span of our study, January 1952 through December 2004. Although this variable shows a clear and distinct annual cycle, reaching a peak in September and a trough in March of each year, the amplitude of the cycle varies strongly with the conditional volatility of the stock market, a strongly autocorrelated and easily predicted variable. The largest magnitude value of $\hat{OR}_t \cdot \hat{\sigma}_t^2$ over our entire sample occurs after the crash of 1987, though other crises are readily apparent, such as the oil price shock of the early 1970s, the currency crises of the late 1990s and the market reaction following the events of 9/11.

[Figure 5 goes approximately here]

The model we estimate to control for time-varying risk aversion is a version of Equation (1) which has the interactive $\hat{OR}_t \cdot \hat{\sigma}_t^2$ variable added. The model is estimated using data spanning January 1952 through to the end of 2004.

$$
\begin{aligned}
r_{i,t} = \mu_i &+ \mu_{i,OR}\hat{OR}_t \\
&+ \mu_{i,OR\cdot\sigma^2}\hat{OR}_t \cdot \hat{\sigma}_t^2 \\
&+ \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5} \rho_{i,j} r_{i,t-j} + \epsilon_{i,t}.
\end{aligned} \tag{7}
$$

Variables are as previously defined, with $\hat{\sigma}_t^2$ representing the predicted volatility of the S&P 500 stock index for period t based on information up to and including period $t-1$. As before, we include five lags of the dependent variable to control for autocorrelation. Results appear in Table X.

[Table X goes approximately here]

We find that including the interactive variable $\hat{OR}_t \cdot \hat{\sigma}_t^2$ leads to statistical insignificance and greatly reduced magnitude for $\hat{OR}_t$, with coefficient estimates that are roughly one tenth their original size. The $\hat{OR}_t \cdot \hat{\sigma}_t^2$ coefficient takes on the previously shown magnitude and sign of the original onset/recovery variable – basically the interactive variable replaces the impact of the onset/recovery variable one-for-one, forcing onset/recovery out of the regression. This is clear, unequivocal evidence that the simple seasonal onset/recovery specification is dominated by a specification which allows the seasonal impact of onset/recovery to attenuate and intensify directly with conditional volatility. Although this does not prove that the seasonal effect arises due to time-varying risk aversion, it is compelling evidence to consider time-varying risk aversion as a plausible potential explanation. Certainly the interactive onset/recovery variable is vastly superior to the contenders explored in previous sections in explaining the opposing seasonality observed in Treasury and equity returns. The economic significance of the effect from the interactive onset/recovery variable is very similar to that of onset/recovery alone, as is easily judged by the relative magnitudes of the coefficients on the variables $\hat{OR}_t$ and $\hat{OR}_t \cdot \hat{\sigma}_t{}^2$ in Tables II and X.

XII Robustness Checks

Up to this point we have investigated, one-at-a-time, various possible explanations for the opposing seasonal patterns in Treasury and equity returns. Now we evaluate robustness of the time-varying risk aversion hypothesis to these various alternative explanations. We form a "super" model which incorporates all of the competing explanations for seasonality presented up to this point. We also consider one last addition, the Sell-in-May-and-Go-Away specification of Bouman and Jacobsen (2002). Bouman and Jacobsen (2002) show a November-April seasonality in equities, which they indicate may be a function of the aggregate incidence of vacation time taken over the April-October period, particularly in Europe. This seasonality is associated with large positive returns to equities over the November-April period relative to the other half of the year in indices around the world. To capture the effect, Bouman and Jacobsen use a dummy variable which equals one for the months November through April, and we adopt their specification. Of interest to us is that the period this specification covers maps to the period when the onset/recovery variable is largest in magnitude, although the onset/recovery variable goes from large positive values in October-November to large negative values in February-March. Inclusion of the Bouman and Jacobsen November-April dummy variable helps us explore the possibility that the onset/recovery variable is simply picking up a shift in the mean return for half the year, not a smoothly changing return seasonality.

We estimate Equation (8) using returns in excess of the 30-day T-bill rate in place of nominal returns, as we did in Section X, as doing so is conventional when using asset-pricing factors like the Fama-French and momentum factors. Our results as insensitive to the use of excess versus nominal returns. The "super" model we estimate is built on Equation (1).[28] Data availability limits us to using data spanning January 1970 through December 2003.

[28] The inclusion of the excess market return removes all or most autocorrelation from the series so that no lags of the return dependent variable are necessary.

$$
\begin{aligned}
r_{i,t} - r_{tb,t} = \mu_i &+ \mu_{i,OR\cdot\sigma^2}\hat{OR}_t \cdot \hat{\sigma}_t^2 \\
&+ \mu_{i,U}U_t + \mu_{i,IP}IP_t + \mu_{i,IPSurp}IPSurp_t + \mu_{i,Default}Default_t \\
&+ \mu_{i,Term}Term_{t-1} + \mu_{i,Inf}Inf_t + \mu_{i,InfSurp}InfSurp_t \\
&+ \mu_{i,ProbC}ProbC_t + \mu_{i,USurpC}USurpC_t + \mu_{i,USurpE}USurpE_t \\
&+ \mu_{i,\sigma_t^2}\hat{\sigma}_t^2 + \mu_{i,Turnover}Turnover_{t-1} \\
&+ \mu_{i,Auction}D_t^{Auction} + \mu_{i,Debt-to-GDP}Debt - to - GDP_t \\
&+ \mu_{i,FOMC}D_t^{FOMC} \\
&+ \mu_{i,SF2}\hat{SF}2_t \\
&+ \mu_{i,Sell-in-May}D_t^{Sell-in-May} \\
&+ \mu_{i,R_m}\hat{R}_{m,t} + \mu_{i,HML}HML_t + \mu_{i,SMB}SMB_t + \mu_{i,MOM}MOM_t \\
&+ \mu_{i,FFDefault}FFDefault_t + \mu_{i,FFTerm}FFTerm_t \\
&+ \mu_{i,Jan}D_t^{Jan} + \epsilon_{i,t} \qquad (8)
\end{aligned}
$$

Variables are as previously defined, and results are provided in Table XI.

[Table XI goes approximately here]

A number of results in Table XI are remarkable. The Sell-in-May variable is negative rather than positive as shown by Bouman and Jacobsen (2002). It appears that the onset/recovery seasonality is unlikely to be a simple function of higher mean returns in the November-April period which the Sell-in-May variable is intended to capture. The surprise in the change in unemployment interacted with the probability of an expansion has an opposite effect in equities than when interacted with the probability of a contraction, and the expansion interaction variable has an opposite impact on equities versus Treasuries. This is similar to the results obtained when the macroeconomic factors were used in isolation, though the statistical significance of these variables is greatly reduced, possibly due to multicollinearity. The Stock and Watson (1989) experimental coincident recession index again has a positive impact on Treasuries, but its impact on equities is negligible, and the statistical significance of the variable is all but gone, again possibly due to multicollinearity. The impact of industrial production, both the expected industrial production (which has a strong impact only for Treasuries) and the surprise (no effect for all series), is very similar to the case when the macroeconomic factors were used in isolation. The change in the default spread and the term structure variable in this large model now have no effect on returns. The inflation surprise variable and expected inflation variable are also forced out of the model for equities, but expected inflation remains a large negative influence on bond returns. The direct impact of conditional market-wide volatility and turnover is negligible in this larger model versus the more parsimonious cross-hedging model. The measure of Treasury debt supply, the auction cycle dummy, and the FOMC dummy variable are now insignificant for all return series. Sentiment is strongly significant only for equities, but is now negative for both equity and bond return series. The pattern of results for the bond and equity return factors of Fama and French (1993) and the momentum factor of Jegadeesh and Titman (1993) is largely undisturbed in this much larger model.

The inclusion of two dozen factors and dummy variables, with the attendant risk of severe multicollinearity, produces virtually no change in the onset/recovery variable's estimated coefficient statistical significance. It seems that the seasonality captured by onset/recovery is not likely caused by any of the obvious suspects, including sentiment, seasonality in macroeconomic cycles and macroeconomic risk (measured by a large number of macroeconomic factors plus stock market volatility), cross-hedging (turnover), the January effect, the Treasury auction cycle, Treasury debt supply, the FOMC meeting cycle, the sell-in-May effect, or well-known bond and equity pricing factors such as HML, SMB, momentum, the default spread, and the term structure of Treasury returns.

In additional unreported robustness checks (available on request), we consider daily instead of monthly data, examine additional sub-periods of the data for stability, adjust directly for inflation, use returns in excess of the 30-day T-bill rate instead of nominal returns in a broad set of models, and use Treasury returns data provided by Ibbotson instead of the CRSP data studied above. We find in all cases that the seasonal effect maintains its economic and statistical significance. In all cases the strength of the statistical significance is recognized most clearly with the use of a system of equations estimation technique, either full information maximum likelihood or GMM estimation. Ignoring the covariance of the regression errors understates the significance of the seasonal effect. Small changes in the number of instruments used to identify model parameters and window-width smoothing parameters employed in GMM estimation lead to qualitatively insignificant differences in our results. In general, the more instruments used to identify model parameters, the more significant (the sharper are) the parameter estimates, consistent with the intuition that the more over-identifying information used, the better able we are to estimate parameters of the system.

XIII Conclusions

We find a striking seasonality in US Treasury returns, previously unnoticed, in which returns to holding US Treasuries are statistically and economically significantly varying through the year. Monthly returns are approximately 80 basis points higher in fall than in winter, providing an extra 30 billion dollars in the early fall than in the late winter, based on recent levels of outstanding US Treasuries bonds and notes exceeding 3 trillion dollars. This seasonality, anomalously large by any measure, is roughly opposite to a previously shown seasonality in equity returns, despite the theoretical positive correlation that must exist between equity and Treasury returns and the unconditional positive correlation that is empirically observed for equity versus Treasury returns.

The seasonality in stocks and Treasuries is unaffected when we control for a range of contemporaneous macroeconomic variables which should proxy for macroeconomic cycles and risk factors, including both shocks and predictable movements in the macroeconomy, suggesting that the seasonality we demonstrate is not related in any obvious way to time-varying risk or macroeconomic cyclicality. Cross-hedging between equities and Treasuries can lead to opposing movements in Treasury and equity returns, as discussed by Connolly, Stivers, and Sun (2005). This is particularly true in times of market uncertainty, say with market crashes, many of which have occurred in the fall when our measure of seasonality is also large. Making use of turnover and market volatility measures suggested by Connolly, Stivers, and Sun, we find evidence of cross-hedging effects, but the findings do not account for the seasonality we consider. Investor sentiment is hypothesized by Baker and Wurgler (2005) to lead to exactly the sort of opposing seasonalities in Treasuries and equities that we find. We construct monthly indices of investor sentiment based on the annual indices of Baker and Wurgler (2006) and find that these indices are indeed associated with opposing movements in Treasury and equity returns, but these findings do not explain the seasonal patterns we consider here. The use of excess returns instead of nominal returns together with the Fama-French equity and bond factors and the momentum factor also does not account for the seasonal pattern. Finally, accounting for various regularities previously identified in returns including the January effect and the sell-in-May seasonal, as well as autocorrelation in returns, the Treasury auction schedule, the FOMC announcement cycle, and the supply of Treasury debt cannot explain away the large seasonal cycle we demonstrate. The seasonality in Treasuries versus equities also persists across various sub-periods and is independent of data frequency (daily versus monthly).

Of all of the models we have considered, the only one which can account for the opposing seasonality we observe in Treasury and equity returns is one that allows an interaction with market volatility, permitting a more pronounced effect during periods of high market volatility. In this way, the seasonality in returns is consistent with time-varying risk aversion, and we note that such an opposing seasonal cycle emerges easily from a theoretical model with (even) a subset of investors experiencing seasonally varying risk aversion.

The seasonal patterns we consider can be explained as a direct function of the empirically observed clinical onset of seasonal affective disorder. The findings are consistent with SAD impacting financial markets through the depression that SAD causes among those affected. If depression leads to increased risk aversion, as suggested by the references KKL cite, this could plausibly lead to the opposing cycles we have shown to be evident in safe versus risky securities. Use of the White (2000) reality test demonstrates that the correlation of this return seasonality with the clinical incidence of SAD symptoms is very unlikely to be the result of data snooping.

It should be emphasized that the opposing seasonal patterns we find in equity and Treasury returns are not consistent with seasonal variation in risk itself. If a seasonal influence moves relatively predictably through the year in a pattern that corresponds to the fluctuations in the clinical onset and recovery from SAD, it is unlikely that smooth variations in *risk* through the course of the year are responsible. Certainly the macroeconomic variables and asset-pricing factors we include in our robustness checks control for the most plausible sources of time-varying risk. In spite of accounting for all of these additional effects, we still find remarkably strong, economically and statistically significant evidence of seasonal effects in both equity and Treasury returns.

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Appendix A: Construction of the Expected and Surprise Macro Series

We require measures of the *expected* change in the unemployment rate and the *expected* growth rate in industrial production. We also need estimates of market participants' real-time *surprise* in the change in unemployment and in the growth of industrial production. Constructing these four series is a multi-step process. We focus first on constructing the change in the unemployment rate series and the unemployment surprise series. We then turn to the expected and surprise industrial production growth rate series. Finally, we detail construction of the two inflation rate surprise series that we use.

A. Construction of the Change in the Unemployment Rate

Following Boyd, Hu, and Jagannathan (2005), we consider several measures of the surprise in the change in the unemployment rate, which is constructed using the realized and expected change in the unemployment rate. We will describe two different ways we estimate the *realized* unemployment rate change (one using "real-time vintage" data, which we describe below, and another using currently available, updated data) and two different ways we compute the *expected* unemployment rate change (one using real-time vintage data, and another using currently available, updated data). As the surprise in the unemployment rate change is calculated as the difference between the realized and the expected, we have available to us four distinct measures of the surprise. Below, we describe each of these four measures in detail, but first we provide some additional information about the realized and expected unemployment rate change series.

Our best estimate of the realized unemployment rate available to market participants in the past comes from the Philadelphia Federal Reserve Bank's real-time vintage unemployment rate data. (For extensive information on the real-time vintage data sets we use, see Croushore and Stark, 2001.) These vintages, or snapshots, of the unemployment data contain the original, historic data which were initially announced at quarterly intervals, on the 15th day of the middle month of each quarter. Because the unemployment data were announced quarterly, any given month's unemployment rate announcement occurred 2 to 10 weeks after the month in question.[29] Thus, when we seek to estimate a particular month's *surprise* in the unemployment rate change, we cannot possibly use truly contemporaneous information about the realized rate, since it had not yet been announced at that point in time. Instead we use the nearest available subsequent realization announcement. For example, if we intend to estimate the February surprise, we use the realized February unemployment rate which is announced on May 15. We believe this use of the real-time vintage data is as close as we can come to estimating market participants' real-time information set. As an alternate estimate, we also use the most recent (latest) data revision available to us in 2005.

Likewise, in forming our best estimate of market participants' expected unemployment rate, we have two possibilities. Our best estimate is a real-time prediction of the unemployment rate change based on using real-time vintage data. We use the model selected by Boyd, Hu, and Jagannathan (2005), including three lags of industrial production growth, one lag of the unemployment rate change, the change in the 3-month T-bill rate, and the change in the default yield spread between Baa and Aaa corporate bonds.[30] (Because the model relies on industrial production data, further details on this model are provided below, after the construction of the industrial production series has been described.) In forming a given month's prediction, we only use information available to market participants in the previous month. For example, in forming the February prediction, we use information that was available to market participants in January, as indicated in the real-time vintage series.[31] Only data available to real time market participants was used in constructing this predicted unemployment rate, either as conditioning information to form forecasts or to estimate model parameters. The result is a series of real-time, out-of-sample predicted values, which we use as an estimate of market participants' expected unemployment rate changes.

[29] It is worth highlighting the timing inherent in the real-time vintage series. For instance, when the original second quarter report was made on May 15th of a given year, data for February, March, and April were announced, and updates were made to the previous announcement which was made in February. The February announcement included data for January, plus December and November from the previous year. After the May report, there were no more updates in real time until the 15th of August, when the May, June and July numbers were reported and all previous data were updated.

[30] Boyd, Hu, and Jagannathan's choice of the model specification for the unemployment rate change was based only on data preceding 1962, so that the model was selected on a sample that pre-dates the 1965-2003 period we examine in the paper, even accounting for lags used in our model.

[31] An implication of the quarterly announcement structure of the historic unemployment rate data is that in June of a given year, for instance, construction of a real-time forecast for the July unemployment rate change can use unemployment rate data no more recent than April.

As an alternate estimate of market participants' expected unemployment rate change, we use a predicted value that comes from the Boyd, Hu, and Jagannathan model using, instead of the real-time vintage data, the most recent (latest) data revision available to us in 2005.

Combining these predicted series and realized series, we compute four distinct measures of the surprise in the unemployment rate change. Our first and primary method is to compute the surprise by comparing the real-time predicted rate change (based on the real-time vintage data) to the nearest available subsequent realization announcement (again using the real-time vintage data). This method comes closest to capturing the surprise market participants would have experienced, being based on very nearly the same information they would have had available during the month in question. Our second method is to compare the real-time vintage prediction to the the most recent (latest) revision available to us today in 2005. That is, for each month, we compare our model's real-time, out-of-sample predicted value to *today's* (current) best estimate of what the actual unemployment rate change was during each month in the past. This second method probably overstates the surprise, as it uses revised data to measure our forecast error, introducing data revisions into the surprise which market participants did not have access to in real time. Our third method uses the predicted value based on the most recent, currently available revision of the data available to us in 2005. Then the surprise is estimated by subtracting this prediction of the revised change in unemployment rate from the real-time vintage unemployment rate change. This third method probably understates the surprise, as it uses revised data in-sample to make "predictions" of real-time unrevised data. Finally, for our fourth method, we use in-sample predictions and realizations based on the most recently updated data to measure the surprise of market participants. This approach uses future information and should be able to "predict" real-time stock and Treasury returns differently than any of the previous three measures, all of which use some real-time vintage data in estimating the surprise in the unemployment rate change.[32]

[32] One could argue that all four measures use some degree of information that may not have been fully available to market participants in real time, though we do our best to come as close as possible to replicating the information set they had at their disposal. To the extent that we are unable to completely avoid the use of some "future" information in constructing some of our macroeconomic series, we give advantage to the macroeconomic variables in "predicting" equity and Treasury returns, which we believe prejudices our robustness check against the finding of a separate seasonal effect.

Results presented in the paper are based on the first method for estimating surprises in the change in unemployment. Unreported robustness checks indicate that our findings regarding the separate seasonal effect are invariant to using any of four methods described above for measuring the surprise in the unemployment rate change. The results presented in the text are based on the first method. Detailed results for the other three methods are available on request.

B. Construction of the Growth in Industrial Production Series and its Use in Forecasting Unemployment

We estimate the surprise in the industrial production growth rate as the difference between an out-of-sample, real-time forecast of the growth in industrial production for month t and the realized time t growth in industrial production.

The original monthly industrial production data were announced monthly, unlike the quarterly announced unemployment rate data. This adds a small degree of complexity to constructing forecasts that market participants might have made in real time. For instance, when forming the unemployment rate change surprise described above, we condition on lagged industrial production growth. Hence, in June of a given year, the forecast for the July unemployment rate change can use industrial production data from May (which was known in June in real time) even though the most recently available unemployment rate change data is for April. This implies that we need to forecast the May and June change in unemployment and the June industrial production growth rate to forecast the July unemployment rate change (and hence form the July unemployment rate change surprise). Finally, we also need to forecast industrial production growth in July based on the May industrial production data so that we can form the surprise in the July industrial production growth rate.

We use the Bayesian Information Criterion (BIC) to pick the forecasting model for industrial production growth. The best model by BIC is a simple AR(13) model. We considered models incorporating lags of the change in the 3-month Treasury bill rate, the change in the corporate bond spread, and the unemployment rate change, as well as models with fewer lags of the industrial production growth, but they were less favored based on BIC. The best model removed all evidence of autocorrelation and heteroskedasticity.

Further details on the mechanics underlying estimation of the surprise in the unemployment rate change and in the industrial production growth rate are as follows. To forecast, for instance, the May change in the unemployment rate, we need the April unemployment rate change data, however, April data were not available to market participants in real time. Only information announced in February would have been available, at which time the unemployment rate data for November, December, and January would have been announced. Hence, data for January is the most recent information a market participant would have had access to in forming the May forecast during the month of April. Real-time estimates of the unemployment rate change surprise in May are therefore based on the unemployment rate change forecast made with the February vintage of real-time unemployment rate data and the April vintage of real-time industrial production data. The implication is that the unemployment rate change forecast has to be made four periods ahead. This forecast is made by rolling out the monthly unemployment rate change model, forecasting the February unemployment rate change using the February vintage unemployment rate data (which includes data only as recent as January) using this forecast to form the March forecast of the unemployment rate change (substituting the forecasted February value for the missing actual February unemployment rate change), and so on, until we make the May unemployment rate change forecast. This forecasting procedure uses April vintage industrial production data, which includes data announced only as recently as March, however to make the May unemployment rate change forecast we need the April industrial production growth rate data. Thus we take our forecasting model for industrial production growth and make a forecast for the April industrial production growth rate, and use this forecast in place of the actual April industrial production growth, forecasting the May unemployment rate change. As we also need the May forecast for the industrial production growth rate to form the May surprise in the industrial production growth rate, we roll out our forecasting model for industrial production growth one period, using forecasted industrial production growth for April in place of actual lagged industrial production growth in the industrial production growth forecasting model.

C. Construction of the Inflation Surprise Series

We calculate the inflation rate surprise in two ways. First, we compare the predicted inflation (calculated as described below) with the actual inflation, as measured in *real time.* (As the real-time inflation measure is only available starting in mid-1994, we splice the 1994-to-present "real-time" inflation series with the 1965-to-1994 "most-recent" inflation series to allow estimation of the macroeconomic model using several decades of data.) Second, we compare the predicted inflation with the actual inflation, as measured *most recently,* taking into account data revisions. The first (real-time) measure probably understates the surprise somewhat, as market participants likely had better data available to them than we assume. The second (revised) measure probably overstates the surprise, taking into account revisions that market participants could not likely have anticipated in real time.

The predicted inflation series is constructed using a time-series structural model, including a lag of the real-time unemployment change, a lag of the change in the 90-day Treasury-bill rate and an ARMA(1,1) time series specification. This model was selected as the best using the BIC criterion, choosing among models with up to 13 lags of inflation, two moving average lags, and one lag of each of the real-time unemployment change, change in the yield spread of AAA and BAA corporate bonds, and change in the 90-day Treasury bill rate. The selected model removed all evidence of autocorrelation and heteroskedasticity at the 5% critical level.

Appendix B: Macroeconomic Data Sources

All of our macroeconomic data span December 1965 through December 2003 except for real-time inflation which is only available starting in mid-1994. Sources for the series we use are provided below.

A. Unemployment Rate

We obtain historic unemployment rates (for individuals 16 years of age and older) from the Bureau of Labor Statistics, and we obtain real-time unemployment rates from the Philadelphia Federal Reserve Bank. We use these series to construct the expected change in the unemployment rate and the surprise in the change in the unemployment rate, as described in Appendix A.

B. Industrial Production

We obtain an index of industrial production from the Board of Governors of the Federal Reserve System, and real-time data come from the Philadelphia As we detail in Appendix A, we use these series to construct the expected growth in industrial production and the surprise in the industrial production growth rate.

C. Spreads

The Aaa and Baa bond yield data, used in constructing the Default variable, are obtained from the Board of Governors of the Federal Reserve System. The series we use are Moody's Seasoned Aaa Corporate Bond Yield and Moody's Seasoned Baa Corporate Bond Yield.

The data we use to construct the Term variable are the 20-year Treasury bond and 30-day Treasury bill return series. Both series are from CRSP. We compute the monthly spread as the difference between the 20-year and 30-day values for each month, then we compute the monthly change in the spread by taking the difference from one month to the next.

D. Business Cycle

We obtain the Stock and Watson experimental coincident recession index from the National Bureau of Economic Research (NBER). This series is a real-time indicator, making use of real-time information only, in determining whether the economy is expanding or contracting at a given point in time.

E. Inflation

We obtain two CPI-based inflation rate series from the Philadelphia Federal Reserve Bank. The first is real-time inflation, announced quarterly, available in real-time format only from mid-1994. The second is most recently revised inflation, available starting in 1965. As we explain in Appendix A, we use these series to construct the inflation surprise variable two different ways.

Appendix C: Time-Varying Risk Aversion and Returns

An underlying returns model in which seasonality in equity and Treasury returns are the reverse of one another may be considered in the following way. Suppose there are two groups of investors, those who suffer cycles in their tolerance for risk (denoted "Cyclical") and those who do not (denoted "Non-Cyclical").[33] For simplicity, suppose as well that each group holds a portfolio containing only equities and Treasuries. In the fall, Cyclical agents become more risk averse, and they wish to hold relatively fewer equities and relatively more safe Treasuries than they already hold. Preferences of the Non-Cyclical agents do not change with the season. Since all equities and Treasuries must ultimately be held, the Non-Cyclical agents must be persuaded to hold the equities that the Cyclical agents do not wish to hold, and to perhaps sell some of their Treasuries, the preference for which has not changed among the Non-Cyclical agents. Equity prices then become relatively depressed in the fall as a consequence of the reduced demand for equities by the Cyclical agents. At the same time, increased demand for Treasuries by the Cyclical agents raises Treasury prices initially in the fall, increasing the willingness of the Non-Cyclical agents to part with their Treasuries to the other group. Equilibrium is restored with expected equity returns rising and expected Treasury returns declining. The opposite happens in the spring as the Cyclical agents' preference for risky versus riskless assets returns to 'normal.' These seasonal movements in relative returns exist in a world in which returns on relatively risky assets offer a (time-varying) premium over safer Treasury returns throughout the year.

We can formalize the relation between Treasury returns and stock returns in the fall and winter seasons as follows. Define r as the expected gross return on stocks and r_f as the expected gross return on a riskfree Treasury security. Then the ratio $\frac{r_f}{r}$ expresses the expected Treasury return relative to the expected stock return.[34] Additionally define $\lambda_C(l)$ as the time-varying degree of relative risk aversion of Cyclical agents, where l refers to the

[33]While the following result could be developed in a model with a representative agent affected by a seasonal in their risk aversion, we incorporate heterogeneity (in whether agents experience time-varying risk aversion) to demonstrate that opposing seasonal patterns in risky versus riskfree assets arise even in the case where only a fraction of investors are affected.

[34]Note that we are considering gross returns, so r_f and r are bounded below by zero. We do not consider the degenerate case where returns are -100%.

length of the night, consistent with our measure of the seasonal effect. Let $S_C\left\{\frac{r_f}{r}, \lambda_C(l)\right\}$ be the demand for stocks by Cyclical agents, where $\frac{\partial S_C}{\partial \frac{r_f}{r}} < 0$, $\frac{\partial S_C}{\partial \lambda_C} < 0$, and $\frac{\partial \lambda_C}{\partial l} > 0$. Let $S_{NC}\left\{\frac{r_f}{r}, \lambda_{NC}\right\}$ be the demand for stocks by Non-Cyclical agents, where similarly $\frac{\partial S_{NC}}{\partial \frac{r_f}{r}} < 0$ and $\frac{\partial S_{NC}}{\partial \lambda_{NC}} < 0$, but $\frac{\partial \lambda_{NC}}{\partial l} = 0$ since the length of day does not impact the risk aversion of individuals unaffected by seasonality.

We know that market clearing requires

$$S_C\left\{\frac{r_f}{r}, \lambda_C(l)\right\} + S_{NC}\left\{\frac{r_f}{r}, \lambda_{NC}\right\} - \overline{S} = 0$$

where $\overline{S}$ is the total stock supply. It follows that

$$\frac{\partial S_C}{\partial \frac{r_f}{r}} d\frac{r_f}{r} + \frac{\partial S_C}{\partial \lambda_C}\frac{\partial \lambda_C}{\partial l} dl + \frac{\partial S_{NC}}{\partial \frac{r_f}{r}} d\frac{r_f}{r} + \frac{\partial S_{NC}}{\partial \lambda_{NC}}\frac{\partial \lambda_{NC}}{\partial l} dl = 0,$$

or since $\frac{\partial \lambda_{NC}}{\partial l} = 0$,

$$\frac{d\frac{r_f}{r}}{dl} = -\frac{\frac{\partial S_C}{\partial \lambda_C}\frac{\partial \lambda_C}{\partial l}}{\frac{\partial S_C}{\partial \frac{r_f}{r}} + \frac{\partial S_{NC}}{\partial \frac{r_f}{r}}} < 0.$$

Thus, the impact of moving into the fall is to decrease the expected Treasury return relative to the expected stock return. We believe the economic mechanism through which the change in expected returns is achieved is by an *initial increase* in Treasury prices (relative to what they would have been in the absence of a seasonal change in risk aversion) and an *initial relative decrease* in equity prices.

Table I
Summary Statistics for Stock Index and Treasury Index Percentage Returns

We present summary statistics for monthly equal-weighted stock index returns and monthly US Treasury security index returns, all obtained from CRSP. For each index return series we present the mean percentage return (Mean), standard deviation (Std), minimum (Min), maximum (Max), skewness (Skew), and kurtosis (Kurt). For each series, the data span January 1952 through December 2004, yielding 636 monthly observations.

Monthly Index	Mean	Std	Min	Max	Skew	Kurt
Stock Index	1.206	5.10	-26.80	33.17	-0.031	4.76
20-year Treasury Index	0.544	2.67	-9.36	15.23	0.496	2.80
10-year Treasury Index	0.525	2.16	-6.68	10.00	0.444	1.72
7-year Treasury Index	0.555	1.80	-7.04	10.75	0.598	3.89
5-year Treasury Index	0.538	1.51	-5.80	10.61	0.577	4.74

Table II
Regression Results for the Seasonality Model on Monthly Equity and Treasury Index Returns

We report coefficient estimates from jointly estimating the following expression for each of the monthly stock and Treasury indices in a GMM framework:

$$\begin{aligned} r_{i,t} &= \mu_i + \mu_{i,OR}\hat{OR}_t \\ &+ \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5}\rho_{i,j}r_{i,t-j} + \epsilon_{i,t}. \end{aligned} \quad (1)$$

Variables are defined as follows. $r_{i,t}$ is the month t return for a given index i, D_t^{Jan} equals one for the month of January and equals zero otherwise, and $\hat{OR}_t$ is instrumented onset/recovery from SAD. We include five lags of the dependent variable to control for autocorrelation. The model is estimated on monthly data spanning January 1952 through December 2004.

In Panel A we present parameter estimates, with associated t-statistics below, calculated using Newey and West (1987) HAC standard errors. At the bottom of Panel A, we present the value of R^2 for each index, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test for up to 12 lags of ARCH. In Panel B we present a Wald χ^2 test, with degrees of freedom in square brackets, for whether the $\hat{OR}_t$ coefficient estimate is jointly statistically different from zero across all the series. One, two, and three asterisks denote significance at the 10, 5, and 1 percent level respectively, based on two-sided tests.

Panel A: Parameter Estimates, T-tests, and Diagnostics

Parameter or Statistic	Stock Index	20-year Treasury Index	10-year Treasury Index	7-year Treasury Index	5-year Treasury Index
μ_{OR}	-2.261***	1.278***	1.058***	0.951***	0.771***
	(-4.28)	(4.78)	(4.95)	(5.52)	(5.55)
μ	0.746***	0.522***	0.454***	0.494***	0.458***
	(6.58)	(8.62)	(9.20)	(11.77)	(12.67)
μ_{Jan}	4.035***	0.025	0.187	-0.039	0.094
	(8.55)	(0.13)	(1.18)	(-0.33)	(0.97)
ρ_1	0.168***	0.056***	0.075***	0.089***	0.126***
	(7.55)	(4.04)	(5.55)	(6.20)	(9.61)
ρ_2	-0.087***	-0.034***	-0.023*	-0.048***	-0.061***
	(-3.89)	(-2.60)	(-1.77)	(-3.85)	(-4.67)
ρ_3	0.012	-0.076***	-0.020	-0.008	0.009
	(0.63)	(-5.13)	(-1.54)	(-0.63)	(0.63)
ρ_4	0.007	0.076***	0.066***	0.032***	-0.011
	(0.39)	(6.01)	(5.42)	(2.86)	(-0.89)
ρ_5	0.024	0.016	-0.024**	0.024**	0.044***
	(1.16)	(1.24)	(-2.33)	(2.38)	(4.20)
R^2	0.0978	0.0273	0.0216	0.0259	0.0328
AR(12)	12.35	12.03	12.08	8.83	9.75
ARCH(12)	21.8 **	67 ***	84.94 ***	75.9 ***	79.05 ***

Panel B: Joint Test Across Indices

Test	χ^2 [degrees of freedom]
$\mu_{i,\hat{OR}}$ jointly equal to 0 across series	55.7 *** [5]

Table III
Correlations Between Monthly Treasury Indices and Monthly Stock Index

For various sample periods, we present correlation coefficients based on the covariance between the monthly CRSP equal-weighted stock index returns and the various monthly US Treasury security index returns. (Each cell contains a coefficient representing the correlation between stock index returns and the Treasury index returns indicated at the top of the column.) N denotes the number of observations in each sample or sub-sample. The full sample includes data spanning January 1952 through December 2004. Each decade sub-period includes 10 years of monthly data, e.g. January 1960 through December 1969. The only exceptions are the 1950s sub-period, which includes the months January 1952 through December 1959, and the 1990s sub-period, which includes January 1990 through December 2004. One, two, and three asterisks denote significance at the 10, 5, and 1 percent level respectively, based on two-sided tests.

	20-year Treasury Index	10-year Treasury Index	7-year Treasury Index	5-year Treasury Index
Full Sample $N = 630$	0.13***	0.12***	0.09**	0.08**
1950s $N = 96$	-0.20**	-0.14	-0.16	-0.26**
1960s $N = 120$	0.06	0.10	0.07	0.09
1970s $N = 120$	0.29***	0.30***	0.21**	0.18*
1980s $N = 120$	0.20**	0.15	0.15*	0.17*
1990s $N = 174$	0.03	-0.01	-0.05	-0.08

Table IV
Summary Statistics for Macroeconomic Factors, Stock Market Uncertainty Variables, Sentiment Variables, Asset Pricing Factors, and Treasury Debt Supply

We present summary statistics for each of a variety of regressors we consider, defined in the text and appendices. Below each variable name is the abbreviation used in the regression models. Details on the construction of the variables and data sources are provided in the appendices. Each observation in all of the series has been multiplied by 100, except for the probability of contraction series, the sentiment indices, and the asset pricing factors. For each series we present the mean (Mean), standard deviation (Std), minimum (Min), maximum (Max), skewness (Skew), and kurtosis (Kurt). The data in Panel A are the macroeconomic factors, and they span December 1965 through December 2003, yielding 457 monthly observations. The data in Panel B are the non-return factors related to stock market uncertainty, and they span December 1952 through December 2004, yielding 636 monthly observations. The data in Panel C are the monthly instrumented versions of Baker and Wurgler's (2006) sentiment indices. They span December 1963 through December 2004, yielding 503 monthly observations. The data in Panel D are common asset pricing factors. They span December 1965 through December 2003, providing 456 monthly observations. The data in Panel E is the debt to GDP variable, measuring Treasury debt supply.

Table IV
Panel A: Macroeconomic Factors

Variable (Abbreviation)	Mean	Std	Min	Max	Skew	Kurt
Expected Change in Unemployment (U)	1.210	10.28	-46.81	57.26	1.175	6.28
Expected Growth in Industrial Production (IP)	0.255	0.33	-2.12	1.41	-1.679	11.33
Industrial Production Surprise (IPSurp)	-0.107	0.72	-3.53	2.14	-0.816	3.06
Change in Baa - Aaa Corporate Bond Spread (Default)	-0.138	11.20	-66.00	55.00	-0.647	7.09
20 year - 30 day Treasury Spread (Term)	0.170	3.00	-9.43	13.95	0.292	1.56
Predicted Inflation (Inf)	0.386	0.23	-0.06	1.34	1.295	1.63
Inflation Surprise (InfSurp)	0.001	0.21	-0.78	1.20	0.454	3.09
Probability of Contraction (ProbC)	0.158	0.28	0.01	0.99	2.016	2.70
Unemployment Surprise during Contraction (USurpC)	0.013	0.08	-0.45	0.69	3.101	22.18
Unemployment Surprise during Expansion (USurpE)	-0.020	0.17	-0.64	0.60	-0.180	1.26

Table IV - Continued

Panel B: Factors Related to Stock Market Uncertainty

Variable (Abbreviation)	Mean	Std	Min	Max	Skew	Kurt
Turnover (Turnover)	0.016	0.10	-0.40	0.69	1.155	5.67
Volatility ($\hat{\sigma}^2$)	0.184	0.17	0.06	3.16	9.519	152.57

Panel C: Sentiment Indices

Variable (Abbreviation)	Mean	Std	Min	Max	Skew	Kurt
SF2RAW (SF2RAW)	0.015	0.84	-1.57	2.65	0.256	-0.35
SF2 (SF2)	0.008	0.81	-1.69	3.01	0.632	0.61

Panel D: Asset Pricing Factors

Variable (Abbreviation)	Mean	Std	Min	Max	Skew	Kurt
Size (SMB)	0.251	3.36	-16.58	21.87	0.525	5.17
Book-to-Market (HML)	0.415	3.05	-12.66	13.71	0.039	2.22
Momentum (MOM)	0.861	4.20	-25.00	18.38	-0.641	5.01
Default Spread (FFDefault)	1.056	0.43	0.32	2.69	1.259	1.51
Term Spread (FFTerm)	0.002	0.03	-0.10	0.14	0.312	1.82
Orthogonalized Excess Market Return ($\hat{R}_m$)	-0.002	4.02	-19.93	14.19	-0.304	1.76

Panel E: Treasury Debt Supply

Variable (Abbreviation)	Mean	Std	Min	Max	Skew	Kurt
Debt-to-GDP Ratio ($Debt-to-GDP$)	0.473	0.13	0.31	0.67	0.233	-1.60

Table V
Robustness Check Controlling for Macroeconomic Factors: Regression Results for Monthly Equity and Treasury Index Returns

We report coefficient estimates from jointly estimating the following expression for each of the monthly stock and Treasury indices in a GMM framework:

$$
\begin{aligned}
r_{i,t} = {} & \mu_i + \mu_{i,OR}\hat{OR}_t \\
& + \mu_{i,U}U_t + \mu_{i,IP}IP_t + \mu_{i,IPSurp}IPSurp_t + \mu_{i,Default}Default_t \\
& + \mu_{i,Term}Term_{t-1} + \mu_{i,Inf}Inf_t + \mu_{i,InfSurp}InfSurp_t \\
& + \mu_{i,ProbC}ProbC_t + \mu_{i,USurpC}USurpC_t + \mu_{i,USurpE}USurpE_t \\
& + \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5}\rho_{i,j}r_{i,t-j} + \epsilon_{i,t}
\end{aligned} \tag{2}
$$

Stock and Treasury index returns ($r_{i,t}$) are regressed on a constant, the instrumented onset/recovery variable ($\hat{OR}_t$), a dummy for the month of January (D_t^{Jan}), and five lags of returns. Additional regressors include the following macroeconomic variables. U_t is the expected change in the unemployment rate, IP_t is the expected growth in industrial production, $IPSurp_t$ is the surprise in industrial production growth, $Default_t$ is the change in the spread between Baa and Aaa corporate bond rates from month $t-1$ to month t, $Term_t$ is the difference between the one-month return on 20-year Treasuries and the one-month return on 30-day Treasuries at month t, Inf_t is the expected inflation rate, $InfSurp_t$ is the surprise in the inflation rate, $ProbC_t$ is the Stock and Watson (1989) experimental coincident recession index (reflecting the probability of an economic contraction), $USurpC_t$ is surprise in the change in unemployment interacted with the probability of a contraction, and $USurpE_t$ is surprise in the change in unemployment interacted with the probability of an expansion (which equals 1 minus the probability of a contraction). The construction of the macro variables and the sources of the data are outlined in the appendices. The model is estimated using data spanning December 1965 through December 2003, the longest span of data available to us using this set of variables.

In Panel A we present parameter estimates, with associated t-statistics below, calculated using Newey and West (1987) HAC standard errors. At the bottom of Panel A, we present the value of R^2 for each index, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test for up to 12 lags of ARCH. In Panel B we present a Wald χ^2 test, with degrees of freedom in square brackets, for whether the $\hat{OR}_t$ coefficient estimate is jointly statistically different from zero across all the series. One, two, and three asterisks denote significance at the 10, 5, and 1 percent level respectively, based on two-sided tests.

Table V - Continued

Panel A: Parameter Estimates, T-tests, and Diagnostics

Parameter or Statistic	Stock Index	20-year Treasury Index	10-year Treasury Index	7-year Treasury Index	5-year Treasury Index
μ_{OR}	-2.306***	1.558***	1.405***	1.328***	1.137***
	(-4.16)	(5.24)	(6.00)	(6.89)	(7.15)
μ_{USurpC}	12.609***	-0.770	-0.142	-0.019	0.685**
	(7.63)	(-1.54)	(-0.34)	(-0.06)	(2.56)
μ_{USurpE}	-1.025	2.137***	1.741***	1.546***	1.230***
	(-1.44)	(4.15)	(4.66)	(5.25)	(5.23)
μ_{ProbC}	-1.682***	0.937***	0.969***	0.790***	0.770***
	(-2.70)	(2.70)	(3.30)	(3.37)	(3.98)
μ_{IPSurp}	0.280	-0.130	-0.034	-0.098	0.013
	(1.17)	(-1.02)	(-0.34)	(-1.25)	(0.22)
μ_{IP}	-0.055	1.749***	1.468***	1.154***	1.378***
	(-0.13)	(7.26)	(7.30)	(7.05)	(10.47)
μ_U	0.135***	0.081***	0.076***	0.064***	0.074***
	(9.13)	(11.18)	(11.73)	(11.94)	(15.73)
$\mu_{Default}$	0.045***	-0.021***	-0.012**	-0.015***	-0.004
	(4.28)	(-3.27)	(-2.24)	(-3.16)	(-1.07)
μ_{Term}	-0.055	-1.236***	0.051**	0.055***	0.066***
	(-1.53)	(-9.54)	(2.29)	(3.13)	(4.77)
$\mu_{InfSurp}$	-3.444***	-1.690***	-0.652**	-0.532**	-0.218
	(-5.79)	(-4.48)	(-2.44)	(-2.34)	(-1.19)
μ_{Inf}	-1.220**	-2.692***	-0.916***	-0.844***	-0.709***
	(-2.48)	(-8.25)	(-3.73)	(-4.08)	(-4.14)
μ_{Jan}	4.594***	0.109	0.091	-0.063	0.077
	(9.51)	(0.49)	(0.57)	(-0.46)	(0.71)
μ	1.129***	0.563***	0.502***	0.689***	0.555***
	(4.41)	(3.02)	(3.49)	(5.69)	(5.66)
ρ_1	0.210***	1.183***	-0.096***	-0.130***	-0.161***
	(11.06)	(9.22)	(-5.62)	(-9.29)	(-10.92)
ρ_2	-0.102***	-0.059***	-0.040***	-0.064***	-0.063***
	(-5.11)	(-4.38)	(-3.18)	(-5.35)	(-5.27)
ρ_3	-0.019	-0.063***	0.012	0.000	0.024*
	(-1.08)	(-4.12)	(0.94)	(0.04)	(1.91)
ρ_4	-0.010	0.037***	0.036***	-0.005	-0.050***
	(-0.52)	(3.49)	(3.25)	(-0.52)	(-5.23)
ρ_5	0.054***	-0.027**	-0.051***	-0.016*	-0.016*
	(2.64)	(-2.20)	(-5.31)	(-1.69)	(-1.72)
R^2	0.1946	0.1695	0.1585	0.1849	0.2225
AR(12)	4.93	15.91	13.51	11.71	12.98
ARCH(12)	6.36	28.22***	26.49***	49.43***	39.33***

Panel B: Joint Test Across Indices

Test	χ^2 [degrees of freedom]
$\mu_{i,\hat{OR}}$ jointly equal to 0 across series	86.8*** [5]

Table VI
Robustness Check Controlling for Stock Market Uncertainty: Regression Results for Monthly Equity and Treasury Index Returns

We report coefficient estimates from jointly estimating the following expression for each of the monthly stock and Treasury indices in a GMM framework:

$$\begin{aligned} r_{i,t} = \mu_i &+ \mu_{i,OR}\hat{OR}_t \\ &+ \mu_{i,\sigma^2}\hat{\sigma}_t^2 + \mu_{i,Turnover}Turnover_{t-1} \\ &+ \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5}\rho_{i,j}r_{i,t-j} + \epsilon_{i,t} \end{aligned} \tag{3}$$

Stock and Treasury index returns ($r_{i,t}$) are regressed on a constant, the instrumented onset/recovery variable ($\hat{OR}_t$), the predicted volatility of the S&P 500 stock index for period t ($\hat{\sigma}_t^2$), the lag of turnover ($Turnover_t$), a dummy for the month of January (D_t^{Jan}), and five lags of returns. The model is estimated using data spanning January 1952 through December 2004.

In Panel A we present parameter estimates, with associated t-statistics below, calculated using Newey and West (1987) HAC standard errors. At the bottom of Panel A, we present the value of R^2 for each index, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test for up to 12 lags of ARCH. In Panel B we present a Wald χ^2 test, with degrees of freedom in square brackets, for whether the $\hat{OR}_t$ coefficient estimate is jointly statistically different from zero across all the series. One, two, and three asterisks denote significance at the 10, 5, and 1 percent level respectively, based on two-sided tests.

Panel A: Parameter Estimates, T-tests, and Diagnostics

Parameter or Statistic	Stock Index	20-year Treasury Index	10-year Treasury Index	7-year Treasury Index	5-year Treasury Index
μ_{OR}	-2.188***	1.083***	0.877***	0.779***	0.623***
	(-4.13)	(3.97)	(4.03)	(4.45)	(4.45)
μ_{σ^2}	0.954	0.996***	0.642**	0.790***	0.639***
	(1.47)	(2.63)	(2.28)	(3.37)	(3.10)
$\mu_{Turnover}$	1.511	-2.125***	-2.211***	-1.941***	-1.664***
	(1.43)	(-3.09)	(-4.31)	(-4.68)	(-5.16)
μ_{Jan}	4.097***	0.030	0.173	-0.040	0.089
	(8.71)	(0.15)	(1.11)	(-0.35)	(0.93)
μ	0.550***	0.361***	0.355***	0.368***	0.357***
	(3.09)	(3.78)	(4.79)	(6.01)	(6.86)
ρ_1	0.166***	0.048***	0.069***	0.080***	0.117***
	(7.02)	(3.38)	(5.06)	(5.57)	(8.64)
ρ_2	-0.088***	-0.027**	-0.010	-0.035***	-0.048***
	(-3.96)	(-2.02)	(-0.76)	(-2.75)	(-3.65)
ρ_3	0.013	-0.074***	-0.017	-0.008	0.008
	(0.68)	(-5.00)	(-1.35)	(-0.62)	(0.60)
ρ_4	0.008	0.074***	0.069***	0.035***	-0.006
	(0.42)	(5.67)	(5.55)	(3.06)	(-0.48)
ρ_5	0.025	0.020	-0.015	0.031***	0.051***
	(1.24)	(1.55)	(-1.41)	(3.02)	(4.81)
R^2	0.1011	0.0345	0.0308	0.0386	0.0456
AR(12)	10.11	13.12	11.91	8.67	10.84
ARCH(12)	21.66**	68.01***	87.88***	77.4***	78.17***

Panel B: Joint Test Across Indices

Test	χ^2 [degrees of freedom]
$\mu_{i,\hat{OR}}$ jointly equal to 0 across series	42.3*** [5]

Table VII
The Seasonal Effect Controlling For Quarterly Treasury Auctions: Regression Results for Monthly Equity and Treasury Index Returns

We report coefficient estimates from jointly estimating the following expression for each of the monthly stock and Treasury indices in a GMM framework:

$$
\begin{aligned}
r_{i,t} &= \mu_i + \mu_{i,OR}\hat{OR}_t \\
&\quad + \mu_{i,Auction}D_t^{Auction} + \mu_{i,Debt-to-GDP}Debt-to-GDP_t + \mu_{i,FOMC}D_t^{FOMC} \\
&\quad + \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5}\rho_{i,j}r_{i,t-j} + \epsilon_{i,t}.
\end{aligned} \tag{4}
$$

Stock and Treasury index returns ($r_{i,t}$) are regressed on a constant, the instrumented onset/recovery variable ($\hat{OR}_t$), a dummy for the months of February, May, August, and November ($D_t^{Auction}$), the debt-to-GDP ratio ($Debt-to-GDP_t$), a dummy for the months during which the FOMC meetings occur, (D_t^{FOMC}), five lags of returns, and a dummy for the month of January (D_t^{Jan}). The model is estimated on monthly data spanning January 1980 through December 2004.

In Panel A we present parameter estimates, with associated t-statistics below, calculated using Newey and West (1987) HAC standard errors. At the bottom of Panel A, we present the value of R^2 for each index, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test for up to 12 lags of ARCH. In Panel B we present a Wald χ^2 test, with degrees of freedom in square brackets, for whether the $\hat{OR}_t$ coefficient estimate is jointly statistically different from zero across all the series. One, two, and three asterisks denote significance at the 10, 5, and 1 percent level respectively, based on two-sided tests.

Panel A: Parameter Estimates, T-tests, and Diagnostics

Parameter or Statistic	Stock Index	20-year Treasury Index	10-year Treasury Index	7-year Treasury Index	5-year Treasury Index
μ_{OR}	-2.785***	2.434***	2.174***	1.881***	1.534***
	(-7.12)	(10.23)	(11.59)	(12.24)	(12.15)
$\mu_{Auction}$	0.356**	-0.039	-0.242**	-0.153*	-0.226***
	(1.96)	(-0.27)	(-2.19)	(-1.77)	(-3.34)
$\mu_{Debt-to-GDP}$	0.441	-1.863***	-2.081***	-2.090***	-2.187***
	(0.68)	(-4.67)	(-6.43)	(-7.41)	(-8.90)
μ_{FOMC}	1.523***	0.122	0.187*	0.092	0.012
	(8.47)	(0.96)	(1.83)	(1.14)	(0.18)
μ_{Jan}	3.488***	0.104	-0.080	0.061	0.050
	(11.24)	(0.64)	(-0.58)	(0.51)	(0.52)
μ	-0.579	1.923***	1.919***	1.960***	2.032***
	(-1.64)	(8.15)	(10.10)	(11.76)	(13.78)
μ_{ρ_1}	0.225***	0.037***	0.031***	0.039***	0.099***
	(15.48)	(3.63)	(3.21)	(4.05)	(10.18)
μ_{ρ_2}	-0.094***	-0.071***	-0.033***	-0.065***	-0.124***
	(-6.84)	(-5.94)	(-2.87)	(-5.60)	(-10.22)
μ_{ρ_3}	-0.038**	-0.048***	0.002	0.013	0.044***
	(-2.27)	(-4.56)	(0.16)	(1.32)	(4.19)
μ_{ρ_4}	-0.064***	0.052***	0.023***	-0.018**	-0.086***
	(-4.13)	(5.98)	(2.85)	(-2.56)	(-10.30)
μ_{ρ_5}	0.048***	0.027***	0.005	0.045***	0.085***
	(2.71)	(2.84)	(0.58)	(5.79)	(9.65)
	(2.61)	(2.99)	(0.66)	(6.18)	(10.09)
R^2	0.146	0.0475	0.054	0.0644	0.1045
AR(12)	10.09	9.88	6.58	8.12	5.85
ARCH(12)	1.73	36.58 ***	33.56 ***	29.56 ***	33.2 ***

Panel B: Joint Test Across Indices

Test	χ^2 [degrees of freedom]
$\mu_{i,\hat{OR}}$ jointly equal to 0 across series	262.6^{***} [5]

Table VIII
The Seasonal Effect Controlling For Investor Sentiment: Regression Results for Monthly Equity and Treasury Index Returns

We report coefficient estimates from jointly estimating the following expression for each of the monthly stock and Treasury indices in a GMM framework:

$$\begin{aligned} r_{i,t} &= \mu_i + \mu_{i,OR}\hat{OR}_t \\ &+ \mu_{i,SF2}\hat{SF2}_t \\ &+ \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5}\rho_{i,j}r_{i,t-j} + \epsilon_{i,t}. \end{aligned} \tag{5}$$

Stock and Treasury index returns ($r_{i,t}$) are regressed on a constant, the instrumented onset/recovery variable ($\hat{OR}_t$), the investor sentiment index ($\hat{SF2}_t$), a dummy for the month of January (D_t^{Jan}), and five lags of returns. The model is estimated on monthly data spanning January 1963 through December 2004, the longest span of data available to us using this set of variables.

In Panel A we present parameter estimates, with associated t-statistics below, calculated using Newey and West (1987) HAC standard errors. At the bottom of Panel A, we present the value of R^2 for each index, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test for up to 12 lags of ARCH. In Panel B we present a Wald χ^2 test, with degrees of freedom in square brackets, for whether the $\hat{OR}_t$ coefficient estimate is jointly statistically different from zero across all the series. One, two, and three asterisks denote significance at the 10, 5, and 1 percent level respectively, based on two-sided tests.

Panel A: Parameter Estimates, T-tests, and Diagnostics

Parameter or Statistic	Stock Index	20-year Treasury Index	10-year Treasury Index	7-year Treasury Index	5-year Treasury Index
μ_{OR}	-2.094***	1.570***	1.222***	1.140***	0.935***
	(-3.70)	(5.34)	(5.35)	(6.10)	(6.14)
μ_{SF2}	-0.300***	0.067	0.038	0.091**	0.104***
	(-2.86)	(0.99)	(0.69)	(1.99)	(2.65)
μ_{Jan}	4.675***	0.148	0.128	-0.042	0.118
	(9.47)	(0.73)	(0.87)	(-0.34)	(1.23)
μ	0.670***	0.612***	0.572***	0.616***	0.568***
	(5.86)	(9.13)	(10.62)	(12.98)	(13.94)
ρ_1	0.181***	0.048***	0.074***	0.073***	0.111***
	(9.02)	(3.82)	(6.02)	(5.98)	(9.19)
ρ_2	-0.086***	-0.041***	-0.036***	-0.061***	-0.078***
	(-4.20)	(-3.49)	(-3.04)	(-5.29)	(-6.43)
ρ_3	0.005	-0.090***	-0.032***	-0.034***	-0.008
	(0.28)	(-6.56)	(-2.71)	(-3.00)	(-0.65)
ρ_4	-0.009	0.068***	0.042***	0.014	-0.030***
	(-0.51)	(5.84)	(4.05)	(1.37)	(-2.72)
ρ_5	0.032*	0.012	-0.026***	0.024**	0.032***
	(1.71)	(0.99)	(-2.66)	(2.43)	(3.32)
R^2	0.1122	0.0289	0.0221	0.0288	0.0364
AR(12)	10.99	12.76	9.74	7.16	6.44
ARCH(12)	14.56	51.52***	69.86***	65.15***	69.18***

Panel B: Joint Test Across Indices

Test	χ^2 [degrees of freedom]
$\mu_{i,\hat{OR}}$ jointly equal to 0 across series	64.7*** [5]

Table IX
Controlling For Asset Pricing Factors: Regression Results for Monthly Equity and Treasury Index Returns

We report coefficient estimates from jointly estimating the following expression for each of the monthly stock and Treasury indices in a GMM framework:

$$\begin{aligned} r_{i,t} - r_{tb,t} = {} & \mu_i + \mu_{i,OR}\hat{OR}_t \\ & + \mu_{i,R_m}\hat{R}_{m,t} + \mu_{i,HML}HML_t + \mu_{i,SMB}SMB_t + \mu_{i,MOM}MOM_t \\ & + \mu_{i,FFDefault}FFDefault_t + \mu_{i,FFTerm}FFTerm_t \\ & + \mu_{i,Jan}D_t^{Jan} + \epsilon_{i,t}. \end{aligned} \tag{6}$$

Stock and Treasury index excess returns ($r_{i,t} - r_{tb,t}$) are regressed on a constant, the instrumented onset/recovery variable ($\hat{OR}_t$), the orthogonalized market return ($\hat{R}_{m,t}$), firm size and book-to-market factors (SMB_t and HML_t), the momentum factor (MOM_t), the long-term Treasury bond return minus the 30-day T-bill rate ($FFTerm_t$), the difference between long-term corporate and government bond returns ($FFDefault_t$), a dummy for the month of January (D_t^{Jan}), and five lags of returns. The model is estimated on monthly data spanning January 1952 through December 2004.

In Panel A we present parameter estimates, with associated t-statistics below, calculated using Newey and West (1987) HAC standard errors. At the bottom of Panel A, we present the value of R^2 for each index, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test for up to 12 lags of ARCH. In Panel B we present a Wald χ^2 test, with degrees of freedom in square brackets, for whether the $\hat{OR}_t$ coefficient estimate is jointly statistically different from zero across all the series. One, two, and three asterisks denote significance at the 10, 5, and 1 percent level respectively, based on two-sided tests.

Panel A: Parameter Estimates, T-tests, and Diagnostics

Parameter or Statistic	Stock Index	20-year Treasury Index	10-year Treasury Index	7-year Treasury Index	5-year Treasury Index
μ_{OR}	-1.865***	0.932**	1.035***	0.886***	0.732***
	(-8.82)	(2.19)	(3.00)	(3.13)	(3.13)
μ_{SMB}	0.865***	-0.071*	-0.057**	-0.070***	-0.051***
	(18.83)	(-1.80)	(-1.97)	(-3.23)	(-2.68)
μ_{HML}	-0.119***	0.003	0.013	-0.005	0.008
	(-3.44)	(0.09)	(0.42)	(-0.18)	(0.37)
μ_{MOM}	-0.218***	0.068*	0.067**	0.060**	0.045**
	(-8.30)	(1.95)	(2.37)	(2.41)	(2.15)
$\mu_{FFDefault}$	0.505***	0.609**	0.528**	0.460**	0.364**
	(4.94)	(2.13)	(2.16)	(2.17)	(2.05)
μ_{FFTerm}	17.281***	8.271*	7.766**	5.573*	6.051**
	(13.26)	(1.95)	(2.51)	(1.94)	(2.40)
μ_{R_m}	1.023***	0.159***	0.128***	0.096***	0.066***
	(56.66)	(4.12)	(4.13)	(4.10)	(3.31)
μ_{Jan}	1.227***	0.292	0.502*	0.233	0.266
	(7.39)	(0.77)	(1.78)	(1.04)	(1.46)
μ	0.240**	-0.522**	-0.494**	-0.352**	-0.276*
	(2.33)	(-2.14)	(-2.38)	(-1.96)	(-1.85)
R^2	0.9609	0.0842	0.0813	0.0875	0.0817
AR(12)	24.04**	17.25	12.63	10.39	12.51
ARCH(12)	71.26***	94.33***	86.61***	109.27***	124.53***

Panel B: Joint Test Across Indices

Test	χ^2 [degrees of freedom]
$\mu_{i,OR}$ jointly equal to zero across series	93*** [5]

Table X
The Seasonal Effect During Risky Periods: Regression Results for Monthly Equity and Treasury Index Returns

We report coefficient estimates from jointly estimating the following expression for each of the monthly stock and Treasury indices in a GMM framework:

$$\begin{aligned} r_{i,t} &= \mu_i + \mu_{i,OR}\hat{OR}_t \\ &\quad + \mu_{i,OR\cdot\sigma^2}\hat{OR}_t \cdot \hat{\sigma}_t^2 \\ &\quad + \mu_{i,Jan}D_t^{Jan} + \sum_{j=1}^{5}\rho_{i,j}r_{i,t-j} + \epsilon_{i,t}. \end{aligned} \tag{7}$$

Stock and Treasury index returns ($r_{i,t}$) are regressed on a constant, the instrumented onset/recovery variable ($\hat{OR}_t$), the volatility-interacted seasonality measure, a dummy for the month of January (D_t^{Jan}), and five lags of returns. The volatility-interacted seasonality measure is constructed by multiplying $\hat{OR}_t$ with the predicted volatility of the S&P 500 stock index for period t ($\hat{\sigma}_t$) which is based on information up to and including period $t-1$. The model is estimated on monthly data spanning January 1952 through December 2004.

In Panel A we present parameter estimates, with associated t-statistics below, calculated using Newey and West (1987) HAC standard errors. At the bottom of Panel A, we present the value of R^2 for each index, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test for up to 12 lags of ARCH. In Panel B we present Wald χ^2 tests, with degrees of freedom in square brackets, for whether the $\hat{OR}_t$ coefficient estimate is jointly statistically different from zero across all the series, and for whether the $\hat{OR}_t \cdot \sigma^2$ coefficient estimate is jointly statistically different from zero across all the series. One, two, and three asterisks denote significance at the 10, 5, and 1 percent level respectively, based on two-sided tests.

Panel A: Parameter Estimates, T-tests, and Diagnostics

Parameter or Statistic	Stock Index	20-year Treasury Index	10-year Treasury Index	7-year Treasury Index	5-year Treasury Index
$\mu_{OR\cdot\sigma^2}$	-2.308***	1.593***	1.367***	1.101***	0.852***
	(-3.58)	(4.11)	(4.41)	(4.86)	(4.48)
μ_{OR}	-0.206	-0.196	-0.205	-0.070	-0.019
	(-0.27)	(-0.41)	(-0.56)	(-0.25)	(-0.08)
μ	0.766***	0.509***	0.447***	0.488***	0.455***
	(6.69)	(8.54)	(9.19)	(11.82)	(12.72)
μ_{Jan}	4.066***	0.032	0.197	-0.029	0.103
	(8.64)	(0.16)	(1.25)	(-0.25)	(1.06)
ρ_1	0.155***	0.048***	0.066***	0.082***	0.119***
	(6.91)	(3.46)	(4.91)	(5.79)	(8.94)
ρ_2	-0.089***	-0.031**	-0.022*	-0.048***	-0.061***
	(-4.02)	(-2.40)	(-1.71)	(-3.80)	(-4.57)
ρ_3	0.008	-0.074***	-0.018	-0.008	0.008
	(0.40)	(-4.98)	(-1.38)	(-0.61)	(0.62)
ρ_4	0.011	0.079***	0.068***	0.033***	-0.010
	(0.59)	(6.10)	(5.50)	(2.87)	(-0.79)
ρ_5	0.028	0.021*	-0.019*	0.029***	0.048***
	(1.34)	(1.65)	(-1.79)	(2.84)	(4.56)
R^2	0.1006	0.0348	0.0295	0.0338	0.0395
AR(12)	11.41	10.63	9.07	8.34	10
ARCH(12)	20.92*	66.1***	86.13***	74.89***	78.45***

Panel B: Joint Test Across Indices

Test	χ^2 [degrees of freedom]
$\mu_{i,OR}$ jointly equal to zero across series	2 [5]
$\mu_{i,OR\cdot\sigma^2}$ jointly equal to zero across series	40.4*** [5]

Table XI
The Seasonal Effect Controlling For All Other Variables: Regression Results for Monthly Equity and Treasury Index Returns

We report coefficient estimates from jointly estimating the following expression for each of the monthly stock and Treasury indices in a GMM framework:

$$
\begin{aligned}
r_{i,t} - r_{tb,t} = \mu_i &+ \mu_{i,OR\cdot\sigma^2}\hat{OR}_t \cdot \hat{\sigma}_t^2 + \mu_{i,Sell-in-May}D_t^{Sell-in-May} \\
&+ \mu_{i,U}U_t + \mu_{i,IP}IP_t + \mu_{i,IPSurp}IPSurp_t + \mu_{i,Default}Default_t \\
&+ \mu_{i,Term}Term_{t-1} + \mu_{i,Inf}Inf_t + \mu_{i,InfSurp}InfSurp_t \\
&+ \mu_{i,ProbC}ProbC_t + \mu_{i,USurpC}USurpC_t + \mu_{i,USurpE}USurpE_t \\
&+ \mu_{i,\sigma_t^2}\hat{\sigma}_t^2 + \mu_{i,Turnover}Turnover_{t-1} \\
&+ \mu_{i,Auction}D_t^{Auction} \\
&+ \mu_{i,Debt-to-GDP}Debt-to-GDP_t \\
&+ \mu_{i,FOMC}D_t^{FOMC} \\
&+ \mu_{i,SF2}\hat{SF}2_t \\
&+ \mu_{i,R_m}\hat{R}_{m,t} + \mu_{i,HML}HML_t + \mu_{i,SMB}SMB_t + \mu_{i,MOM}MOM_t \\
&+ \mu_{i,FFDefault}FFDefault_t + \mu_{i,FFTerm}FFTerm_t \\
&+ \mu_{i,Jan}D_t^{Jan} + \epsilon_{i,t} \qquad (8)
\end{aligned}
$$

Stock and Treasury index excess returns ($r_{i,t} - r_{tb,t}$) are regressed on a constant, the instrumented onset/recovery variable ($\hat{OR}_t$), a dummy for the month of January (D_t^{Jan}), and the following variables. U_t is the expected change in the unemployment rate, IP_t is the expected growth in industrial production, $IPSurp_t$ is the surprise in industrial production growth, $Default_t$ is the change in the spread between Baa and Aaa corporate bond rates from month $t-1$ to month t, $Term_t$ is the difference between the one-month return on 20-year Treasuries and the one-month return on 30-day Treasuries at month t Inf_t is the expected inflation rate, $InfSurp_t$ is the surprise in the inflation rate, $ProbC_t$ is the Stock and Watson (1989) experimental coincident recession index (reflecting the probability of an economic contraction), $USurpC_t$ is surprise in the change in unemployment interacted with the probability of a contraction, $USurpE_t$ is surprise in the change in unemployment interacted with the probability of an expansion (which equals 1 minus the probability of a contraction), the predicted volatility of the S&P 500 stock index for period t, the lag of turnover ($Turnover_t$), a dummy for the months of February, May, August, and November ($D_t^{Auction}$), the debt to GDP ratio ($Debt-to-GDP_t$), a dummy for the months during which the FOMC meetings occur, (D_t^{FOMC}), our instrumented investor sentiment index ($\hat{SF}2_t$), and a dummy for the months November through April ($D_t^{Sell-in-May}$). $\hat{R}_{m,t}$ is the orthogonalized market return, SMB_t and HML_t are firm size and book-to-market factors, MOM_t is the momentum factor, $FFTerm_t$ is the long-term Treasury bond return minus the 30-day T-bill rate, and $FFDefault_t$ is the difference between long-term corporate and government bond returns. The model is estimated on monthly data spanning January 1970 through December 2003, the longest span of data available to us using this set of variables.

In Panel A we present parameter estimates, with associated t-statistics below, calculated using Newey and West (1987) HAC standard errors. At the bottom of Panel A, we present the value of R^2 for each index, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test for up to 12 lags of ARCH. In Panel B we present a Wald χ^2 test, with degrees of freedom in square brackets, for whether the $\hat{OR}_t$ coefficient estimate is jointly statistically different from zero across all the series. One, two, and three asterisks denote significance at the 10, 5, and 1 percent level respectively, based on two-sided tests.

Table XI - Continued

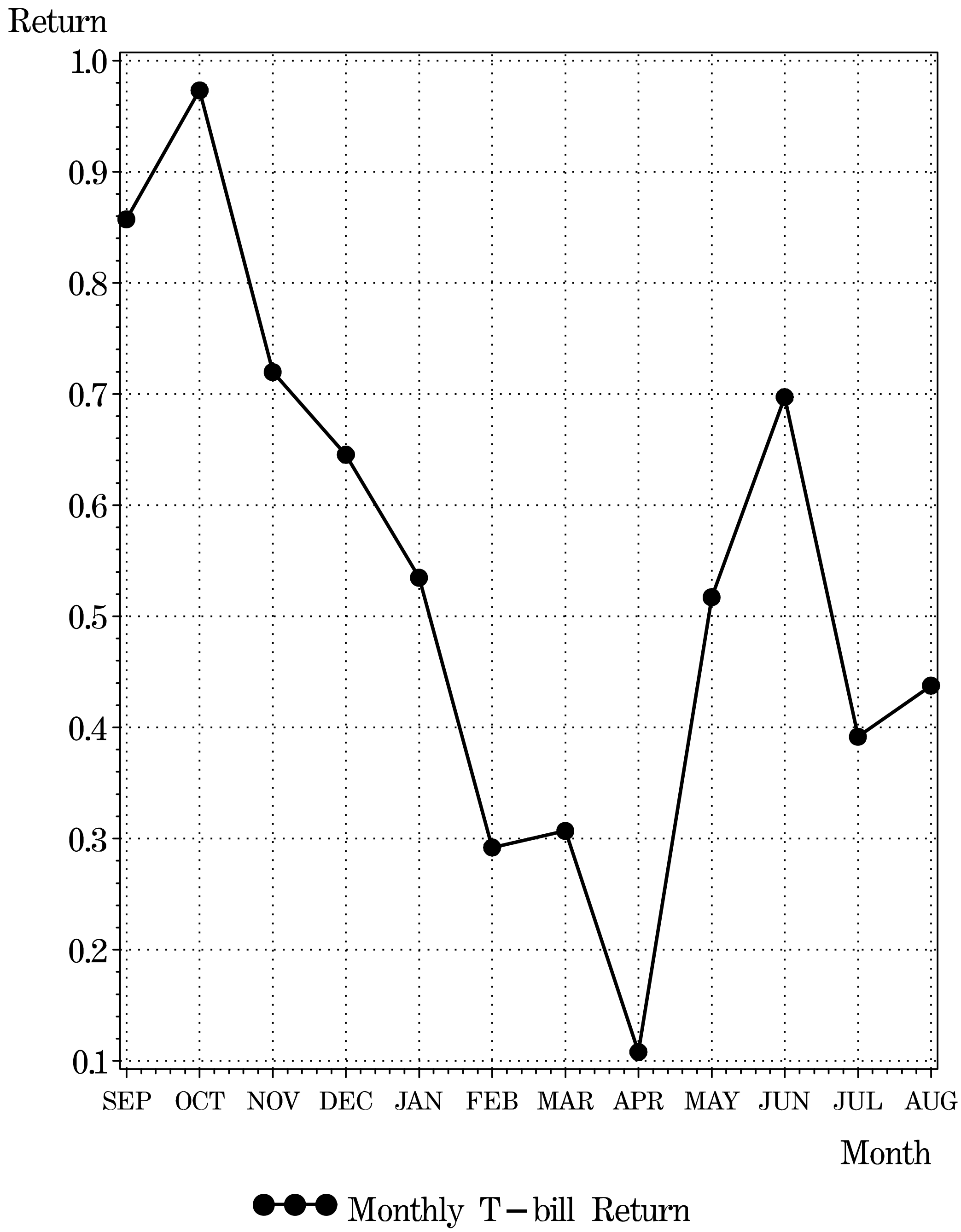
Panel A: Parameter Estimates, T-tests, and Diagnostics

Parameter or Statistic	Stock Index	20-year Treasury Index	10-year Treasury Index	7-year Treasury Index	5-year Treasury Index
$\mu_{OR\cdot\sigma^2}$	-2.278***	0.833*	0.975***	0.786***	0.622***
	(-9.79)	(1.93)	(2.71)	(2.65)	(2.68)
$\mu_{Sell-In-May}$	-0.359***	-0.389	-0.185	-0.232	-0.219
	(-2.68)	(-1.21)	(-0.74)	(-1.12)	(-1.34)
μ_{USurpC}	2.262***	0.461	1.311	0.973	1.622*
	(3.12)	(0.31)	(1.10)	(0.83)	(1.81)
μ_{USurpE}	-0.548*	2.117**	1.644**	1.653***	1.276***
	(-1.90)	(2.49)	(2.56)	(2.96)	(2.78)
μ_{ProbC}	0.027	0.666	0.815	0.682	0.615*
	(0.08)	(0.92)	(1.45)	(1.48)	(1.67)
μ_{IPSurp}	-0.074	0.008	0.065	0.067	0.130
	(-0.71)	(0.03)	(0.35)	(0.42)	(1.10)
μ_{IP}	-0.290	1.497***	1.340***	1.075***	1.158***
	(-1.14)	(2.96)	(3.71)	(2.98)	(3.75)
μ_U	-0.010	0.058**	0.063***	0.053***	0.054***
	(-0.98)	(2.44)	(3.25)	(3.18)	(3.62)
$\mu_{Default}$	0.002	-0.021	-0.004	-0.009	-0.004
	(0.30)	(-1.13)	(-0.25)	(-0.64)	(-0.38)
μ_{Term}	0.016	-0.149	-0.063	0.063	0.059
	(0.23)	(-0.64)	(-0.34)	(0.39)	(0.42)
$\mu_{InfSurp}$	0.168	-1.445*	-0.718	-0.470	-0.228
	(0.61)	(-1.71)	(-1.23)	(-0.95)	(-0.51)
μ_{Inf}	0.130	-2.244***	-1.783***	-1.584***	-1.462***
	(0.52)	(-2.66)	(-3.06)	(-2.97)	(-3.16)
$\mu_{Volatility}$	-0.214	0.013	-0.144	0.119	0.032
	(-1.18)	(0.03)	(-0.33)	(0.34)	(0.12)
$\mu_{Turnover}$	0.999*	-1.090	-1.344	-1.253	-1.140
	(1.75)	(-0.68)	(-1.14)	(-1.33)	(-1.55)
$\mu_{Auction}$	-0.036	0.378	0.242	0.302	0.235
	(-0.26)	(1.30)	(1.02)	(1.44)	(1.34)
$\mu_{Debt-to-GDP}$	0.469	0.375	-0.067	-0.105	-0.146
	(0.83)	(0.26)	(-0.07)	(-0.12)	(-0.19)
μ_{FOMC}	-0.045	-0.165	-0.142	-0.179	-0.235
	(-0.29)	(-0.48)	(-0.50)	(-0.80)	(-1.31)
μ_{SF2}	-0.253***	-0.296	-0.232	-0.187	-0.154
	(-3.03)	(-1.58)	(-1.63)	(-1.58)	(-1.64)
μ_{SMB}	0.767***	-0.061	-0.063**	-0.068***	-0.050**
	(13.86)	(-1.36)	(-1.98)	(-2.66)	(-2.34)
μ_{HML}	-0.211***	0.033	0.025	0.020	0.020
	(-6.46)	(0.91)	(0.88)	(0.80)	(0.97)
μ_{MOM}	-0.226***	0.107***	0.107***	0.090***	0.072***
	(-8.35)	(2.73)	(3.43)	(3.24)	(3.21)
$\mu_{FFDefault}$	1.175***	0.522	0.276	0.253	0.202
	(6.69)	(1.40)	(0.94)	(1.06)	(0.98)
μ_{FFterm}	17.137**	13.743	7.252	-6.039	-4.833
	(2.42)	(0.60)	(0.39)	(-0.36)	(-0.32)
μ_{R_m}	1.009***	0.173***	0.140***	0.103***	0.070***
	(43.66)	(3.57)	(3.52)	(3.52)	(2.79)
μ_{Jan}	2.004***	0.546	0.420	0.354	0.371
	(8.02)	(0.93)	(1.03)	(1.03)	(1.42)
μ	-0.608	-0.025	0.197	0.286	0.335
	(-1.26)	(-0.02)	(0.23)	(0.38)	(0.51)
R^2	0.9641	0.2645	0.2471	0.275	0.2928
AR(12)	11.14	9.94	11.98	12.78	13.34
ARCH(12)	54.71 ***	42.46 ***	34.64 ***	70.83 ***	66.44 ***

Panel B: Joint Test Across Indices

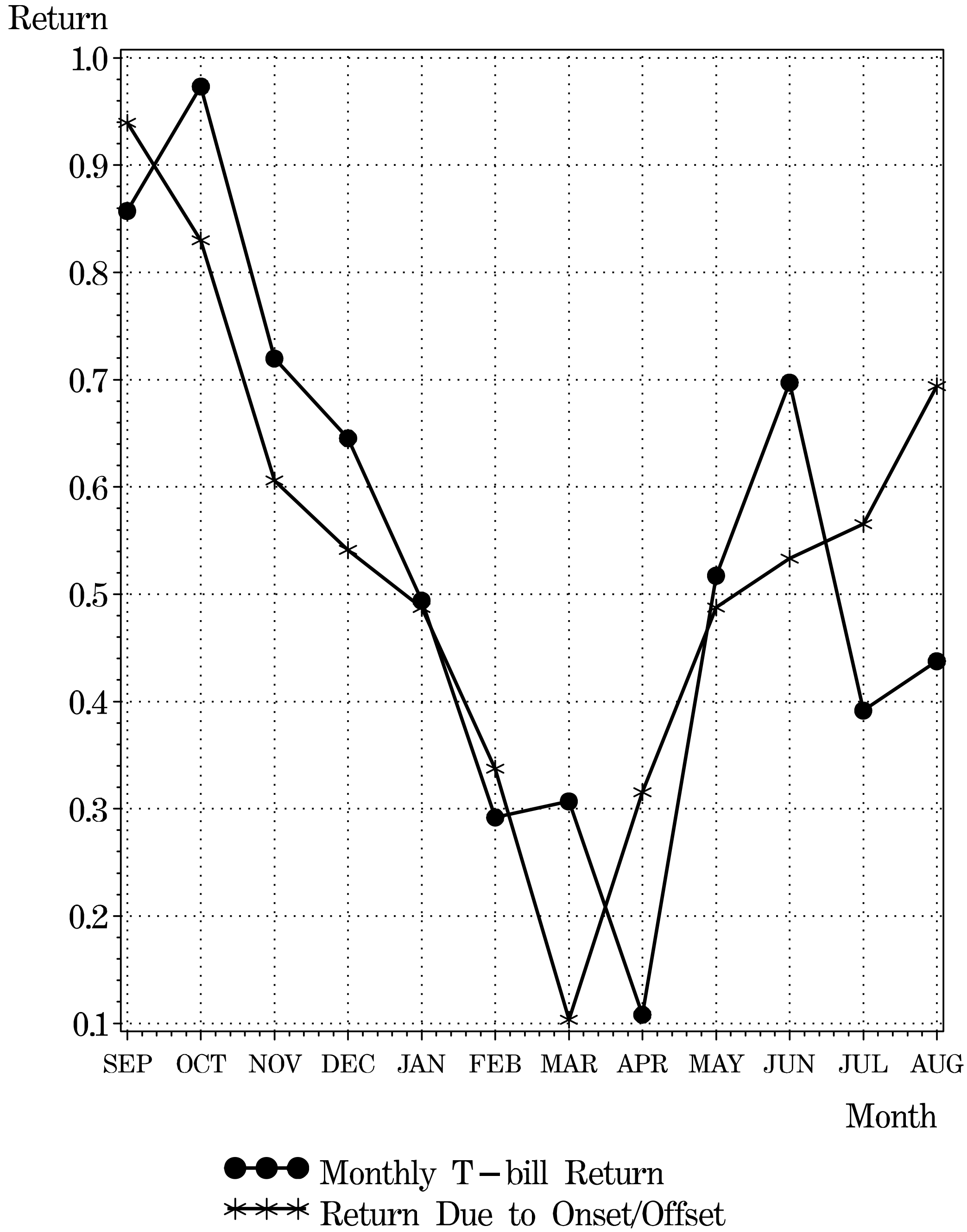
Test	χ^2 [degrees of freedom]
$\mu_{i,OR}$ jointly equal to zero across series	116.9*** [5]

Figure 1
Average Monthly Percentage Treasury Returns for the 5, 7, 10, and 20-year Maturities



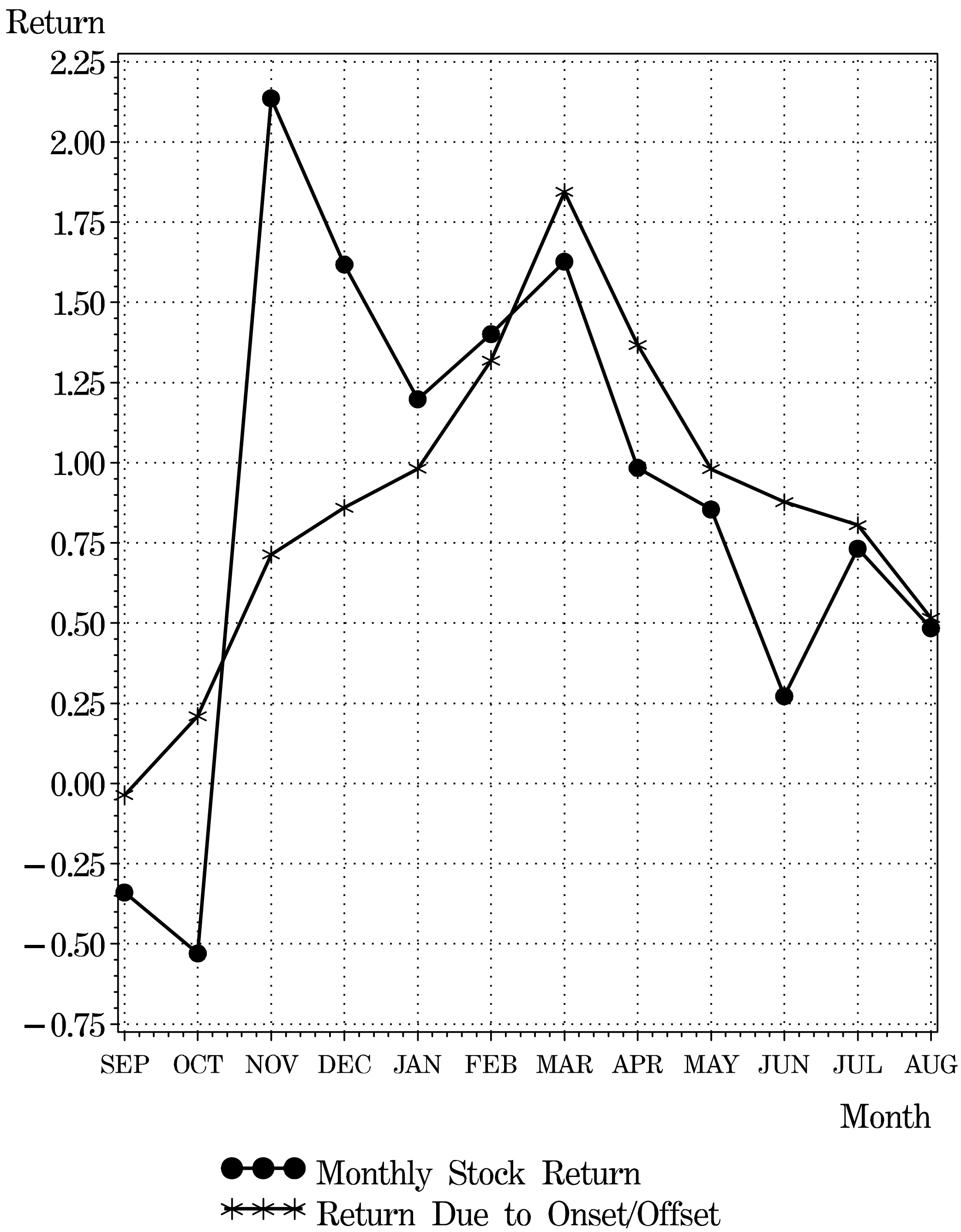
Average monthly Treasury returns. The monthly averages are computed across the 5, 7, 10, and 20-year maturity Treasury indices for the full range of CRSP data we consider, January 1952 through December 2004.

Figure 2
Unconditional Monthly Average Treasury Returns Versus the Conditional Return Due to Onset/Recovery



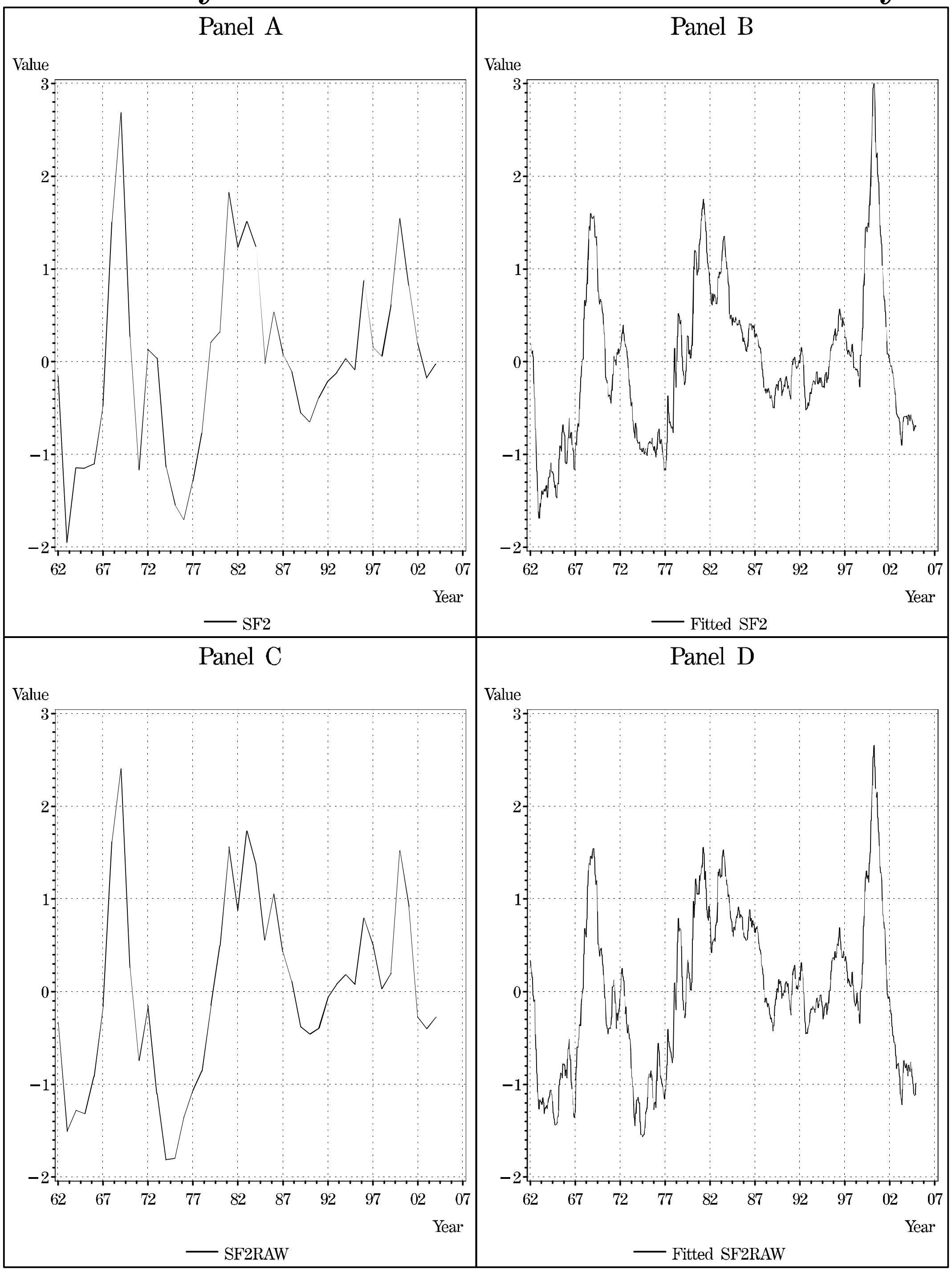
Average monthly Treasury returns, conditional and unconditional. The monthly unconditional averages are computed as simple averages by month across the 5, 7, 10, and 20-year maturity Treasury indices for the full range of CRSP data we consider, January 1952 through December 2004. The mean return for the month of January has been adjusted to remove the January seasonal in bond returns. The estimated monthly conditional Treasury returns are due to the seasonality variable $\hat{OR}_t$.

Figure 3
Unconditional Equal-Weighted Stock Returns Versus the Conditional Return Due to Onset/Recovery



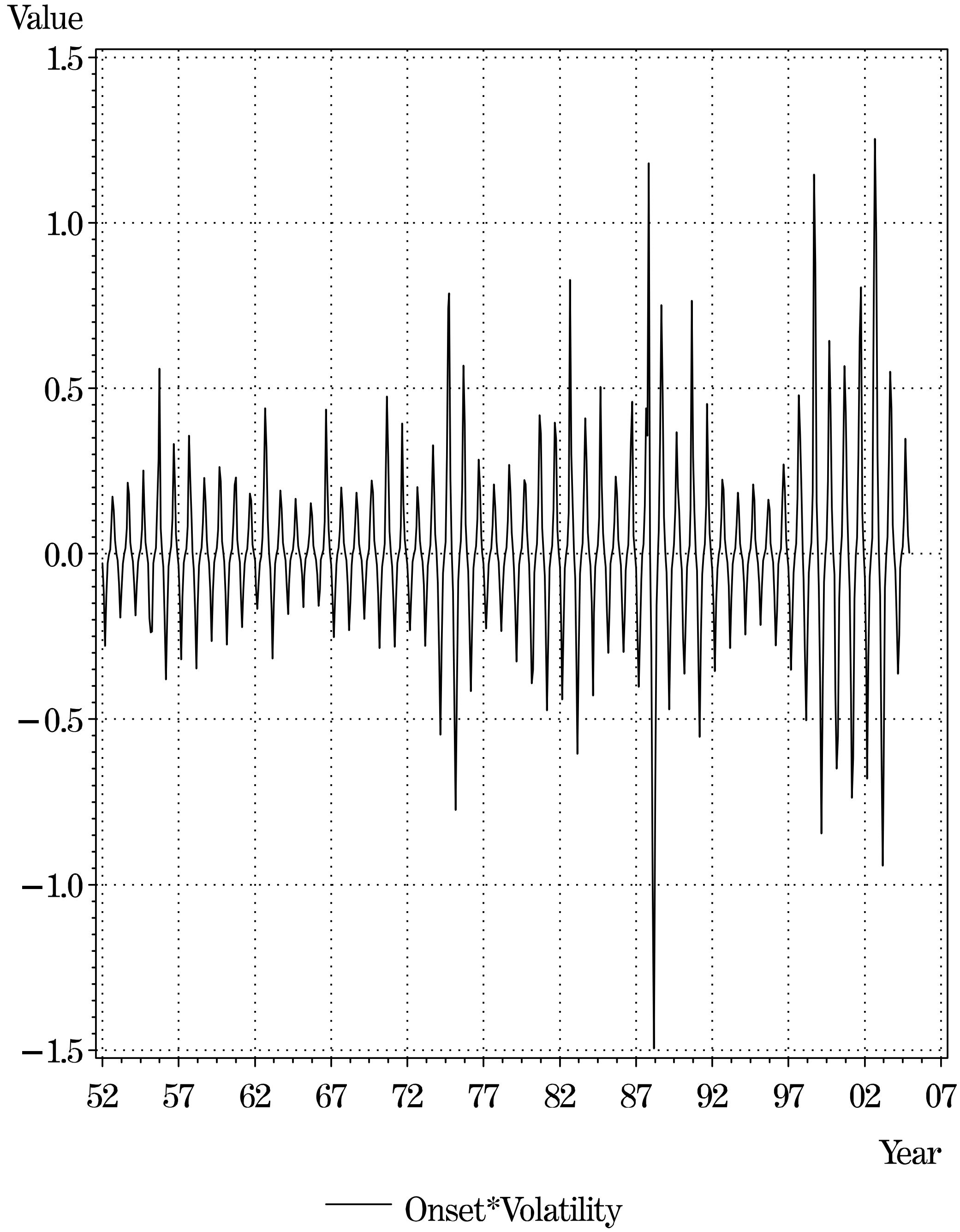
Monthly unconditional stock returns versus monthly conditional stock returns due to the seasonality variable. The monthly unconditional average returns are computed for the CRSP equal-weighted stock index based on the full range of data we consider, January 1952 through December 2004. The January mean return has been adjusted to remove the January effect, by subtracting off the January coefficient value, an adjustment of roughly 3 percent. The estimated monthly conditional return is due to the seasonality variable $\hat{OR}_t$.

Figure 4
The Baker-Wurgler Sentiment Indices
Annually and Instrumented to be Monthly



Sentiment indices, annual compared to monthly. In Panels A and C we present the original Baker and Wurgler (2006) sentiment indices, SF2 and SF2RAW, and in Panels B and D we present the monthly indices we produce based on instrumental variables techniques fitted to these annual sentiment indices.

Figure 5
Onset/Recovery Interacted With Volatility



Monthly values of the interactive variable $\hat{OR}_t \cdot \hat{\sigma}_t^2$, plotted over the time span of our study, January 1952 through December 2004.