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Systematic cojumps, market component portfolios and scheduled macroeconomic announcements

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Abstract: This study provides evidence of common bivariate jumps (i.e., systematic cojumps) between the market index and style-sorted portfolios. Systematic cojumps are prevalent in book-to-market portfolios and hence, their risk cannot easily be diversified away by investing in growth or value stocks. Nonetheless, large-cap firms have less exposure to systematic cojumps than small-cap firms. Probit regression reveals that systematic cojump occurrences are significantly associated with worse-than-expected scheduled macroeconomic announcements, especially those pertaining to the Federal Funds target rate. Tobit regression shows that Federal Funds news surprises are also significantly related to the magnitude of systematic cojumps.

JEL classifications: C1; E44; G11; G12

Keywords: Systematic cojumps; Scheduled macroeconomic announcements; Market component portfolios; Federal Funds rate

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* Corresponding author. The views expressed in this study are those of the authors and not necessarily those of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

1. Introduction

Empirical asset pricing literature typically characterizes the log price process as a combination of continuous and discontinuous sample paths; see, for example, Andersen et al. (2007), Beber and Brandt (2010) and Rangel (2011). Related to these studies, Das and Uppal (2004) define cojumps as infrequent discontinuous sample paths that occur simultaneously across multiple assets (see also Dungey et al., 2009; Lahaye et al., 2011; Dungey and Hvozdyk, 2012). It is important to consider cojumps – in addition to individual jumps – in order to properly diversify portfolios. Das and Uppal (2004) find that cojumps reduce the benefits of portfolio diversification and can expose highly levered portfolios to large losses. Similarly, Cont and Kan (2011) show that cojump is a key determinant in modelling default contagion. In contrast, Pukthuanthong and Roll (2015) find that individual jumps identified across various countries are only weakly correlated, which the authors interpret as suggesting that cross-border diversification could provide reasonable protection against idiosyncratic jumps.

The present study characterizes systematic cojumps, which we define as common bivariate jumps in prices between the market index and its component portfolios sorted based on market capitalization (size) and book-to-market (B/M) price ratio. Similarly, Gilder et al. (2014) define simultaneous jumps in the market index and cojumps among the underlying stocks as systematic cojumps. Fundamental portfolio theory suggests that systematic cojumps are non-diversifiable, because common jumps observed across the market portfolio's underlying components are likely due to market-wide news and this news produces jumps in the market portfolio (Bollerslev et al., 2008, p.234; Gilder et al., 2014, p.443). The present study examines whether this really happens by scrutinizing the effect of regularly scheduled macroeconomic announcements on systematic cojumps. In linking cojumps to macroeconomic announcements, this study extends the research by Gilder et al. (2014), who show that systematic cojumps are related to the timing of macroeconomic announcements and Dungey et al. (2009), Evans (2011), Lahaye et al. (2011) and Dungey and Hvozdyk (2012), who provide similar findings for cojumps identified separately across individual assets or market indices. Nevertheless, our study differs from previous work in three major respects.

First, we draw on recent advances in nonparametric multivariate jump-diffusion modelling to extract systematic cojumps rather than by identifying jumps from individual assets and then aggregating them to form cojumps (Gilder et al., 2014). Gnabo et al. (2014) show that abnormally large comovements identified across different asset classes cannot be detected otherwise using the univariate jump-diffusion approach and therefore they develop a cojump test. This motivates the present study to identify systematic cojumps using a nonparametric multivariate econometric model; this alleviates the type II cojump error specified by Gnabo et al. (2014).[1]

Second, the present study investigates how scheduled macroeconomic announcements affect systematic bivariate cojumps between the market index and its style-sorted component portfolios. Maio (2014) argues that small and value stocks are more vulnerable to monetary shocks than large and growth stocks; see also Gertler and Gilchrist (1994). This is because small and value firms with low equity-valuation are typically financially constrained, hence making them more susceptible to lending shocks (Maio, 2014, p.323). Maio (2014) finds that the returns of small and value stocks respond more to monthly changes in the Federal Funds target rate than the returns of large and growth stocks. However, he does not consider other scheduled macroeconomic announcements. In a related study, Cenesizoglu (2011) investigates the daily return reactions of style-sorted portfolios to various macroeconomic announcements. He finds that large and growth stocks tend to react significantly and negatively to 'good' employment news, but no evidence of a significant reaction in small and value

[1] Alternatively, we could have considered the multivariate cojump test of Bollerslev et al. (2008) to analyze systematic cojumps. However, since this test only detects whether two or more series cojump within a specified interval period (which is quarterly in the current context, as discussed in Section 4.1), it is not particularly helpful to our study which requires the identification of systematic cojumps on a daily basis.

stocks. Both Cenesizoglu (2011) and Maio (2014) only consider the reactions of the first moment of returns. The present study extends their work by considering higher moment in the form of systematic cojumps.

Third, Gilder et al. (2014) analyze the association between systematic cojumps and announcement indicator variables. In contrast, we analyze both cojump intensity and cojump magnitude and relate these attributes to the first two moments of announcement expectations. The efficient markets paradigm implies that systematic cojumps react to the first conditional moment of announcements, namely announcement surprises or realized less expected news. That is, we hypothesize that asset prices react swiftly to new information – the unanticipated component of macroeconomic announcements – rather than the mere existence of scheduled releases.[2] We also conjecture that systematic cojumps react to the second moment of news – i.e., the dispersion of market expectations – which reflects the disagreement of agents' beliefs (Wongswan, 2006). Accounting for dispersion of expectations is crucial because resolution of heterogeneity in market expectations may affect systematic cojumps even if announcement surprises do not.

We presage our empirical findings as follows. There is evidence of systematic cojumps in the style-sorted portfolios. Systematic cojumps are ubiquitous in portfolios sorted on B/M price ratio. This is bad news for investors and asset managers interested in style rotation strategies, because our finding implies that they cannot simply avoid systematic cojump risk by investing in growth or value stocks (see also Bollerslev et al., 2008 and Gilder et al., 2014). Recently, Pukthuanthong and Roll (2015) show that individual jumps identified across international stock markets are weakly correlated and not driven by shocks to global factors. Taken together, the findings in Pukthuanthong and Roll (2015) and our study suggest that investors should diversify their investments overseas, rather than

[2] Maheu and McCurdy (2004) find that unusual news events contribute considerably to jumps in price variation of individual stocks.

pursuing a 'growth-value' style rotation strategy in the domestic market. At the same time, however, we also show that large-cap firms exhibit fewer systematic cojumps than small-cap firms, which suggests that the former mitigates cojump risk better than the latter.

We then use probit and Tobit regressions to show that macroeconomic announcement surprises are associated with cojump intensity and amplitude. Inoue and Kilian (2004) show that data mining can result in spurious rejection of no-reaction hypothesis more often than it should. To circumvent this problem, we closely follow the recommendation of Kilian and Vega (2011) and perform an extensive Monte-Carlo simulation exercise to assess the statistical significances of the regression parameter estimates.

The empirical findings reveal heterogeneous reactions to macroeconomic news. In particular, unanticipated Federal Funds rate news is strongly associated with systematic cojump occurrence and size in all the style-sorted portfolios. This is good news for investors and portfolio managers who were searching for factors to explain systematic cojumps; Federal Funds target news does so. At the same time, however, our finding also implies that even the most risk-averse investors cannot completely avoid macroeconomic risk emanating from the Federal Funds because it consistently affects systematic cojumps. Unanticipated information related to other macroeconomic variables (such as labor statistics) have much less effect.

We expect greater dispersion of announcement expectations (i.e., the cross-sectional variation of analysts' expectations) to raise systematic cojumps because heterogeneity in agents' beliefs reflects greater uncertainty prior to the release of news. Very few studies on macroeconomic announcements have used the dispersion of news forecasts as a measure of information uncertainty. Wongswan (2006) finds a significant positive relationship between the dispersion of expectations and trading volume of international equity markets. Huang (2015) shows that the dispersion of expectations significantly influences both volatilities and jumps in U.S. bond futures. We extend this literature by showing that the dispersion of analysts' expectations is generally not a significant factor affecting systematic cojumps. However, dispersion of expectations pertaining to nonfarm payroll statistics and Institute of Supply Management index do significantly affect the cojumps of some portfolios.

We also ask whether systematic cojumps react asymmetrically to unexpectedly 'good' and 'bad' news. The economic and psychology literature implies that bad news creates more uncertainty and thus larger price revisions (or jumps), than good news; see, for example, Vonk (1996) and Barberis et al. (1998). As such, we hypothesize that systematic cojumps react more to bad news than to good news. The empirical findings support this hypothesis, with bad (i.e., contractionary) news about the Federal Funds influencing systematic cojumps more than good news.[3]

We structure the remainder of this study as follows. Section 2 develops the systematic cojump–macroeconomic announcement hypotheses. Section 3 describes the portfolio and macroeconomic data. Section 4 begins by discussing the results pertaining to the identified systematic cojumps across the market component portfolios. A detailed analysis of the systematic cojump-macroeconomic announcement relationship follows. Section 5 concludes.

2. Hypotheses development

We develop three hypotheses, stated in the alternative form, to guide our systematic cojump-macroeconomic announcement analyses.

Gilder et al. (2014) show a significant relationship between systematic cojumps and indicator variables for scheduled macroeconomic news. In contrast, we conjecture that systematic cojumps react to additional information, the size of the news surprises, which are measured as realized less

[3] One might think that unexpectedly higher interest rates would be associated with greater future growth if the Federal Reserve has superior information but Faust et al. (2004) find little evidence for this hypothesis. Instead, we simply interpret higher interest rates as "bad news" because they reduce stock prices.

expected macroeconomic news. We hypothesize that announcement surprises contribute positively to an increased likelihood of observing systematic cojumps in the market component portfolios.

We also examine how systematic cojumps react to the second moment (i.e., dispersion) of announcement expectations. Wongswan (2006) argues that the second moment of news forecasts, which we measure using the cross-sectional standard deviation of analysts' expectations of macroeconomic announcements, reflects the disagreement of agents' beliefs. Furthermore, Pasquariello and Vega (2007) develop a parsimonious model of speculative trading to show that a high dispersion of beliefs across informed traders in response to noisy public announcements contributes to a higher contemporaneous correlation between order flow and bond yield changes. As such, we hypothesize that a larger dispersion of announcement expectations – greater heterogeneity of beliefs – increases the probability of systematic cojumps.

Therefore, we hypothesize the following:

H.1: *Systematic cojump occurrences are positively related to the magnitude of the announcement surprises and dispersion of analysts' expectations of the announcements.*

The second hypothesis concerns asymmetric reactions to macroeconomic news. Barberis et al. (1998) develop a parsimonious model of investor sentiment and show that 'bad' ('good') news surprises are typically followed by additional 'bad' ('good') surprises. This implies that worse-than-expected news tends to create more uncertainty, and thus larger price revisions or jumps, than better-than-expected news. Barberis et al.'s finding can be linked to Kahneman and Tversky's (1979) prospect theory, which predicts that people make decisions with respect to a reference point and are more concerned about losses than about gains with respect to that point. Likewise, the psychology literature regarding 'impression formation' demonstrates that the behavior of a dislikeable person generates more severe consequences than likable behavior (Vonk, 1996). This suggests that unfavorable information has a greater effect on impressions than favorable information. Together, these arguments lead to the following hypothesis:

H.2: *'Bad' news explains systematic cojumps more strongly than does 'good' news.*

The third hypothesis evaluates the impact of macroeconomic news surprises and dispersion of analysts' expectations on the magnitude of systematic cojump.[4] We conjecture a positive relationship between news surprises and analysts' dispersion, and the systematic cojump size, because large news and analysts' dispersion should naturally drive systematic cojumps with a higher magnitude than modest news and dispersion:

H.3: *The magnitude of systematic cojump is positively related to announcement surprises and dispersion of analysts' expectations of the announcements.*

3. Data description

3.1. Portfolio data

This study uses the Center for Research in Security Prices (CRSP) value-weighted composite index as the market portfolio, as well as the standard value-weighted portfolios of Fama and French (1992) that are based on B/M price ratio and size.[5] BM1, …, BM10 (S1, …, S10) represent decile portfolios formed in ascending order based on B/M price ratio (market capitalization). Following prior literature, we refer to BM1 as 'growth stocks', BM10 as 'value stocks', S1 as 'small stocks' and S10 as 'large stocks'. The sample period begins on January 2, 1986, a common starting date dictated by the availability of macroeconomic variable forecasts as detailed in Section 3.2 below, and ends on December 31, 2013, for a total of 7,060 daily observations.

< Insert Table 1 here >

< Insert Figure 1 here >

Panel A of Table 1 reports summary statistics of the daily continuously compounded returns (expressed in percentages) of the stock portfolios and Figure 1 plots the corresponding annualized

[4] We are grateful to an anonymous referee for suggesting this analysis.

[5] We extract the B/M and size-deciled portfolio data from Kenneth R. French's Internet data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

mean returns. The Figure illustrates that value (i.e., high B/M) stocks have had higher mean returns than growth (i.e., low B/M) stocks, thus providing credence to the ‘stock-returns-value-premium’ effect commonly documented in the asset pricing literature (Chen et al., 2008). On the other hand, large-cap stocks have typically had higher mean returns than have small-cap stocks, a finding that is consistent with the ‘reversed stock-returns-firm-size’ anomaly reported by Horowitz et al. (2000). Finally, the Jarque-Bera statistics indicate a clear rejection of normality in daily portfolio returns.

3.2. Scheduled macroeconomic announcements

Prior empirical studies have typically related scheduled macroeconomic announcements to jumps detected separately in individual assets (Beber and Brandt, 2010; Evans, 2011; Rangel, 2011). In contrast, we investigate systematic cojumps between the market index and its component portfolios, and relate them to five key macroeconomic variables: the Federal Funds (FED) target rate released by the Federal Open Market Committee (FOMC), changes in nonfarm payroll (NFP) statistics, seasonally adjusted unemployment rate (UMP), seasonally adjusted producer price index (PPI) and the Institute of Supply Management (ISM) index.[6] We consider past research in selecting the macroeconomic variables. Bernanke and Kuttner (2005) demonstrate that the FED is one of the most closely watched announcements in the U.S. Moerman and van Dijk (2010) show that inflation is a key element in forecasting stock returns. Boyd et al. (2005) find that the stock market is sensitive to the dynamics of the labor market whereas Andersen and Bollerslev (1998, p.240) refer to NFP as the ‘king of all announcements’ because of the significant sensitivity of most asset prices to its release

[6] Rangel (2011) argues that important inflationary information content is primarily contained in the PPI, because the PPI announcements always precede the consumer price index (CPI) announcements. He further shows that the CPI variable has negligible impact on the jump intensity of S&P500 Index. In preliminary work, we had experimented with several other macroeconomic variables commonly examined in related studies – the seasonally adjusted CPI, the seasonally adjusted industrial production (IP) index that defines the condition of the production side of the economy, retail sales (RS) that indicates general economic health and the seasonally adjusted housing start (HS) statistics that represent the situation in the real estate market – and found that the coefficient estimates of the probit regression Equation (5), defined below, based on these variables are mainly statistically insignificant. To conserve space, we report their findings in Internet Appendices.

(see also Wongswan, 2006; Cenesizoglu, 2011). Finally, the forward-looking ISM is important because it describes the perceived state of the U.S. economy.

For NFP, UMP, PPI and ISM, we extract the as-first-reported data and survey expectations of these variables from Haver Analytics, which in turn collect the data from various sources, including International Money Market Services (MMS), Informa and Action Economics. As is standard in the literature on macroeconomic announcements (Balduzzi et al., 2001; Cenesizoglu, 2011), we standardize news surprises to more easily compare and interpret coefficients across regressors:

$$S_{t,k} = \frac{A_{t,k} - F_{t,k}}{\sigma_k}, \qquad (1)$$

where $A_{t,k}$ is the actual data for macro variable k announced on day t and $F_{t,k}$ refers to the consensus market expectation obtained as the median estimate of professional survey forecast from the Haver Analytics database. The survey forecast error ($A_{t,k} - F_{t,k}$) in the numerator is standardized by its time-series sample standard deviation σ_k to control for differences in the units of measurement of various macroeconomic variables.[7] The standard deviation σ_k is computed using only observations on surprises on announcements days.

We follow Kuttner (2001) and studies such as Rangel (2011) and León and Sebestyén (2012) in defining the Federal Funds target rate forecast error as:

$$A_{t,\mathrm{FED}} - F_{t,\mathrm{FED}} = \frac{D}{D-d}\left(f_t^0 - f_{t-1}^0\right), \qquad (2)$$

where f_t^0 is the Federal Funds rate implied in the current month Federal Funds futures contract on date t, d is the day of the month of the current FOMC meeting, D is the number of days in the month

[7] It is probable that only large surprises are related to systematic cojumps occurrences identified from Equation (4), discussed below. As such, for robustness, we repeat the empirical analysis by focusing on non-trivial announcement surprises. More concretely, following the recommendation of Brenner et al. (2009), the spread between the actual and forecast news is deemed a 'surprise' if and only if the absolute forecast error $|A_{t,k} - F_{t,k}|$ is above 5 basis points for FED, UMP and PPI, respectively, 0.2 for ISM and 20,000 for NFP. The results, unreported here but are contained in Internet Appendices, are qualitatively similar to those reported in Section 4.3.

and the scaling factor $D/(D–d)$ accounts for the timing of the FOMC announcement within a given month.[8]

Panel B of Table 1 provides descriptive statistics for the announcement surprises.[9] The estimated means of the standardized surprises (calculated from Equation (1)) are slightly negative for most of the variables considered, but they not materially different from zero. This corroborates prior findings (see, for example, Balduzzi et al., 2001) that the survey expectations are approximately unbiased. The lower part of Panel B reports the number of concurrent announcement days between two macroeconomic variables. Since both NFP and UMP figures are always reported simultaneously in the same U.S. Employment Report, they are considered as a single (joint) labor statistics news release in the panel. The panel reveals that the other variables considered in the current study are rarely announced concurrently, with the most coincidences (19 times in 28 years) between NFP-UMP and ISM releases.

4. Empirical results

Our goal is twofold. First, we analyze systematic cojumps between the market index and its component portfolios; then we examine how the identified systematic cojumps react to scheduled macroeconomic announcements. To accomplish these objectives, we employ a two-step strategy developed in the spirit of Jiang et al. (2011), Lahaye et al. (2011), Elkamhi et al. (2012) and Lee (2012). Step One involves identifying systematic cojumps using a variant of the nonparametric

[8] We source the FED surprises data from Kenneth Kuttner's personal website (http://econ.williams.edu/people/knk1). Note that prior to February 1994, the FOMC did not publicly announce their monetary policy decisions. Instead, market participants had to infer the monetary policy decisions from the size and type of open market operations from the Trading Desk at the New York Fed. As such, it is likely that the pre-1994 FED surprises are based on Kenneth Kuttner's personal judgment.

[9] The FED news surprise data were sampled beginning from June 1989 as the Federal Funds futures market was not available prior to mid-1989. All the non-zero FED news surprises were mainly found between June 1989 and June 2008; after this period, the FED rate has been constant at approximately 15-25 basis points (bps) and the FOMC did not report a point target rate until 2015. In addition, the ISM announcement surprises were collected beginning from January 1990 due to limited professional survey forecast data. Also, since we only consider trading-day returns for the stock portfolios, the total announcements for monthly NFP, UMP and PPI are unsurprisingly less than 336 (28 years x 12 monthly observations per year) throughout the entire sample period. There were, for example, four cases in which the PPI statistics were released on non-trading days, resulting in 332 PPI news releases.

multivariate jump detection technique in Boudt et al. (2011). Section 4.1 details this. Sections 4.2 to 4.5 present the empirical results relating systematic cojumps to macroeconomic news.

4.1. Defining systematic cojumps

Boudt et al. (2011) provide an extensive simulation experiment to show that their econometric technique usefully estimates realized covariance between two return series in a jump-robust fashion by downweighting returns with large local outliers relative to neighboring returns. We adjust their technique to accommodate our objective in detecting daily systematic cojumps.

Consider an N-dimensional log-price process $p(s)$ of portfolio i and the market index (MKT), and define the daily return of the portfolio on day t as $r_{i,t} = p(i, t) - p(i, t\text{-}1)$. N equals 2 for our study of systematic cojumps between a single portfolio and MKT. We consider quarterly horizon with τ varies between 62 and 65 (trading-day) observations per quarter to ensure sufficient observations are available to compute the necessary statistics.

We detect outliers in the portfolio i-MKT bivariate normalized returns within the localized quarterly window using the Mahalanobis distance:

$$d_{i,t} = \frac{\mathbf{r}_t' \hat{\Sigma}^{-1} \mathbf{r}_t}{1/\tau}, \tag{3}$$

where $\mathbf{r}_t$ is the 2 x 1 (i.e., portfolio i-MKT) asset return vector and $\hat{\Sigma}$ is the robustly estimated variance-covariance matrix. We follow the recommendation of Boudt et al. (2011) and estimate $\hat{\Sigma}$ with the Minimum Covariance Determinant (MCD) estimate of Rousseeuw (1984) and Rousseeuw and Van Driessen (1999).[10] Under the null of no jumps, $d_{i,t}$ follows a χ_2^2 distribution. Therefore, examining the presence of systematic cojumps between portfolio i and MKT involves testing if $d_{i,t}$

[10] We adapt the programming code used to compute the fast MCD algorithm from http://wis.kuleuven.be/stat/robust. We thank the research group on Robust Statistics at the University of Leuven for making their programming codes available to the general public.

is greater than χ_2^2 (β=97.5%).[11] To facilitate the study of news effects on jumps, the existence of an identified systematic cojump between portfolio *i* and MKT on day *t* is expressed as an indicator variable:

$$\mathrm{J}_{i,t} = \begin{cases} 1 \text{ if } d_{i,t} > \chi_2^2(97.5\%) \\ 0 \quad \text{otherwise} \end{cases} . \tag{4}$$

< Insert Figure 2 here >

Figure 2 illustrates the systematic cojump identification technique through an example involving the BM1-MKT combination in 1991Q3. Panel A plots the daily BM1-MKT bivariate returns. The solid ellipse denotes the extent of the joint distribution of normal diffusion returns so paired returns that lie outside the ellipse are outliers, denoted as systematic cojumps. The technique identifies five systematic cojumps between BM1 and MKT. Panel B shows the robust Mahalanobis distance for the daily bivariate returns in the localized 1991Q3 window, with the dotted horizontal line representing the benchmark $\chi_2^2(97.5\%) = 7.4$ critical value. For example, the BM1-MKT bivariate return on August 21 is identified as a systematic cojump with $d_{i,t}$ = 35.5, which is well above the 7.4 critical value. Note that August 21 coincides with the release of a positive FED news forecast error ($A_{t,\mathrm{FED}} - F_{t,\mathrm{FED}}$ = 12 bps).[12]

< Insert Figure 3 here >

[11] We set β = 97.5% as a compromise between what Boudt et al. (2011) and Gnabo et al. (2014) employ in their respective studies. We also experimented with a more restrictive β = 99% and obtain a similar (unreported) qualitative findings.

[12] Panel B of Figure 2 also reveals that BM1 systematically cojumped with MKT on July 1 and August 19, although there were no scheduled macroeconomic announcements on these days. It is probable that the identified systematic cojumps react to ad hoc news not related to the scheduled announcements considered in this study. For example, the Warsaw Pact was formally dissolved on July 1, 1991, and the attempted overthrow of the Soviet Union's then President Mikhail Gorbachev was on August 19, 1991. In Section 4.3 below, we formulate a regression model to exclusively focus on scheduled macroeconomic announcement days and examine whether news surprises on announcement days affect systematic cojumps.

Figure 3 plots the economically significant means of the annualized systematic cojump probabilities identified from Equation (4).[13] Panel A reveals all B/M-deciled portfolios tend to jump concurrently with the market index for approximately 20 times per annum. This is especially bad news for investors interested in style rotation strategies because our finding implies that value stocks cojump with the market portfolio at approximately the same rate as growth stocks. This also suggests that systematic cojumps of value stocks cannot be easily avoided through diversification using growth stocks. In a related study, Pukthuanthong and Roll (2015) show that individual jumps identified across eighty-two international stock market indices are weakly correlated and not driven by shocks to global factors. Therefore, the finding in Pukthuanthong and Roll's study, together with ours, suggests that investors may be better off pursuing an international diversification strategy than a 'growth-value' style rotation strategy in the domestic market.

Panel B shows that systematic cojump probability declines with firm size. The smallest-cap portfolio, S1, jumps concurrently with the market index for approximately 23 times per annum, and this tendency decreases almost monotonically to 19 times per annum for the larger-cap portfolio, S9. The two-sample z-statistic of the null that the systematic cojump proportions for S9 and S1 are equal is 3.08, and the analogous statistic for the null that the S1 and S10 jump proportions are equal is 1.86.[14] Our finding has important implications for investors because it suggests that investing in large-capitalization stocks has significantly less exposure to systematic cojumps than investing in small-capitalization stocks.[15] Put it differently, our findings suggest that large-cap stocks more usefully mitigate the risk of systematic cojumps than do small-cap stocks. Our finding is also

[13] Internet Appendices contain results based on the bivariate cojump test of Jacod and Todorov (2010), which further supports the finding that jumps in the market index and portfolio i tend to arrive concurrently.
[14] Let p_i (p_j) equal the probability of observing systematic cojumps in portfolio i (portfolio j) over the full sample period of n. The two-sample z-statistic to test the null hypothesis H_0: $p_i = p_j$ against the alternative hypothesis H_1: $p_i \neq p_j$ is normally distributed as $\hat{p}_i - \hat{p}_j \sim N[0, \hat{p}(1-\hat{p})(1/n + 1/n)]$ where $\hat{p}$ is the estimate of common cojump proportions over the full sample period.
[15] We reach qualitatively similar findings when identifying systematic cojumps over a substantially longer 1965-2013 sample period. Internet Appendices present our robustness findings.

consistent with Jiang and Yao (2013) who show that small stocks tend to have higher jump returns than large stocks. The negative jump-firm size relationship found here and in Jiang and Yao (2013) could be explained by prior literature (see, for example, Bhushan, 1989) showing that small firms tend to have low analyst followings because of frequent credit-constrained situations.[16] This yields costly information acquisition about these firms relative to large firms (Maio, 2014).

4.2. Correlation among systematic cojumps

Our analysis focuses on bivariate cojumps but we can also get some idea of how common cojumps involving more than two portfolios are by examining the correlation of indicator variables for bivariate cojumps. In addition to the 20 cojump portfolios (10 B/M and 10 size), we also calculate two "sum" variables, which are the sum of the B/M and size cojump indicators, respectively. The B/M sum, for example, would equal 0 if there were no B/M cojumps on a day, 2 if two B/M portfolios cojumped with the market index and 10 if all B/M portfolios cojumped with the market index on a day.

< Insert Table 2 here >

Both panels of Table 2 provide similar inference. The correlations between the indicator series are positive and fairly high, ranging from 0.46 for the correlation between BM1 and BM2 cojump indicators to 0.83 for the correlation between S2, S3 and S4 with the size "sum." That is, systematic cojumps tend to frequently occur together.

In addition to studying the correlations of the bivariate cojumps, we also tested for cojumps among all 11-portfolios – the 10 B/M or size portfolios plus the market – at nominal sizes of 2.5% and 1%, respectively. We find (unreported) evidence of a fair amount of simultaneous cojumps

[16] Nevertheless, two key features distinguish our study from Jiang and Yao's. Methodologically, Jiang and Yao (2013) examine jumps in price variation estimated separately from individual stocks, whereas we focus on systematic cojumps between the stock portfolios and the market index. Second, Jiang and Yao (2013) form their conclusions based on jump returns, defined as the cumulative magnitude of stock returns on jump days, whereas Figure 3 is based on the arrivals of systematic cojumps per annum.

across all portfolios. At the 2.5% level, all B/M and size portfolios jumped with the market on about 19.6% and 19.7% of days, respectively. At the 1% level, all B/M and size portfolios jumped with the market on about 9.4% and 9.4% of days, respectively.

4.3. Testing hypothesis H.1

Figure 2 provides anecdotal evidence suggesting that the arrival of macroeconomic news is not entirely restricted to scheduled announcement days. To the extent that systematic cojumps associated with scheduled macroeconomic announcements are not dissimilar to those related to ad hoc macroeconomic news, one might struggle to find a significant announcement-day effect. To alleviate this concern, we first focus exclusively on scheduled announcement days and estimate the following probit regression:

$$\Pr\left(\mathrm{J}_{i,t}=1\right)=\Phi\left(\alpha_i+\beta_{i,k}\left|\mathrm{S}_{t,k}\right|\right), \tag{5}$$

where Pr(.) is the probability that systematic cojumps have occurred, $\mathrm{J}_{i,t} = 1$ if a systematic cojump is identified on day t and 0 otherwise (see Equation (4)), $\Phi(.)$ denotes the standard Normal cumulative distribution function and $\mathrm{S}_{t,k}$ refers to the standardized announcement surprises as constructed in Equation (1).

Equation (5) is similar in spirit to the event study type of ordinary least square regression commonly adopted by existing literature to examine macroeconomic announcement impacts on asset price returns (see, for example, Kilian and Vega (2011)). This equation uses the unexpected component of the announcement, i.e., *news*, rather than all the information in the scheduled release, for explaining systematic cojumps. In this, we follow Jiang et al. (2011), Lahaye et al. (2011) and León and Sebestyén (2012) in using announcement surprises, rather than Gilder et al. (2014) who use indicator variables for macroeconomic announcements as explanatory variables. We also use the absolute magnitude of the announcement surprises, $|\mathrm{S}_{t,k}|$, rather than $\mathrm{S}_{t,k}$, in Equation (5) to explain systematic cojumps, where $\beta_{i,k}$ measures the marginal impact of absolute announcement surprises; see also Jiang et al. (2011), Lahaye et al. (2011) and León and Sebestyén (2012).

< Insert Table 3 here >

Table 3 reports the parameter of interest, $\beta_{i,k}$, which is highlighted in bold if the null hypothesis of no reaction (H_0: $\beta_{i,k} = 0$) is rejected in favor of the alternative hypothesis of a positive reaction (H_A: $\beta_{i,k} > 0$) at the one-tailed 5% level of significance (see hypothesis H.1 again).[17] Because we test five regression models, we risk spurious type I rejection error. To mitigate this risk, we follow the Monte-Carlo simulation strategy proposed by Kilian and Vega (2011) to simulate distributions and draw statistical inference in the presence of multiple models.[18] First, we randomly draw the binary systematic cojump dependent variable in Equation (5) from a Poisson process whose mean rate of occurrence is calibrated such that the number of simulated occurrences of systematic cojumps matches the number of actual occurrences. In a similar manner, the news forecast errors ($A_{t,k} - F_{t,k}$) that formulate the independent variable in Equation (5) are randomly generated from a Normal distribution whose mean and variance are calibrated from the actual news forecast errors (see Panel B of Table 1). In each simulation, we regress the randomly drawn binary dependent variable on the randomly drawn standardized news forecast errors (in absolute value) with the sample size equal to that used in the actual regression.[19] Then, the z-statistic of the estimated $\beta_{i,k}$ and McFadden's pseudo-R^2 statistic are recorded. This procedure is repeated 1,000 times, allowing the 95th percentile of the

[17] Kilian and Vega (2011) also prefer the one-sided t-test to study the responses of oil price returns to macroeconomic announcement.
[18] When examining the responsiveness of energy price returns to macroeconomic announcement surprises, Kilian and Vega (2011) review the work of Inoue and Kilian (2004) and note that the conventional asymptotic Student t-test tends to reject the null hypothesis of no predictability more often than it should when the same regression model is tested using different regressors.
[19] There are typically 10%-15% systematic cojump-announcement coincidences relative to the sample observations in probit Equation (5).

recorded statistics to serve as the one-sided robust critical value for the supremum of the *z*-test and pseudo-R^2 statistic reported in the table.[20]

Table 3 reveals that systematic cojump occurrences are significantly higher and positively related to the magnitude of FED announcement surprises for all portfolios. In contrast, there is no conclusive evidence of a positive relationship for the other four regressors; those $\hat{\beta}_{i,k}$ coefficients are insignificant at the 5% level. Further supporting this finding is the 'Avg' row in the table which demonstrates that the means of $\hat{\beta}_{\mathrm{B/M,FED}}$ and $\hat{\beta}_{size,\mathrm{FED}}$ are 0.35 and 0.33, respectively. These estimates are much higher than the mean coefficient estimates of the other explanatory variables.[21]

To provide a more meaningful interpretation of the slope coefficient estimates, the $\partial\Phi/\partial S_k$ columns in Table 3 report, in square brackets, the proportional impact on the systematic cojump probability of a unit increase in the absolute standardized surprise of macroeconomic variable k.[22] The 'Avg' row succinctly summarizes our finding: on average, a unit standard deviation increase in unexpected absolute FED news raises the systematic cojump probability of the B/M-deciled (size-deciled) portfolio by 6.13% (6.45%), which is more than three times the average proportional increase in jump probability associated with the next best explanatory variable, the NFP.

[20] Some of the macroeconomic variables considered in this study have unique features. For example, 32 out of 332 PPIs (i.e., nearly 10% of the observed PPIs) have $A_{t,\mathrm{PPI}} - F_{t,\mathrm{PPI}} = -0.2$. This may indicate that the PPI news forecast errors are not normally distributed. As such, we experimented with an alternative procedure by bootstrapping (with replacement) the standardized news surprises from the actual data. The 95[th] one-sided robust critical values obtained from this bootstrap strategy are similar to those derived from the Monte-Carlo simulation method currently employed. The results of the bootstrapping procedure are available upon request from the authors.
[21] The news surprise standardization procedure in Equation (1) implies that the estimated slope coefficient magnitudes corresponding to different economic variables in probit regression Equation (5) are on the same scale and hence are directly comparable to each other.
[22] The marginal effect is calculated as follows. Consider the probit regression involving the BM1–FED combination. The untabulated α_{BM1} intercept estimate is –1.51. As such, the corresponding $\Phi(-1.51) = 6.6\%$, which is the systematic cojump probability on zero FED announcement surprise. At the same time, Table 3 shows that the estimated $\beta_{\mathrm{BM1,FED}}$ is statistically significant at 0.38. Hence, upon a unit increase in the absolute standardized FED news surprise, the overall impact is such that $\Phi(-1.51+0.38) = 13\%$ and the incremental increase in systematic cojump probability is calculated as 13.0% – 6.6% = 6.4%, which is shown in square bracket in the table.

Table 3 also shows that the pseudo-R^2 statistics for the FED announcement surprises are not only considerably larger than those reported for other economic measures, they also exceed the 95% optimal cut-off pseudo-R^2, which we omit for brevity. The FED announcement surprises clearly dominate the other macroeconomic news in explaining the probability of systematic cojumps.

Equation (5) assesses the announcement surprise impact of each macroeconomic variable separately. Although the bottom portion of Panel B in Table 1 reveals that most macroeconomic variables are seldom announced concomitantly, it is possible that the variables should be jointly estimated to avoid omitted variable bias. In addition, it is crucial to analyze the second moment of news forecasts because widely dispersed market expectations may affect systematic cojumps even if announcement surprises do not (Wongswan, 2006).

To investigate the joint impact of news surprises and the dispersion of expectations, we build upon the specification of Jiang et al. (2011), Lahaye et al. (2011), Elkamhi et al. (2012) and Lee (2012) and estimate the following joint probit regression over the full 1986-2013 sample period:

$$\Pr(\mathrm{J}_{i,t}=1)=\Phi\left(\alpha_{\mathrm{i}}^{\mathrm{all}}+\alpha_{\mathrm{i}}^{\mathrm{A}}\cdot \mathrm{I}(\mathrm{A}_t=1)+\sum_{k}^{5}\beta_{i,k}\left|\mathrm{S}_{t,k}\right|+\sum_{k\neq FED}^{4}\gamma_{i,k}\mathrm{SD}_{t,k}+\lambda_{\mathrm{i}}^{\mathrm{A}}\cdot \mathrm{I}(\mathrm{A}_t=1\,|\,\mathrm{pre2004})\right), \quad (6)$$

where $\mathrm{S}_{t,k}$ refers to the standardized announcement surprises, which enter with absolute values because we hypothesize that cojumps are related to larger surprises of either sign. $\mathrm{SD}_{t,k}$ is the cross-sectional standard deviation of analysts' expectations regarding the announcements, which is normalized by its own time-series sample standard deviation. Haver Analytics provides the dispersion data. Due to data constraints, the analysis spans a narrower sample period covering April 1, 2004 to December 31, 2013 and there is no dispersion data for the FED because the expectation is implied from the Federal Funds futures contracts rather than from surveys.[23] The $\mathrm{I}(\mathrm{A}_t=1)$

[23] As a robustness test, we repeat the analysis of Equation (6) by using two proxies for interest rate uncertainty on Federal Funds rate announcement days. The two proxies are the Bank of America–Merrill Lynch Option Volatility Estimate (MOVE) index and the implied volatility of three-month Eurodollar interest rates to proxy the Federal Funds rate uncertainty. Neely (2005) finds that the three-month Eurodollar rates closely track the Federal Funds rates from 1986 to

dichotomous dummy variable is equal to 1 on generic announcement days and 0 otherwise; this allows for different baseline hazard rates on announcement day ($\alpha_i^{all} + \alpha_i^{A}$) versus non-announcement days (α_i^{all}).[24] The variable α_i^{A} measures the difference in these baseline rates.[25]

< Insert Table 4 here >

Table 4 reports the key parameter estimates of Equation (6). Statistical inference is drawn from the Kilian and Vega (2011) Monte-Carlo simulation procedure, as described above, with two minor adjustments. First, the release dates of the news shocks in the simulations for Equation (6) are set exogenously as given by the actual release dates. This maintains the unique features and interaction of different news arrivals. Second, the $SD_{t,k}$ independent variables in the simulations are bootstrapped (with replacement) from the actual dispersion data to maintain positivity of the data.

The left portion of Table 4 shows that systematic cojumps of different portfolios react differently to macroeconomic news surprises. FED news surprises are clearly the most influential as the coefficients are statistically significant for every portfolio and always the largest for each portfolio. The average $\hat{\beta}_{\text{B/M,FED}}$ and $\hat{\beta}_{size\text{,FED}}$ are 0.32 and 0.33, respectively. In contrast, the other macroeconomic variables have mostly insignificant effects (at the 5% level) on the cojumps, although the PPI and ISM have a few significant coefficients. These include the NFP, which has

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2001 and the implied volatility of the three-month Eurodollar rates reasonably measures uncertainty of the Federal Funds rates. The results using the MOVE index and implied volatility of the three-month Eurodollar rates, reported in the Internet Appendices, are similar to those reported in Table 4.

[24] We gratefully acknowledge an anonymous referee for alluding to this issue.

[25] We jointly estimate the impact of the news surprise ($S_{t,k}$) and dispersion ($SD_{t,k}$) variables although they are not strongly correlated. Unfortunately, the sample period for the dispersion data is much shorter than that of the news surprise data. As such, we include the $I(A_t = 1|\text{pre2004})$ dummy variable, which is equal to 1 on generic announcement days prior to April 2004 and 0 thereafter, in Equation (6) to compensate for missing values in the shorter dispersion sample period. One might be concerned that the missing dispersion data bias the regression estimates. To alleviate this concern, we compare the results reported herein (which use a longer sample period with a compensation for missing dispersion values via the $I(A_t = 1|\text{pre2004})$ dummy variable) to the shorter, common sample that spans from April 2004 to December 2013. The unreported results (especially for the $\gamma_{i,k}$ coefficents) based on the shorter sample period are basically consistent with those reported herein, but the longer sample permits more precise estimates of the regression coefficients. Full results are available from the authors upon request.

been previously shown to be one of the most influential macroeconomic announcements in affecting U.S. financial asset returns (Andersen and Bollerslev, 1998; Wongswan, 2006; Cenesizoglu, 2011).[26]

The right portion of Table 4 suggests that the dispersion of analysts' expectations regarding the macroeconomic variables has only a limited impact on cojumps. The $\beta_{i,\mathrm{NFP}}$ ($\beta_{i,\mathrm{ISM}}$) estimates are statistically significantly positive in only three (two) out of ten B/M-sorted portfolios in BM3, BM6 and BM9. In other words, a heightening of disagreements among market participants regarding NFP and ISM forecasts raises systematic cojump probabilities in several of the B/M sorted portfolios. Overall, this finding weakly supports the hypothesis that greater dispersion of announcement expectations tends to spur systematic cojumps.

The penultimate column of Table 4 reports the α_i^A increment announcement day baseline hazard rate effect. That is, α_i^A estimates the difference between the baseline cojump hazard rate and the baseline rate on days of announcements. Although the estimates are mostly positive and insignificant (at the 5% level) for the B/M-deciled portfolios, they are all positive and occasionally significant (at the 5% level) for the size-deciled portfolios, with $\alpha_{\mathrm{B/M}}^A$ and α_{size}^A averaging 0.08 and 0.16, respectively.

4.4. Testing hypothesis H.2

Equation (6) gauges the reaction of systematic cojumps to announcement surprises. As discussed in Section 2, research by Vonk (1996) and Barberis et al. (1998) implies that the jump reaction depends not merely on the magnitude but also on the sign of the announcement surprise. To accommodate this, we modify Equation (6) to separately model the cojump probability as a function of positive and negative announcement surprises:

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[26] Our finding is also consistent with the prior empirical work of Bernanke and Blinder (1992) that shows that the Federal Funds rate, as a measure of monetary policy, is an excellent reduced-form predictor of unemployment and inflation, since shocks to the Federal Funds rate feed to and affect the real economy.

$$\Pr(J_{i,t}=1)=\Phi\left(....+\sum_{k}^{5}\left(\beta_{i,k}^{+}S_{t,k}I_{t,k}^{+}+\beta_{i,k}^{-}\left|S_{t,k}\right|I_{t,k}^{-}\right)+....\right), \tag{7}$$

where $I_{t,k}^{+}$ ($I_{t,k}^{-}$) is equal to one if the news surprise for variable *k* is positive (negative) on day *t* and zero otherwise, $\beta_{i,k}^{+}$ ($\beta_{i,k}^{-}$) measures the jump probability reaction to positive (absolute negative) standardized announcement surprise and all other variables are defined as in Equation (6). A positive or negative surprise could represent 'good' or 'bad' news and the interpretation of 'good' or 'bad' news depends on the type of macroeconomic variable. FED, UNE, and PPI surprises are deemed 'bad' if the surprise is positive (i.e., when $A_{t,k} > F_{t,k}$); otherwise, they are categorized as 'good'. NFP and ISM surprises are deemed 'good' if nonfarm payroll or ISM index was surprisingly higher than expected; otherwise, they are classified as 'bad.'

< Insert Table 5 here >

Panel A of Table 5 reports the $\beta_{i,k}^{+}$ and $\beta_{i,k}^{-}$ estimates, with other estimated coefficients are suppressed since they are qualitatively similar to those reported in Table 4. It is evident from the panel that systematic cojumps respond heterogeneously to 'good' versus 'bad' news. Remarkably, worse-than-expected FED news (i.e., when the Federal Funds target rate is unexpectedly high) has the strongest positive relationship with systematic cojump occurrences. Positive ('bad') FED news surprises have larger effects on the likelihood of systematic cojumps than do negative ('good') FED news surprises. The column labelled "FED" in Panel B of Table 5 shows that 4 of these 20 differences are statistically significant at the 5 percent level. Therefore, our finding is consistent with hypothesis H.2 that unexpectedly 'bad' FED news affects systematic cojump probability more than surprisingly 'good' FED news.

The asymmetric impacts of PPI and ISM news on the size-deciled portfolios further support this conjecture that bad news is more likely to cause cojumps. The average $\beta_{\text{size,PPI}}^{+}$ ($\beta_{\text{size,ISM}}^{-}$) is 0.25

(0.21), suggesting that bad PPI (ISM) news is associated with unreported systematic cojump probability increase of 3.12% (4.83%) (not reported in the table) relative to the long-run unconditional jump probability, holding other variables to zero. Their individual $\beta^{+}_{i,\text{PPI}}$ $(\beta^{-}_{i,\text{ISM}})$ estimates are statistically significant in seven (four) out of ten size-deciled portfolios and their signs are also consistently positive, as hypothesized. On the contrary, their $\beta^{-}_{i,\text{PPI}}$ $(\beta^{+}_{i,\text{ISM}})$ counterparts, which are associated with good PPI (ISM) news, are all statistically insignificant, have negative sign in a number of cases and are substantially lower in magnitude. In other words, unexpectedly good PPI and ISM news is associated with lower (but statistically insignificant) probabilities of systematic cojumps. Finally, the table shows that good news about NFP often has a positive and statistically significant effect on systematic cojumps, very likely because such news increases the likelihood of future interest rate increases. The coefficient estimates for UMP are never statistically significant but those for bad news are nearly uniformly larger than those for good news.

Panel B of Table 5 reports the difference between the estimated slope coefficients of bad and good news of Equation (7). Hypothesis H.2 implies that $\hat{\beta}^{\text{bad}}_{i,k} - \hat{\beta}^{\text{good}}_{i,k} > 0$ i.e., a standardized unit of bad macroeconomic news increases the likelihood of systematic cojumps more often than a standardized unit of good macroeconomic news. With the exception of the NFP, Panel B supports this hypothesis; almost all of the differences in $\hat{\beta}^{\text{bad}}_{i,k} - \hat{\beta}^{\text{good}}_{i,k}$ are positive. Panel B reveals that the differences in $\hat{\beta}^{\text{bad}}_{i,\text{FED}} - \hat{\beta}^{\text{good}}_{i,\text{FED}}$ are significantly different from zero (at the 5% level) in four out of 20 portfolios, using Wald tests. For the NFP (PPI) coefficients, there are 15 (seven) statistically significant differences, at the 10% level, among the twenty cases. We conclude that the more important macroeconomic announcements appear to have asymmetric effects on the likelihood of systematic cojumps.

Finally, the rightmost column of Table 5 displays results from likelihood ratio tests (LRTs) of the null that the restriction to the symmetric model is appropriate. That is, a high test statistic rejects the joint null hypothesis of symmetric coefficients. For the B/M (size) portfolios, there are three (five) significant tests among the ten portfolios, providing mixed support for asymmetry. Not surprisingly, the rejections from the LRTs are correlated with rejections from the Wald tests in Panel B of Table 5 that the difference in the good-bad coefficients are zero.

4.5. Testing hypothesis H.3

The previous sub-sections analyzed the effect of macroeconomic announcements on the likelihood of systematic cojumps. This sub-section examines the macroeconomic news surprise impact on the *magnitude* of those systematic cojumps by estimating the following Tobit regression:

$$Y_{i,t}^* = \alpha_i^{all} + \alpha_i^A \cdot I(A_t = 1) + \sum_k^5 \beta_{i,k} \left| S_{t,k} \right| + \sum_{k \neq FED}^4 \gamma_{i,k} SD_{t,k} + \lambda_i^A \cdot I(A_t = 1 \mid pre2004) + \varepsilon_{i,t}, \quad (8)$$

where $\varepsilon_{i,t} \sim N(0, \sigma_i)$, and

$$Y_{i,t} = \begin{cases} r_{i,t}^* & \text{if } Y_{i,t}^* > 0 \\ 0 & \text{if } Y_{i,t}^* \leq 0 \end{cases}, \quad (9)$$

where $Y_{i,k}^*$ is the latent cojump magnitude and $Y_{i,t}$ is the observed magnitude of systematic cojumps, which is defined as $|r_{i,t}| \times |r_{MKT,t}|$.

Given that we found some evidence of asymmetry in the probit structure, we also considered whether an asymmetric Tobit structure was appropriate. That is, we estimated a version of Equation (8) in which the coefficients on news were allowed to take different values for positive and negative news. Likelihood ratio tests failed to reject the restriction to a symmetric relationship for 16 of the 20 cases at the 10 percent level, however. Therefore, we decided that the mixed evidence favoured the symmetric structure and we report those results.

< Insert Table 6 here >

Table 6 reports the symmetric Tobit results that confirm a strong FED news surprise effect on the magnitude of systematic cojumps. In particular, the $\beta_{i,\text{FED}}$ coefficient has the expected positive sign and is statistically significant in all portfolios, with a mean coefficient estimate of 6.83 and 6.23 for B/M and size-deciled portfolios, respectively. Although we omit the results for brevity, the cross-section mean of the marginal effect (evaluated at the mean of the explanatory variable) of FED news surprise is 0.48 for B/M-deciled portfolios, and 0.46 for size-deciled portfolios. That is, these estimates suggest that a one standard deviation FED news surprise is associated with nearly 50 basis point increase in the magnitude of cojumps. On the other hand, the coefficients on the other macroeconomic news are mostly insignificant at the 5% level.

The right-hand panel of Table 6 displays the coefficients on the standard deviations of survey responses about announcement expectations, that is, the heterogeneity among investors. Again, there is no measure of heterogeneity for the FED variable because the Federal Funds futures market, not a survey, provides the expectation of the FED announcement.[27] Among these SD variables, uncertainty about NFP payrolls and the ISM release often raise the magnitude of systematic cojumps in a statistically significant way.

5. Concluding remarks

This paper defines systematic cojumps as common bivariate jumps in price covariation between the market index and its component portfolios delineated by size and B/M price ratio. These bivariate jumps are distinctively different from price jumps identified separately across individual assets as commonly studied in the existing literature. For each style-sorted portfolio, we estimate systematic cojumps using an adaptation of the nonparametric multivariate jump detection technique of Boudt et al. (2011), thus mitigating the potential type II error specified by Gnabo et al. (2014).

[27] As with Table 4, we tried using the MOVE measure of implied volatility for interest rates to proxy for the different concept of dispersion of forecasts and found that inclusion of that variable did not substantially change the results in Table 6.

We use these estimated cojumps to answer two questions: How often does the market portfolio cojump with B/M and size portfolios and how do these systematic cojumps react to scheduled macroeconomic announcements?

We show that systematic cojumps are prevalent in portfolios sorted on B/M price ratio, averaging about 20 systematic cojumps per year. This is bad news for domestic investors and asset managers interested in 'growth-value' style rotation strategies, since our finding suggests that they cannot simply avoid systematic cojump risk by investing in growth or value stocks, as systematic cojumps are approximately equally prevalent in each. We also find that large-cap stocks cojump with the market much less than do small-cap stocks, however, suggesting that the former mitigate cojump exposure more usefully than the latter. This finding is thus of interest to investors who seek to avoid or minimize systematic cojump risk.

We then study the relationship between the identified systematic cojumps and scheduled announcements emanating from five key macroeconomic variables: the Federal Funds target rate, nonfarm payroll, unemployment rate, producer price index and the Institute for Supply Management index. We examine the relation of these news surprises and the heterogeneity in expectations to both systematic cojump intensity and systematic cojump amplitude.

The robust probit and Tobit regression results reveal that Federal Funds target news is by far the most dominant factor in affecting both systematic cojump attributes. Interestingly, the nonfarm payroll statistic, which has been shown in previous studies to be one of the most influential scheduled macroeconomic announcements in affecting U.S. financial asset returns, has only a modest impact on systematic cojumps. In addition, consistent with the notion that bad news tends to produce more uncertainty and thus larger price revisions or jumps, than does good news, we demonstrate that positive Federal Funds shocks (i.e., surprise interest rate increases) are more influential than their negative counterparts in increasing the probability of systematic cojumps. Finally, we find that bad

PPI and ISM news affects systematic cojump probability of occurrence more than does good PPI and ISM news, but the dispersion of analysts' expectations for NFP and ISM releases has only a modest effect on systematic cojump intensity and amplitude.

Identifying circumstances where cojumps occur is useful to investors and portfolio managers for diversification purposes. The striking explanatory power of the Federal Funds rate for systematic cojumps in all the style-sorted portfolios supports the arguments of Bollerslev et al. (2008) and Gilder et al. (2014) that scheduled macroeconomic announcements drive common jumps across the market portfolio's underlying components. From a practical perspective, investors and portfolio managers searching for factors to explain systematic cojumps should consider particularly the Federal Funds rate. At the same time, however, our finding also suggests that investors exhibit caution when considering systematic cojump-avoidance strategies because systematic cojumps are not immune to the macroeconomic risk related to the Federal Funds rate.

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Table 1: Descriptive statistics for stock portfolios and macroeconomic variables

Panel A reports summary statistics (sample mean, robust standard error adjusted for heteroscedasticity and autocorrelation, skewness, excess kurtosis and *p*-value of the Jacque-Bera normality test) of the daily continuously compounded returns of B/M and size portfolios . The daily portfolio returns are expressed in percentages. The 'Avg' estimates refer to the row average of all the figures in the respective columns. The top portion of Panel B reports descriptive statistics of macroeconomic variables, with the number of announcement surprises is lower than the total number of announcements due to zero news surprises. The bottom portion of Panel B reports the number of concurrent announcement days between different macroeconomic variables. The sample period covers from January 2, 1986 to December 31, 2013.

	Mean (x100)	Std error (x100)	Skewness	Excess kurtosis	Jacque-Bera
BM1	3.78	1.41	–0.60	13.48	< 0.001
BM2	4.15	1.33	–0.85	17.11	< 0.001
BM3	4.46	1.29	–1.09	23.20	< 0.001
BM4	4.12	1.35	–1.26	22.25	< 0.001
BM5	4.18	1.31	–0.92	21.80	< 0.001
BM6	3.95	1.33	–0.80	14.32	< 0.001
BM7	4.47	1.26	–1.14	23.03	< 0.001
BM8	4.04	1.35	–1.20	28.05	< 0.001
BM9	4.64	1.37	–1.16	19.96	< 0.001
BM10	4.90	1.62	–0.87	13.73	< 0.001
Avg	*4.27*	*1.36*	*–0.99*	*19.69*	< 0.001
S1	3.79	1.35	–1.19	13.23	< 0.001
S2	3.70	1.56	–0.63	9.59	< 0.001
S3	4.24	1.54	–0.64	7.98	< 0.001
S4	3.75	1.52	–0.65	8.70	< 0.001
S5	4.27	1.51	–0.61	7.89	< 0.001
S6	4.47	1.42	–0.75	10.41	< 0.001
S7	4.63	1.41	–0.86	12.96	< 0.001
S8	4.37	1.42	–0.81	13.80	< 0.001
S9	4.44	1.34	–1.03	19.98	< 0.001
S10	3.86	1.27	–-1.13	24.88	< 0.001
Avg	*4.15*	*1.43*	*–0.83*	*12.94*	< 0.001

Panel A: Stock portfolios

	FED	NFP	UMP	PPI	ISM
Units of measurement	%	in thousand	%	mth-to-mth Δ (in %)	index
# of ancts	221	329	329	332	286
# of anct surprises	123	328	245	286	285
Mean of unstdized anct surprises	–0.026	–11.03	–0.035	–0.024	0.026
Stdev of unstdized anct surprises	0.097	104.20	0.158	0.400	2.039
Mean of stdized anct surprises	–0.271	–0.106	–0.218	–0.061	0.013

	FED	NFP/UMP	PPI	ISM
FED	–			
NFP/UMP	9	–		
PPI	8	1	–	
ISM	5	19	1	–

Panel B: Macroeconomic variables

Table 2: Correlations between cojump indicators

The table displays correlations between indicator variables for the bivariate cojumps. Panel A displays results for the B/M portfolios while Panel B displays results for the size portfolios. The portfolios are as in Figure 3, with the exception of the “sum” portfolios, which is the sum of the indicator variables for the other 10 portfolios.

BM2	BM3	BM4	BM5	BM6	BM7	BM8	BM9	BM10	sum	
0.46	0.48	0.50	0.51	0.53	0.51	0.51	0.51	0.50	0.75	BM1
	0.47	0.46	0.45	0.48	0.47	0.47	0.46	0.46	0.71	BM2
		0.48	0.46	0.48	0.49	0.50	0.51	0.48	0.73	BM3
			0.48	0.50	0.46	0.45	0.47	0.45	0.72	BM4
				0.47	0.47	0.47	0.46	0.44	0.71	BM5
					0.48	0.48	0.48	0.47	0.74	BM6
						0.51	0.52	0.46	0.73	BM7
							0.52	0.49	0.74	BM8
								0.50	0.74	BM9
									0.72	BM10

Panel A: B/M portfolios

S2	S3	S4	S5	S6	S7	S8	S9	S10	sum	
0.68	0.61	0.58	0.57	0.54	0.51	0.50	0.44	0.57	0.76	S1
	0.73	0.70	0.65	0.59	0.54	0.53	0.47	0.59	0.83	S2
		0.71	0.69	0.62	0.56	0.53	0.46	0.61	0.83	S3
			0.70	0.63	0.57	0.54	0.46	0.61	0.83	S4
				0.67	0.57	0.54	0.44	0.62	0.82	S5
					0.62	0.56	0.46	0.66	0.81	S6
						0.59	0.50	0.65	0.77	S7
							0.51	0.61	0.75	S8
								0.51	0.66	S9
									0.82	S10

Panel B: Size portfolios

Table 3: Results for individual probit Equation (5)

The table reports the estimated slope coefficient $\beta_{i,k}$ of Equation (5) when tested on B/M and size portfolios. The $\partial\Phi/\partial S_k$ column reports the incremental change in systematic cojump probability (expressed in percentages) implied by the estimated slope coefficient relative to the unconditional probability of observing a jump implied by the corresponding untabulated intercept estimate of the equation. The slope and $\partial\Phi/\partial S_k$ estimates are highlighted in bold if the null hypothesis (H_0: $\beta_{i,k} = 0$) is rejected in favor of the alternative hypothesis (H_A: $\beta_{i,k} > 0$) at the one-tailed 5% level of significance, which is drawn from simulated robust critical values constructed from a Monte-Carlo simulation procedure. The R^2 column reports pseudo-R^2 statistics (expressed in percentages) of the actual data, which are highlighted in bold if they are higher than the 95% optimal cut-off R^2 obtained from the Monte-Carlo simulation procedure. The 'Avg' estimates refer to the row average of all the figures in the respective columns. The sample period covers from January 2, 1986 to December 31, 2013.

	FED			NFP			UMP			PPI			ISM		
	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2
BM1	**0.38**	**[6.42]**	**8.8**	0.11	[1.72]	0.3	0.04	[0.62]	0.0	0.08	[1.20]	0.1	0.00	[0.05]	0.0
BM2	**0.33**	**[7.08]**	**6.6**	-0.01	[-0.26]	0.0	0.21	[3.32]	1.0	0.10	[1.59]	0.3	0.15	[2.61]	0.5
BM3	**0.34**	**[4.88]**	**8.5**	0.08	[1.20]	0.2	0.12	[1.68]	0.3	0.07	[1.22]	0.1	-0.02	[-0.37]	0.0
BM4	**0.31**	**[5.91]**	**5.9**	0.15	[2.47]	0.6	0.11	[1.92]	0.3	0.18	[2.89]	0.8	-0.03	[-0.56]	0.0
BM5	**0.45**	**[7.71]**	**11.6**	0.11	[1.53]	0.3	0.06	[0.89]	0.1	0.15	[2.16]	0.6	-0.04	[-0.61]	0.0
BM6	**0.33**	**[6.44]**	**6.7**	0.10	[1.58]	0.3	0.09	[1.40]	0.2	0.14	[2.32]	0.5	-0.08	[-1.55]	0.1
BM7	**0.33**	**[5.67]**	**7.0**	0.11	[1.60]	0.3	0.06	[0.89]	0.1	0.05	[0.77]	0.1	-0.06	[-0.90]	0.1
BM8	**0.45**	**[7.61]**	**11.2**	0.21	[2.92]	1.3	0.09	[1.29]	0.2	0.09	[1.51]	0.2	-0.09	[-1.57]	0.1
BM9	**0.31**	**[5.02]**	**6.3**	0.17	[3.04]	0.7	0.06	[1.19]	0.1	0.04	[0.66]	0.0	-0.16	[-2.86]	0.5
BM10	**0.24**	**[4.61]**	**3.5**	0.11	[1.60]	0.3	0.09	[1.29]	0.2	0.13	[2.04]	0.5	0.25	[4.11]	1.3
Avg	*0.35*	*[6.13]*	*7.6*	*0.11*	*[1.74]*	*0.4*	*0.09*	*[1.45]*	*0.3*	*0.10*	*[1.63]*	*0.3*	*-0.01*	*[-0.16]*	*0.3*
S1	**0.28**	**[6.22]**	**4.6**	0.16	[2.31]	0.7	0.13	[1.97]	0.4	0.09	[1.17]	0.2	-0.08	[-1.71]	0.1
S2	**0.35**	**[6.98]**	**7.5**	0.18	[2.43]	0.9	0.13	[1.80]	0.5	0.09	[1.49]	0.2	0.01	[0.14]	0.0
S3	**0.33**	**[6.12]**	**7.0**	0.16	[2.22]	0.7	0.12	[1.66]	0.3	0.11	[1.74]	0.3	0.07	[1.40]	0.1
S4	**0.33**	**[6.74]**	**6.9**	0.12	[1.75]	0.4	0.07	[0.96]	0.1	0.14	[2.26]	0.5	0.08	[1.62]	0.1
S5	**0.54**	**[11.51]**	**13.3**	0.15	[2.29]	0.6	0.19	[2.85]	1.0	0.05	[0.71]	0.1	0.06	[1.21]	0.1
S6	**0.30**	**[5.63]**	**5.7**	0.11	[1.84]	0.3	0.23	[3.46]	1.3	-0.05	[-0.79]	0.1	0.10	[2.03]	0.2
S7	**0.30**	**[5.79]**	**5.6**	0.12	[1.87]	0.3	0.18	[2.81]	0.8	0.08	[1.36]	0.2	0.15	[2.99]	0.5
S8	**0.32**	**[5.98]**	**6.6**	0.05	[0.80]	0.1	0.07	[1.14]	0.1	0.16	[2.45]	0.7	0.21	[4.41]	0.9
S9	**0.22**	**[4.11]**	**3.0**	0.13	[2.02]	0.4	0.14	[2.14]	0.5	0.02	[0.31]	0.0	0.07	[1.41]	0.1
S10	**0.27**	**[5.41]**	**4.4**	0.16	[2.27]	0.6	0.16	[2.28]	0.6	0.07	[0.98]	0.1	0.17	[3.08]	0.6
Avg	*0.33*	*[6.45]*	*6.5*	*0.13*	*[1.98]*	*0.5*	*0.14*	*[2.11]*	*0.6*	*0.07*	*[1.17]*	*0.2*	*0.08*	*[1.66]*	*0.3*

Table 4: Results for symmetric probit Equation (6)

The table reports the key coefficient estimates of Equation (6) when tested on B/M and size portfolios. The estimates are highlighted in bold if the null hypothesis is rejected in favor of the alternative hypothesis at the one-tailed 5% level of significance, which is drawn from simulated robust critical values constructed from a Monte-Carlo simulation procedure. The R^2 column reports pseudo-R^2 statistics (expressed in percentages) of the actual data, which are highlighted in bold if they are higher than the 95% optimal cut-off R^2 obtained from the Monte-Carlo simulation procedure. The 'Avg' estimates refer to the row average of all the figures in the respective columns. The sample period covers from January 2, 1986 to December 31, 2013.

	$\beta_{i,k}$					$\gamma_{i,k}$				α_i^A	R^2
	FED	NFP	UMP	PPI	ISM	NFP	UMP	PPI	ISM		
BM1	**0.33**	0.04	0.03	0.17	0.11	0.24	-0.16	-0.18	-0.01	0.07	**0.5**
BM2	**0.35**	-0.10	0.19	0.08	0.07	0.09	-0.07	-0.01	0.07	-0.01	**0.9**
BM3	**0.27**	-0.02	0.09	0.06	0.06	**0.29**	-0.16	0.12	**0.14**	-0.12	**0.7**
BM4	**0.30**	0.07	0.11	**0.24**	0.02	0.17	-0.18	-0.17	0.07	0.17	**0.8**
BM5	**0.43**	0.05	0.06	0.16	0.05	0.20	-0.17	-0.09	0.01	0.16	**0.7**
BM6	**0.32**	0.01	0.11	**0.20**	0.03	**0.35**	-0.32	-0.19	0.01	0.22	**0.8**
BM7	**0.31**	0.04	0.07	0.07	-0.06	0.27	-0.24	-0.01	0.04	0.11	0.5
BM8	**0.39**	0.09	0.04	0.16	-0.02	0.20	-0.18	-0.06	0.06	0.09	**0.7**
BM9	**0.27**	0.14	0.08	0.17	-0.23	**0.34**	-0.17	0.00	**0.19**	-0.09	**0.9**
BM10	**0.26**	0.02	0.03	**0.24**	**0.21**	0.12	-0.11	-0.27	-0.03	0.23	**0.7**
Avg	*0.32*	*0.03*	*0.08*	*0.15*	*0.02*	*0.23*	*-0.18*	*-0.09*	*0.05*	*0.08*	*0.7*
S1	**0.32**	0.00	0.08	0.02	0.08	**0.32**	-0.31	-0.16	0.04	0.14	**0.7**
S2	**0.35**	0.00	0.02	0.10	0.09	0.20	-0.16	-0.01	0.05	0.03	**0.6**
S3	**0.33**	0.05	0.07	0.17	0.18	0.17	-0.16	-0.09	0.00	0.07	0.5
S4	**0.35**	0.04	0.01	0.18	**0.20**	-0.24	0.03	-0.15	0.00	0.24	**0.8**
S5	**0.56**	0.02	0.11	0.15	0.18	-0.25	0.04	-0.24	-0.04	0.28	**1.2**
S6	**0.29**	-0.01	0.12	0.09	0.18	0.07	-0.05	-0.18	0.04	0.11	**0.7**
S7	**0.31**	0.04	0.10	0.16	0.17	-0.05	0.00	-0.10	0.03	0.21	**0.8**
S8	**0.31**	0.03	0.12	0.15	**0.27**	-0.06	-0.03	-0.08	0.05	0.07	**1.0**
S9	**0.22**	0.05	0.13	0.02	0.10	0.06	-0.17	-0.01	0.05	**0.27**	**0.8**
S10	**0.30**	0.04	0.09	0.09	0.17	-0.02	-0.08	-0.15	0.00	0.16	0.5
Avg	*0.33*	*0.03*	*0.08*	*0.11*	*0.16*	*0.02*	*-0.09*	*-0.12*	*0.02*	*0.16*	*0.8*

Table 5: Results for asymmetric probit Equation (7)

Panel A reports the $\beta^{+}_{i,k}$ and $\beta^{-}_{i,k}$ slope coefficients estimated from Equation (7) when tested on B/M and size portfolios. The estimates are highlighted in bold if the null hypothesis (H_0: $\beta_{i,k} = 0$) is rejected in favor of the alternative hypothesis (H_A: $\beta_{i,k} > 0$) at the one-tailed 5% level of significance, which is drawn from simulated robust critical values constructed from a Monte-Carlo simulation procedure. Panel B reports $\beta^{bad}_{i,k} - \beta^{good}_{i,k}$ and performs a Wald test on whether the difference is statistically different from zero (F-statistics are not presented). Panel C reports pseudo-R^2 statistics (expressed in percentages) of the actual data, which are highlighted in bold if they are higher than the 95% optimal cut-off R^2 obtained from the Monte-Carlo simulation procedure, and the log-likelihood ratio test (LRT) statistics between Equations (6) and (7). The asterisks *, ** and *** in Panels B and C denote significances at the 10%, 5% and 1% levels, respectively. The 'Avg' estimates refer to the row average of all the figures in the respective columns. The sample period covers from January 2, 1986 to December 31, 2013.

	Panel A										Panel B					Panel C	
	FED		NFP		UMP		PPI		ISM		FED	NFP	UMP	PPI	ISM		
Coef	$\beta^{+}_{i,k}$	$\beta^{-}_{i,k}$	$\beta^{-}_{i,k}$	$\beta^{+}_{i,k}$	$\beta^{+}_{i,k}$	$\beta^{-}_{i,k}$	$\beta^{+}_{i,k}$	$\beta^{-}_{i,k}$	$\beta^{-}_{i,k}$	$\beta^{+}_{i,k}$	$\beta^{+}_{i,k}-\beta^{-}_{i,k}$	$\beta^{-}_{i,k}-\beta^{+}_{i,k}$	$\beta^{+}_{i,k}-\beta^{-}_{i,k}$	$\beta^{+}_{i,k}-\beta^{-}_{i,k}$	$\beta^{-}_{i,k}-\beta^{+}_{i,k}$	R^2	LRT
Type	Bad	Good	Bad	Good	Bad	Good	Bad	Good	Bad	Good	Diff	Diff	Diff	Diff	Diff		
BM1	**0.57**	**0.33**	-0.26	**0.25**	0.10	-0.01	**0.33**	-0.02	0.14	0.09	0.24	-0.51 **	0.11	0.35 *	0.05	**0.8**	10.5 *
BM2	**0.50**	**0.37**	-0.40	0.10	0.23	0.18	0.18	-0.04	0.11	0.04	0.13	-0.50 **	0.05	0.22	0.06	**1.1**	7.5
BM3	0.50	**0.27**	-0.21	0.13	0.10	0.08	0.18	-0.08	0.08	0.05	0.23	-0.34 *	0.02	0.26	0.03	**0.8**	5.3
BM4	**0.97**	**0.26**	-0.09	**0.24**	0.19	0.06	**0.45**	0.03	0.14	-0.10	0.71 **	-0.33 *	0.13	0.42 **	0.24	**1.2**	15.9 ***
BM5	**0.71**	**0.44**	-0.18	**0.25**	0.14	0.00	0.22	0.12	0.10	0.00	0.27	-0.43 **	0.14	0.10	0.10	**0.9**	5.9
BM6	**0.74**	**0.31**	-0.12	0.14	0.08	0.13	**0.36**	0.07	0.04	0.05	0.44	-0.26	-0.05	0.29	-0.01	**1.0**	6.6
BM7	**0.56**	**0.29**	-0.10	0.16	0.20	-0.06	**0.24**	-0.18	0.01	-0.15	0.26	-0.26	0.25	0.42 **	0.16	0.7	8.7
BM8	**0.65**	**0.37**	-0.04	0.23	0.12	-0.04	0.25	0.08	0.07	-0.11	0.28	-0.26	0.16	0.17	0.18	**0.8**	4.7
BM9	**0.84**	**0.24**	-0.04	**0.32**	0.16	0.01	**0.35**	-0.03	-0.12	-0.34	0.61 **	-0.36 **	0.15	0.38 **	0.22	**1.3**	13.5 **
BM10	0.34	**0.27**	-0.20	0.19	0.12	-0.04	**0.28**	0.20	**0.32**	0.04	0.07	-0.39 *	0.15	0.08	0.28	**0.9**	6.4
Avg	*0.64*	*0.31*	*-0.16*	*0.20*	*0.14*	*0.03*	*0.28*	*0.01*	*0.09*	*-0.04*	*0.32*	*-0.36*	*0.11*	*0.27*	*0.13*	*1.0*	*8.50*
S1	**0.70**	**0.30**	-0.19	0.17	0.19	-0.01	0.12	-0.06	0.16	0.00	0.40	-0.36 *	0.20	0.18	0.16	**0.8**	7.3
S2	**0.46**	**0.36**	-0.24	0.20	0.13	-0.05	0.22	-0.04	0.08	0.10	0.09	-0.44 **	0.18	0.26	-0.03	**0.8**	7.3
S3	**0.74**	**0.31**	-0.13	0.21	0.15	0.01	**0.34**	-0.01	**0.27**	0.09	0.43	-0.34 *	0.15	0.34 *	0.19	**0.7**	9.7 *
S4	**0.92**	**0.32**	-0.17	**0.25**	0.14	-0.08	**0.27**	0.13	**0.26**	0.16	0.60 **	-0.42 **	0.22	0.14	0.10	**1.1**	10.2 *
S5	**0.99**	**0.52**	-0.14	0.19	0.21	0.03	**0.31**	-0.01	**0.27**	0.10	0.48	-0.33 *	0.19	0.33	0.17	**1.4**	9.4 *
S6	**0.84**	**0.26**	-0.19	0.16	0.20	0.07	**0.27**	-0.09	0.21	0.18	0.58 *	-0.35 *	0.13	0.36 *	0.03	**1.0**	10.2 *
S7	**0.73**	**0.29**	-0.17	**0.23**	0.22	0.01	**0.25**	0.10	0.14	0.22	0.43	-0.40 **	0.21	0.15	-0.08	**1.0**	8.1
S8	**0.76**	**0.29**	-0.12	0.19	0.21	0.06	**0.28**	0.03	**0.35**	0.20	0.47	-0.30	0.15	0.25	0.15	**1.2**	7.9
S9	0.48	**0.20**	-0.07	0.16	0.20	0.07	0.16	-0.15	0.18	0.00	0.28	-0.23	0.13	0.31	0.18	**1.0**	6.1
S10	**1.16**	**0.24**	-0.12	**0.23**	0.12	0.09	**0.30**	-0.10	0.18	0.22	0.92 ***	-0.34 *	0.03	0.40 *	-0.03	**0.9**	16.5 ***
Avg	*0.78*	*0.31*	*-0.15*	*0.20*	*0.18*	*0.02*	*0.25*	*-0.02*	*0.21*	*0.13*	*0.47*	*-0.35*	*0.16*	*0.27*	*0.08*	*1.0*	*9.28*

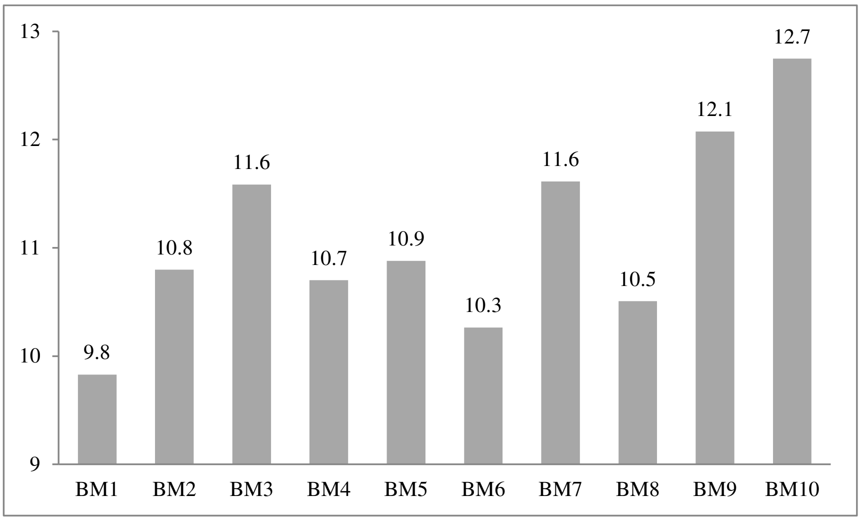
Table 6: Results for symmetric Tobit Equation (8)

The table reports the key coefficient estimates of Equation (8) when tested on B/M and size portfolios. The estimates are highlighted in bold if the null hypothesis is rejected in favor of the alternative hypothesis at the one-tailed 5% level of significance, which is drawn from simulated robust critical values constructed from a Monte-Carlo simulation procedure. The R^2 column reports pseudo-R^2 statistics (expressed in percentages) of the actual data, which are highlighted in bold if they are higher than the 95% optimal cut-off R^2 obtained from the Monte-Carlo simulation procedure. The 'Avg' estimates refer to the row average of all the figures in the respective columns. The sample period covers from January 2, 1986 to December 31, 2013.

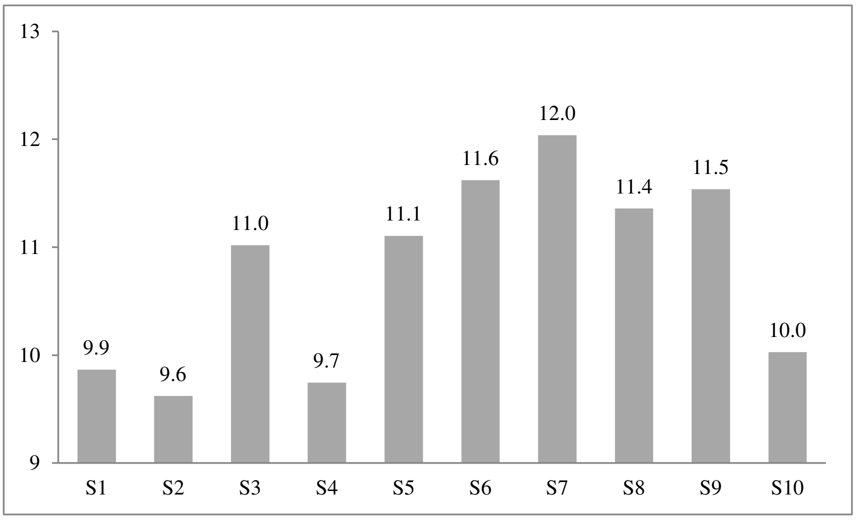
	$\beta_{i,k}$					$\gamma_{i,k}$				α_i^A	R^2
	FED	NFP	UMP	PPI	ISM	NFP	UMP	PPI	ISM		
BM1	**7.25**	1.17	0.33	3.67	1.92	5.42	-3.67	-4.01	-0.15	0.90	0.3
BM2	**7.42**	-1.28	3.21	2.13	1.23	1.84	-1.45	-0.60	1.52	-0.34	0.4
BM3	**7.22**	-0.16	1.56	0.16	0.92	**7.14**	-4.00	3.70	**3.30**	-2.91	0.3
BM4	**6.52**	2.17	2.29	**5.10**	0.37	4.38	-4.28	-3.60	1.46	3.02	0.4
BM5	**7.95**	1.72	1.03	3.65	-0.69	5.07	-3.93	-1.72	1.72	2.34	0.3
BM6	**6.19**	0.84	2.05	4.33	0.73	**7.10**	-6.68	-4.09	0.14	4.43	0.4
BM7	**6.35**	1.39	1.24	1.96	-1.50	**6.23**	-5.33	-0.75	0.80	2.57	0.2
BM8	**6.90**	2.02	0.65	3.54	-2.17	5.32	-4.17	-1.02	**2.97**	0.45	0.3
BM9	**6.51**	3.39	1.46	4.00	-5.72	**7.47**	-4.11	-0.48	**5.00**	-2.05	**0.5**
BM10	**5.96**	0.95	0.52	**5.35**	4.00	3.96	-3.04	-5.97	-0.21	4.60	0.3
Avg	*6.83*	*1.22*	*1.44*	*3.39*	*-0.09*	*5.40*	*-4.07*	*-1.85*	*1.66*	*1.30*	*0.4*
S1	**4.26**	0.32	0.94	0.47	0.96	**5.05**	-4.74	-2.39	0.57	2.08	0.3
S2	**5.70**	0.33	0.19	0.33	1.10	**4.81**	-3.54	1.18	0.79	0.46	0.3
S3	**5.81**	1.03	0.91	2.68	2.50	**4.07**	-3.17	-1.47	0.02	1.09	0.3
S4	**6.45**	1.11	0.12	3.23	3.14	-3.41	0.15	-2.75	0.13	3.87	0.4
S5	**6.89**	0.75	1.07	2.22	2.87	-3.41	0.51	-3.75	-0.30	3.95	**0.5**
S6	**6.17**	0.24	1.83	1.92	3.16	2.48	-1.66	-3.47	0.74	1.81	0.4
S7	**6.54**	1.05	1.47	3.21	2.94	-0.85	-0.07	-2.23	0.55	3.69	0.4
S8	**7.01**	1.15	1.98	3.33	**4.99**	-0.83	-0.87	-1.98	0.96	1.50	**0.5**
S9	**5.67**	1.40	2.40	1.10	2.01	1.63	-3.83	-0.62	1.14	5.47	0.4
S10	**7.82**	1.51	1.86	2.63	3.85	-0.26	-1.94	-3.66	-0.05	3.28	0.3
Avg	*6.23*	*0.89*	*1.28*	*2.11*	*2.75*	*0.93*	*-1.92*	*-2.12*	*0.45*	*2.72*	*0.4*

Figure 1: Annualized mean returns of stock portfolios

Panels A and B plot the annualized continuously compounded mean returns of B/M and size portfolios, respectively. The sample means are annualized by multiplying the daily estimates (reported in Panel A of Table 1) by 260, and they are expressed in percentages. The sample period is from January 2, 1986 to December 31, 2013.



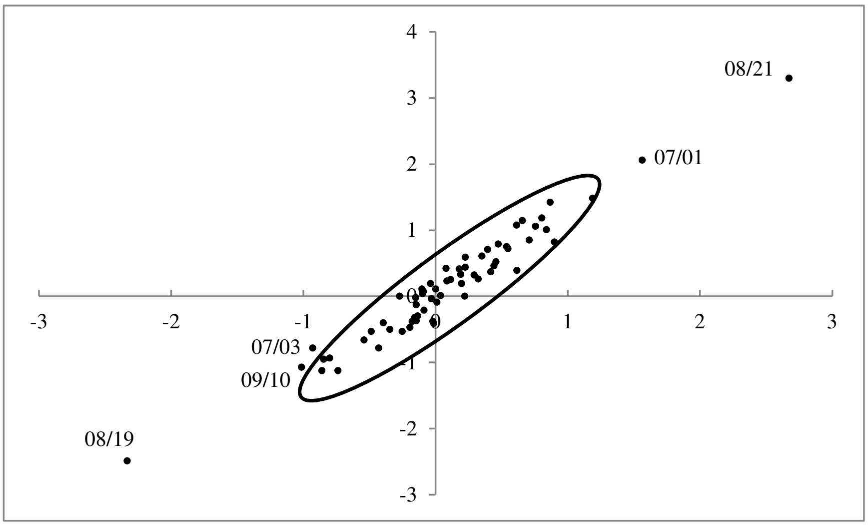
Panel A: B/M portfolios



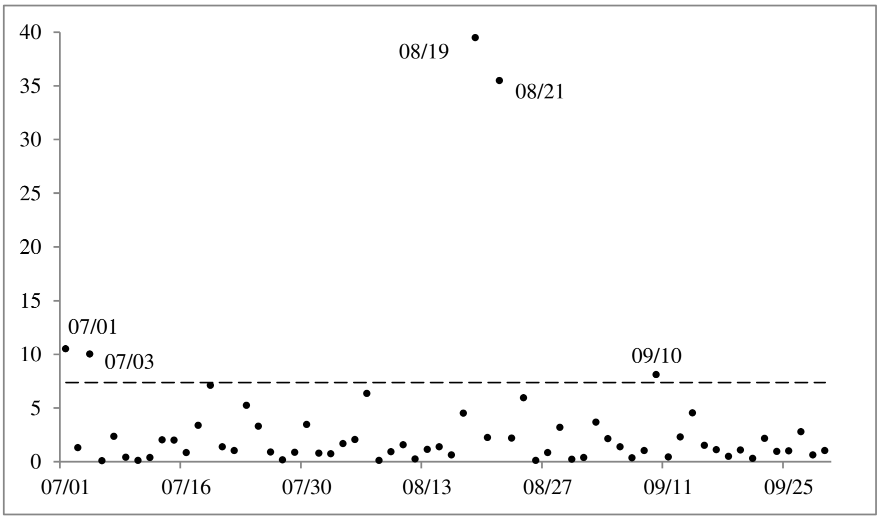
Panel B: Size portfolios

Figure 2: Systematic cojump identification of BM1 in 1991Q3

Panel A plots the daily bivariate returns (expressed in percentages) between BM1 (y-axis) and MKT (x-axis) in 1991Q3. Daily bivariate returns that lie outside the solid ellipse are identified by Equation (4) as extreme outliers or systematic cojumps. Panel B plots the robust Mahalanobis distances of BM1-MKT bivariate returns in the localized 1991Q3 window, with the dotted horizontal line representing the $\chi_2^2(97.5\%) = 7.4$ critical value.



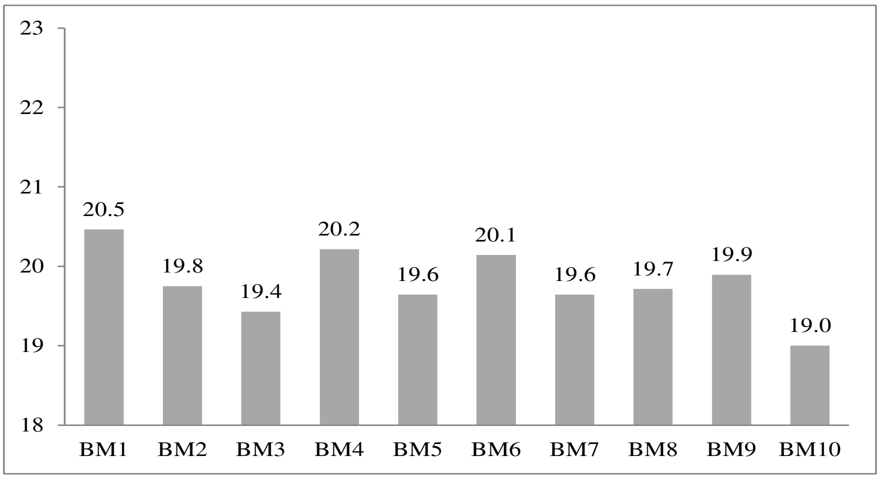
Panel A: BM1-MKT daily bivariate returns



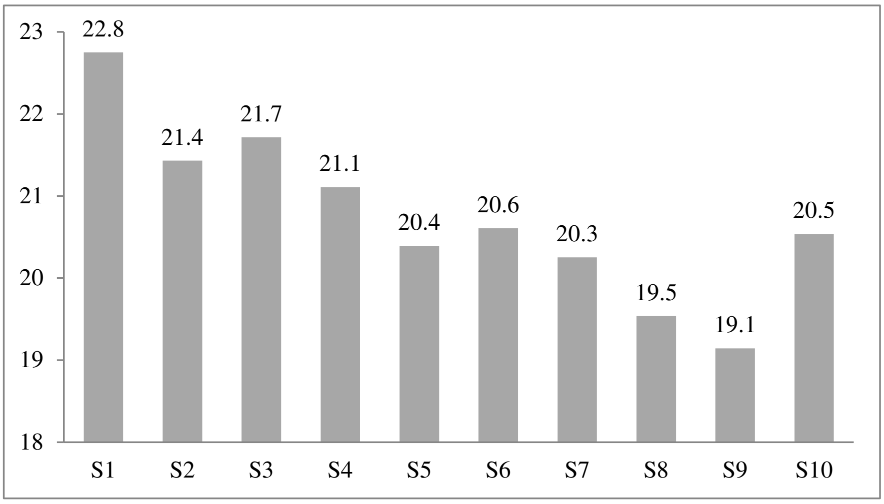
Panel B: Robust Mahalanobis distances

Figure 3: Systematic cojumps of stock portfolios

Panels A and B plot the means of annualized systematic cojumps of B/M and size portfolios, respectively. The annualized systematic cojump statistic is calculated as the total number of systematic cojumps identified from Equation (4) divided by 28, which is the number of years in the sample period from January 2, 1986 to December 31, 2013.



Panel A: B/M portfolios



Panel B: Size portfolios

Systematic cojumps, market component portfolios and scheduled macroeconomic announcements

Internet Appendices

Internet Appendix A-1

This appendix presents the bivariate cojump test results of Jacod and Todorov (2010). The Jacod-Todorov test, which is the preferred non-parametric test by Todorov (2010) in examining daily cojumps between equity price jumps and VIX volatility jumps, examines realized correlation (RC) between the squared jumps in X and Y series over a given interval T_n:

$$RC_{Tn} = \frac{V_{Tn}(X,Y,2)}{\sqrt{V_{Tn}(X,4)V_{Tn}(Y,4)}} , \tag{I.1}$$

where:

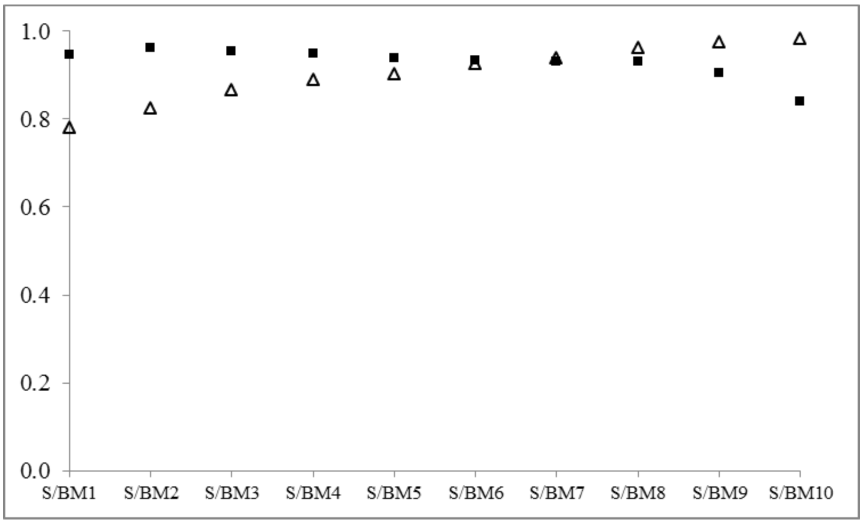
$$V_{Tn}(X,Y,z) = \sum_{i}^{Tn} |\Delta X_i|^z \times |\Delta Y_i|^z . \tag{I.2}$$

In the current context, X refers to the daily (log) price level of the market portfolio, Y is the daily (log) price level of portfolio *i* and $T_n \approx 22 \times 3$ (trading days) in each quarter. $RC_{Tn} = 0$ means disjoint arrival of jumps, whereas $RC_{Tn} = 1$ indicates perfect dependence between the jumps in X and Y, since, in the presence of cojump between X and Y, $V_{Tn}(X,Y,2) \approx \sum |\Delta X_s|^2 \times |\Delta Y_s|^2, V_{Tn}(X,4) \approx \sum |\Delta X_s|^4$ and $V_{Tn}(Y,4) \approx \sum |\Delta Y_s|^4$. We refer interested readers to the seminal paper by Jacod and Todorov (2010) for more details.

Figure A-1 presents the results, which show a strong dependence in realized jumps in covariation between the value-weighted CRSP market index and its component portfolios. In other words, there is evidence of systematic cojumps between the market index and its component portfolios.

Figure A-1: Jacod-Todorov's test statistics

This figure plots the sample median of Jacod-Todorov's jump test statistics between the CRSP value-weighted market index and its component portfolios sorted on B/M price ratio (■) and size (Δ). The sample period covers from January 2, 1986 to December 31, 2013.

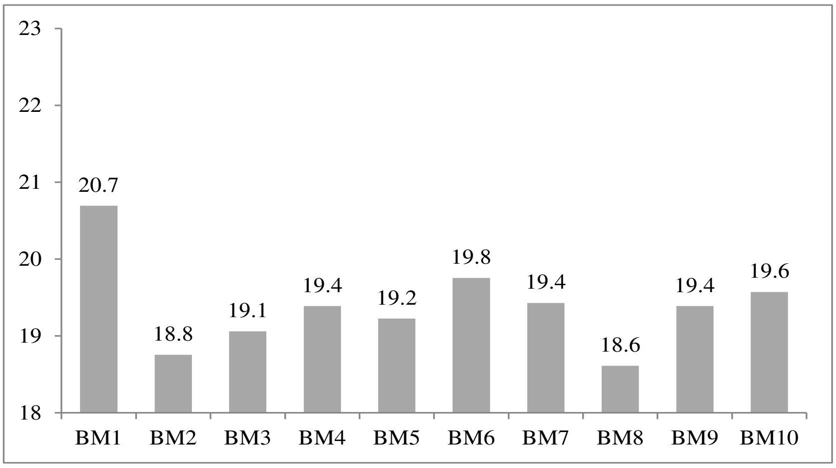


Internet Appendix A-2

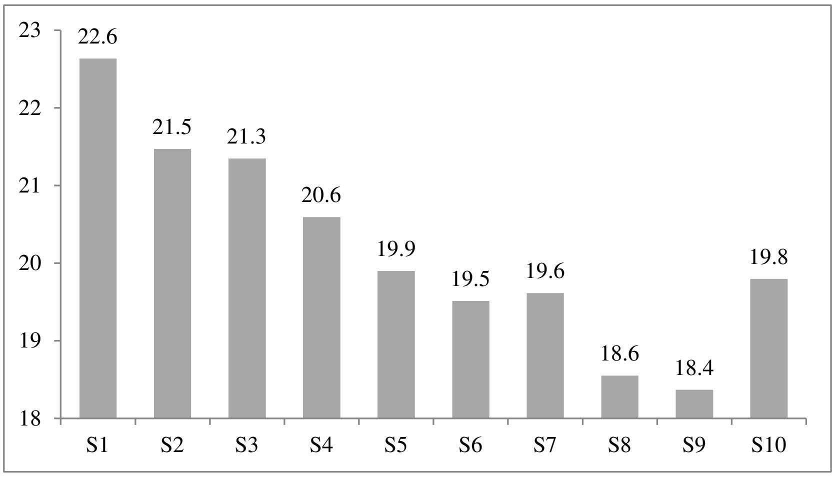
This appendix presents the results for annualized systematic cojumps of the B/M- and size-deciled portfolios when the data are estimated using the modified multivariate jump test of Boudt et al. (2011) over a substantially longer sample period that spans nearly half a century (1965–2013). The starting 1965 period corresponds to that analyzed by Welch and Goyal (2008) in examining the out-of-sample predictability of stock returns.

The results, presented in Figure A-2, reveal that B/M-deciled portfolios tend to jump concomitantly with the market index for 19-20 times per annum, whereas systematic cojumps appear to occur more frequently in small-capitalization stocks than in large-capitalization stocks. We find similar qualitative results using a narrower 1986-2013 sample period as in the main text.

Figure A-2: Systematic cojumps of stock portfolios over 1965-2013 sample period
Description of this figure is provided in Figure 3 of the main text. The sample period covers from January 4, 1965 to December 31, 2013.



Panel A: B/M portfolios



Panel B: Size portfolios

Internet Appendix A-3

This appendix presents the results for probit regression Equation (5) specified in the main text for four other macroeconomic variables commonly examined in related studies: the seasonally adjusted consumer price index (CPI), the seasonally adjusted industry production index (IP), retail sales (RS) and the seasonally adjusted housing start statistics (HS).

Table A-1 presents the slope coefficient estimates, which are mostly insignificant at the 5% level. That is, the absolute news surprises in CPI, IP, RS and HS are hardly related to the probabilities of systematic cojumps in B/M and size portfolios.

Table A-1: Results for probit model Equation (5) for CPI, IP, RS and HS

Description of this table is provided in Table 3 of the main text.

	CPI			IP			RS			HS		
	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2
BM1	0.13	[1.66]	0.4	0.16	[1.97]	0.8	-0.12	[-1.52]	0.3	-0.02	[-0.27]	0.0
BM2	-0.10	[-1.40]	0.2	0.05	[0.76]	0.1	-0.09	[-1.05]	0.2	-0.34	[-4.37]	1.8
BM3	0.21	[2.79]	1.2	0.20	[3.04]	1.3	0.05	[0.71]	0.1	-0.12	[-1.41]	0.3
BM4	-0.06	[-0.80]	0.1	0.06	[0.70]	0.1	0.03	[0.35]	0.0	-0.09	[-1.19]	0.2
BM5	-0.10	[-1.28]	0.2	0.08	[1.23]	0.2	0.11	[1.41]	0.4	-0.10	[-1.25]	0.2
BM6	-0.15	[-2.59]	0.5	0.13	[1.64]	0.5	0.01	[0.19]	0.0	0.05	[0.52]	0.1
BM7	0.02	[0.30]	0.0	-0.04	[-0.63]	0.0	0.03	[0.41]	0.0	0.13	[1.60]	0.5
BM8	**0.23**	**[3.04]**	1.5	0.03	[0.40]	0.0	0.05	[0.56]	0.1	-0.31	[-3.74]	1.5
BM9	0.14	[1.60]	0.5	0.03	[0.49]	0.0	0.03	[0.47]	0.0	-0.30	[-4.07]	1.6
BM10	0.07	[0.76]	0.1	0.04	[0.56]	0.0	-0.04	[-0.57]	0.1	-0.15	[-2.06]	0.4
Avg	*0.04*	*[0.41]*	*0.5*	*0.07*	*[1.01]*	*0.3*	*0.01*	*[0.10]*	*0.1*	*-0.12*	*[-1.63]*	*0.7*
S1	**0.25**	**[3.49]**	1.6	0.05	[0.63]	0.1	-0.14	[-1.76]	0.4	-0.13	[-2.25]	0.3
S2	0.08	[1.29]	0.2	0.05	[0.63]	0.1	-0.11	[-1.59]	0.2	-0.15	[-2.34]	0.4
S3	0.02	[0.31]	0.0	-0.05	[-0.65]	0.1	0.03	[0.31]	0.0	-0.29	[-4.89]	1.4
S4	0.12	[1.77]	0.4	-0.07	[-1.10]	0.1	-0.03	[-0.38]	0.0	-0.22	[-3.37]	0.8
S5	0.09	[1.25]	0.2	-0.04	[-0.54]	0.0	0.06	[0.80]	0.1	-0.12	[-1.74]	0.3
S6	-0.10	[-1.42]	0.2	-0.02	[-0.21]	0.0	-0.04	[-0.57]	0.1	-0.08	[-1.05]	0.2
S7	0.12	[1.68]	0.3	-0.17	[-2.89]	0.5	0.13	[1.35]	0.6	0.03	[0.27]	0.0
S8	0.10	[1.19]	0.2	0.07	[0.88]	0.1	0.03	[0.39]	0.0	0.15	[1.67]	0.6
S9	0.21	[2.30]	1.2	0.07	[0.81]	0.1	-0.15	[-2.14]	0.4	-0.15	[-1.55]	0.4
S10	0.02	[0.31]	0.0	0.20	[2.45]	1.5	0.01	[0.08]	0.0	0.07	[0.94]	0.1
Avg	*0.09*	*[1.22]*	*0.4*	*0.01*	*[0.00]*	*0.3*	*-0.02*	*[-0.35]*	*0.2*	*-0.09*	*[-1.43]*	*0.5*

Internet Appendix A-4

It is probable that only sufficiently large announcement surprises are associated with the identified systematic cojumps. As such, this appendix re-runs the empirical analysis of probit regression Equation (5) by focusing only on non-trivial announcement surprises. Specifically, following Brenner et al. (2009), we define the difference between the actual and expected announcement as a 'surprise' if and only if the absolute news forecast error $|A_{t,k} - F_{t,k}|$ is above 5 basis points (bps) for FED, UMP and PPI, respectively, 0.2 for ISM and 20,000 for NFP.

Table A-2 presents the results, which are qualitatively similar to the findings reported in Table 3 of the main text.

Table A-2: Results for probit model Equation (5) with large news surprises

Description of this table is provided in Table 3 of the main text.

	FED			NFP			UMP			PPI			ISM		
	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2	$\beta_{i,k}$	$\partial\Phi/\partial S_k$	R^2
BM1	**1.02**	**[16.1]**	**18.5**	0.12	[1.92]	0.3	-0.08	[-1.36]	0.1	-0.04	[-0.71]	0.0	-0.05	[-0.98]	0.0
BM2	0.31	[9.93]	2.2	0.00	[-0.03]	0.0	0.23	[3.75]	0.7	0.03	[0.54]	0.0	0.08	[1.45]	0.1
BM3	0.45	[9.97]	5.0	-0.01	[-0.10]	0.0	0.16	[2.25]	0.3	0.11	[1.81]	0.2	-0.08	[-1.72]	0.1
BM4	0.35	[9.94]	2.8	0.16	[2.73]	0.4	0.12	[2.06]	0.2	0.17	[2.81]	0.6	-0.14	[-2.96]	0.3
BM5	**1.35**	**[19.0]**	**24.4**	0.10	[1.47]	0.2	0.14	[1.94]	0.3	0.06	[1.06]	0.1	-0.13	[-2.43]	0.3
BM6	**0.48**	**[12.8]**	5.4	0.11	[1.79]	0.2	0.13	[1.99]	0.2	0.08	[1.47]	0.1	-0.15	[-3.00]	0.4
BM7	**0.51**	**[11.8]**	6.7	0.05	[0.76]	0.0	0.14	[1.94]	0.3	0.05	[0.76]	0.0	-0.16	[-2.75]	0.4
BM8	**1.21**	**[18.7]**	**21.1**	0.26	[3.64]	1.4	0.10	[1.45]	0.1	0.01	[0.18]	0.0	-0.10	[-1.76]	0.2
BM9	0.47	[10.3]	5.6	0.20	[3.62]	0.7	0.10	[1.86]	0.1	0.01	[0.18]	0.0	-0.18	[-3.28]	0.5
BM10	0.40	[9.27]	4.1	0.04	[0.63]	0.0	0.10	[1.45]	0.1	**0.25**	**[3.39]**	1.5	0.18	[3.35]	0.6
Avg	*0.65*	*[12.8]*	*9.6*	*0.10*	*[1.64]*	*0.3*	*0.11*	*[1.73]*	*0.2*	*0.07*	*[1.15]*	*0.3*	*-0.07*	*[-1.41]*	*0.3*
S1	0.43	[11.9]	4.4	0.11	[1.78]	0.2	0.08	[1.21]	0.1	0.15	[1.85]	0.5	-0.12	[-2.79]	0.2
S2	**0.53**	**[13.9]**	6.8	0.19	[2.59]	0.7	0.24	[3.00]	0.8	0.16	[2.63]	0.6	-0.05	[-0.98]	0.0
S3	0.43	[11.9]	4.4	0.12	[1.79]	0.2	0.16	[2.21]	0.3	0.16	[2.52]	0.6	-0.01	[-0.30]	0.0
S4	0.47	[13.4]	5.2	0.14	[2.00]	0.4	0.29	[3.30]	1.2	**0.25**	**[3.63]**	1.4	-0.02	[-0.37]	0.0
S5	**1.86**	**[30.7]**	**30.3**	0.20	[2.92]	0.7	0.28	[3.89]	1.1	0.06	[0.97]	0.1	0.01	[0.22]	0.0
S6	0.38	[10.1]	3.5	0.11	[1.78]	0.2	0.22	[3.52]	0.6	-0.02	[-0.33]	0.0	0.01	[0.17]	0.0
S7	0.30	[8.85]	2.1	0.13	[2.06]	0.3	0.21	[3.29]	0.6	0.07	[1.27]	0.1	0.11	[2.35]	0.2
S8	0.35	[10.1]	2.9	0.04	[0.64]	0.0	0.11	[1.78]	0.1	0.21	[3.06]	1.0	0.14	[3.06]	0.3
S9	0.43	[8.93]	4.9	0.10	[1.73]	0.2	0.33	[4.31]	1.5	-0.01	[-0.09]	0.0	0.02	[0.33]	0.0
S10	0.32	[8.72]	2.4	0.10	[1.69]	0.2	0.22	[3.12]	0.7	0.11	[1.49]	0.2	0.10	[1.94]	0.2
Avg	*0.55*	*[12.9]*	*6.7*	*0.12*	*[1.90]*	*0.3*	*0.21*	*[2.96]*	*0.7*	*0.11*	*[1.70]*	*0.4*	*0.02*	*[0.36]*	*0.1*

Internet Appendix A-5

This appendix re-estimates the probit regression Equation (6) on the FED, UMP, NFP, PPI and ISM, with the Bank of America–Merrill Lynch Option Volatility Estimate (MOVE) index is used to proxy for uncertainty regarding the Federal Funds rate on announcement days. The MOVE is a yield curve weighted index of the normalized Black's (1976) implied volatility of one-month Treasury options traded over-the-counter. This index weights 20% for 2-year Treasury contracts, 20% for 5-year contracts, 40% for 10-year contracts and 20% for 30-year contracts.

Table A-3 presents the results, which are qualitatively similar to those reported in Table 4 of the main text.

Table A-3: Results for symmetric probit Equation (6) with MOVE

Description of this table is provided in Table 4 of the main text.

	$\beta_{i,k}$					$\gamma_{i,k}$					α_i^A	R^2
	FED	NFP	UMP	PPI	ISM	FED	NFP	UMP	PPI	ISM		
BM1	**0.37**	-0.01	0.00	0.11	0.05	-0.01	0.25	-0.12	-0.09	0.04	-0.08	**0.6**
BM2	**0.34**	-0.08	**0.21**	0.11	0.10	0.00	0.08	-0.10	-0.08	0.03	0.14	**0.9**
BM3	**0.37**	-0.04	0.06	0.02	0.02	-0.07	**0.28**	-0.20	0.06	0.10	0.10	**0.8**
BM4	**0.32**	0.06	0.10	**0.21**	0.00	-0.03	0.17	-0.17	-0.14	0.08	0.14	**0.8**
BM5	**0.37**	0.03	0.05	0.12	0.02	0.05	0.22	-0.08	0.06	0.10	-0.20	**0.7**
BM6	**0.33**	0.00	0.10	0.18	0.01	-0.02	**0.35**	-0.30	-0.14	0.03	0.14	**0.8**
BM7	**0.32**	0.00	0.04	0.03	-0.10	0.01	**0.28**	-0.18	0.08	0.10	-0.09	0.5
BM8	**0.46**	0.05	0.01	0.11	-0.07	-0.04	0.20	-0.16	-0.02	0.08	0.05	**0.7**
BM9	**0.28**	0.12	0.06	0.14	-0.25	0.01	**0.35**	-0.15	0.03	**0.21**	-0.15	**1.0**
BM10	**0.23**	0.03	0.03	**0.25**	**0.22**	0.00	0.13	-0.09	-0.23	-0.01	0.14	**0.7**
Avg	*0.34*	*0.02*	*0.06*	*0.13*	*0.00*	*-0.01*	*0.23*	*-0.16*	*-0.05*	*0.08*	*0.02*	*0.7*
S1	**0.31**	0.02	0.09	0.04	0.10	-0.02	**0.32**	-0.32	-0.18	0.04	0.16	**0.7**
S2	**0.38**	0.00	0.01	0.09	0.08	-0.03	0.19	-0.17	-0.03	0.03	0.10	**0.6**
S3	**0.34**	0.02	0.04	0.13	0.14	0.01	0.18	-0.10	0.01	0.06	-0.14	0.5
S4	**0.36**	0.02	-0.01	0.15	0.17	-0.02	-0.22	0.07	-0.08	0.05	0.09	**0.7**
S5	**0.61**	-0.01	0.07	0.09	0.14	-0.06	-0.23	0.06	-0.17	0.00	0.19	**1.1**
S6	**0.32**	-0.02	0.11	0.07	0.17	-0.03	0.07	-0.06	-0.17	0.04	0.14	**0.7**
S7	**0.30**	0.03	0.09	0.15	0.16	-0.01	-0.04	0.03	-0.05	0.07	0.08	**0.7**
S8	**0.30**	0.02	0.11	0.13	**0.26**	0.02	-0.05	0.00	-0.03	0.08	-0.05	**1.0**
S9	**0.20**	0.03	0.11	0.00	0.08	0.02	0.07	-0.11	0.08	**0.12**	0.04	**0.8**
S10	**0.25**	0.06	0.11	0.11	0.19	0.02	-0.01	-0.05	-0.10	0.02	0.03	0.5
Avg	*0.34*	*0.01*	*0.07*	*0.10*	*0.15*	*-0.01*	*0.03*	*-0.07*	*-0.07*	*0.05*	*0.06*	*0.7*

Internet Appendix A-6

This appendix re-estimates the probit regression Equation (6) on the FED, UMP, NFP, PPI and ISM, with the implied volatility of three-month Eurodollar interest rates is used to proxy for uncertainty regarding the Federal Funds rate on announcement days. The implied volatility data, which spans over a limited sample period from January 1986 to June 2001, is sourced from Neely (2005).

Table A-4 presents the results, which are qualitatively similar to those reported in Table 4 of the main text.

Table A-4: Results for symmetric probit Equation (6) with implied volatility of three-month Eurodollar rates

Description of this table is provided in Table 4 of the main text.

	$\beta_{i,k}$					$\gamma_{i,k}$					α_i^A	R^2
	FED	NFP	UMP	PPI	ISM	FED	NFP	UMP	PPI	ISM		
BM1	**0.45**	0.00	-0.01	0.10	0.05	-0.12	0.25	-0.13	-0.12	0.02	-0.02	**0.6**
BM2	**0.31**	-0.08	**0.21**	0.11	0.11	0.06	0.08	-0.10	-0.06	0.04	0.10	**0.9**
BM3	**0.33**	-0.04	0.07	0.03	0.03	-0.07	**0.29**	-0.17	0.10	**0.13**	-0.04	**0.7**
BM4	**0.32**	0.06	0.10	**0.22**	0.00	-0.03	0.17	-0.16	-0.13	**0.10**	0.08	**0.8**
BM5	**0.58**	0.03	0.03	0.11	0.00	-0.19	0.21	-0.13	-0.03	0.05	0.05	**0.7**
BM6	**0.35**	0.00	0.10	0.18	0.01	-0.05	**0.35**	-0.30	-0.14	0.04	0.14	**0.8**
BM7	**0.35**	0.01	0.04	0.03	-0.10	-0.04	**0.27**	-0.19	0.06	0.08	-0.03	0.5
BM8	**0.46**	0.05	0.01	0.11	-0.06	-0.07	0.21	-0.14	0.00	0.09	-0.02	**0.7**
BM9	**0.30**	0.12	0.06	0.14	-0.26	0.00	**0.35**	-0.16	0.02	**0.21**	-0.12	**1.0**
BM10	**0.28**	0.03	0.03	**0.25**	**0.21**	-0.09	0.12	-0.11	-0.27	-0.03	0.22	**0.7**
Avg	*0.37*	*0.02*	*0.06*	*0.13*	*0.00*	*-0.06*	*0.23*	*-0.16*	*-0.06*	*0.07*	*0.04*	0.8
S1	**0.30**	0.02	0.09	0.04	0.10	-0.02	**0.32**	-0.32	-0.16	0.04	0.13	**0.7**
S2	**0.35**	0.00	0.02	0.10	0.08	0.01	0.20	-0.15	0.00	0.05	0.00	**0.6**
S3	**0.38**	0.02	0.04	0.12	0.14	-0.07	0.18	-0.12	-0.02	0.04	-0.06	0.5
S4	**0.38**	0.03	-0.01	0.15	0.17	-0.07	-0.22	0.07	-0.08	0.05	0.09	**0.8**
S5	**0.74**	-0.01	0.07	0.09	0.14	-0.21	-0.23	0.07	-0.17	0.01	0.16	**1.2**
S6	**0.30**	-0.02	0.12	0.08	0.17	-0.01	0.07	-0.04	-0.15	0.06	0.05	**0.7**
S7	**0.31**	0.03	0.09	0.15	0.16	-0.02	-0.04	0.03	-0.05	0.07	0.08	**0.7**
S8	**0.33**	0.02	0.11	0.13	**0.25**	-0.01	-0.06	-0.02	-0.05	0.07	0.03	**1.0**
S9	**0.25**	0.03	0.10	-0.01	0.07	-0.06	0.07	-0.13	0.05	**0.09**	0.14	**0.8**
S10	**0.28**	0.06	0.10	0.10	0.19	-0.02	-0.02	-0.07	-0.13	0.00	0.12	0.5
Avg	*0.36*	*0.02*	*0.07*	*0.09*	*0.15*	*-0.05*	*0.03*	*-0.07*	*-0.08*	*0.05*	*0.07*	0.8

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