



When does the stock market listen to economic news? New evidence from copulas and news wires



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ABSTRACT

We study association between macroeconomic news and stock market returns using the statistical theory of copulas, and a new comprehensive measure of news based on textual review and classification of news wires. We find the impact of economic news on equity returns to be nonlinear and asymmetric. In particular, controlling for economic conditions and surprises associated with releases of economic data, we find that the market reacts strongly and negatively to the most unfavourable macroeconomic news, but appears to largely discount the good news. Further, the most-unfavorable news creates price drift, and we document that selling stocks short in the wake of unusually-bad news yields annual abnormal gross returns greater than four percent.

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1. Introduction

The impact of macroeconomic news on the stock market has been the subject of considerable amount of research during the past thirty years. Asset pricing theory suggests that news about macroeconomic factors such as employment or the level of output should influence financial markets, since it carries information about the aggregate investment opportunities set of the economy (see Merton (1973) and Breeden (1979)). Despite this, empirical evidence supporting market effects of real economic news remains weak and surprisingly mixed¹. In many cases, important macroeconomic news is found to have no effect at all. For example, Flannery and Protopapadakis (2002) examine the market impact of 17 macroeconomic announcements and find that among other key variables, news relating to industrial production, unemployment and the real GNP appears to have no significant impact on stock prices. Similarly, earlier studies such as, for example, Pearce and Roley (1985)

and Jain (1988) find that the markets largely discount statistical announcements about industrial production and unemployment, even after taking prior expectations into the account. Ghent (2010) also fails to find a significant market reaction to GDP and unemployment news.

The different stages of the business cycle can change the context within which macroeconomic signals are interpreted, and the market impact of news becomes more apparent once the current economic conditions are taken into the account. Boyd et al. (2005) and McQueen and Roley (1993) find that news about rising unemployment has a negative effect on stock prices during economic contractions, since it can indicate lower corporate earnings and dividends, but a positive effect during expansions, as it may signal a greater likelihood of lower interest rates. More recently, Birz and Lott (2011) find that after controlling for both the market expectations and the stages of the business cycle, the market reacts significantly to GDP and unemployment announcements.

While the importance of economic conditions that may influence the market's interpretation and reaction to news is becoming better understood, interestingly, no studies appear to focus on characteristics of news associated with greatest market impact. For example, controlling for economic conditions and expectations, does unusually-good or unusually-bad news lead to stronger market response? If so, is there asymmetry in this relationship? In

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¹ Previous studies found statistically-significant association between stock market returns and various monetary variables such different interest rates (e.g. Chen et al. (1986); Chen (1991); Chan et al. (1998)) and monetary aggregates (e.g. Cornell (1983); Pearce and Roley (1983); Pearce and Roley (1985)).

other words, is the market effect of economic news non-linear and asymmetric? The aim of this paper is to fill this gap.

We re-assess the market effect of macroeconomic news using a relatively-new statistical methodology based on the theory of conditional copulas, and a new comprehensive measure of macroeconomic news that is derived from textual classification and indexing of news wires. Our measure quantifies polarity, intensity and volume of news related to U.S. employment, industrial activity, housing and construction, the energy market, and monetary conditions. In addition to the news that relate to scheduled releases of economic statistics, our measure captures qualitative signals such as, for example, comments made by senior U.S. policy officials, policy developments, as well as man-made and natural disasters that may have an economic impact, and is arguably the broadest measure of economic news used in the literature to date.

By adopting the copula approach, we are able to construct a flexible model that allows for non-linear and asymmetric market effects of economic news that may vary with news intensity. To our knowledge, this represents the first application of copulas to the analysis of the news-stock market relationship. Using the copula model, we map the association between economic news and the stock market in high detail and find that, controlling for surprises associated with releases of economic data and prevailing economic conditions, the market impact of news is heavily skewed toward the most unfavorable announcements, which tend to be associated with significant market declines in all stages of the business cycle. In other words, it appears that it is only when the news is all doom and gloom, the market really listens. Since we're able to isolate the data-revealing component of news, we show that the qualitative economic news that our index captures does have a significant market effect. Lastly, we document that selling stocks short following particularly-unfavorable news yields abnormal annual gross return exceeding four percent, suggesting that the market fails to fully price such news in timely manner. Since we solely draw upon the freely-available sources of news, our results appear to contradict the semi-strong form of market efficiency which precludes the possibility of obtaining such excess return on the basis of publicly-available information.

This paper is organized as follows. Section 2 details the construction of our news variable, which we call the macroeconomic news index. The index is based on manual review and classification of news-wire releases, and we review the data sources, indexing methodology, and the resulting index series in this section. Section 3 introduces the copula approach and details our modeling methodology. Section 4 presents empirical results relating to the market impact of economic news and the associated trading rule. Lastly, a discussion of the results is provided in Section 5.

2. Our news variable: the macroeconomic news index

Recent evidence suggests that the stock market reaction to economic news may not be limited to responses to scheduled statistical releases. For example, while many failed to find any significant relationship between GDP announcements and the stock market in the past, [Birz and Lott \(2011\)](#) document substantial market reaction to output-related news using a more comprehensive news measure based on the classification of newspaper headlines of [Lott and Hassett \(2004\)](#).

We adopt a similar general approach and develop a new quantitative measure of U.S. macroeconomic news that is based on full textual review and classification of releases carried by major business news wires. In terms of economic coverage, professional news wire services differ from newspapers in several important ways, and we begin by detailing our news data sources and the indexing methodology.

2.1. Sources of economic news

We use the Thomson Reuters Newswires (TRN) and the Dow Jones Energy Service (DJES) as the sources of public information that underpins the news variable that we construct. Thomson Reuters is one of the largest news providers in the world, and maintains several newswires that cover a variety of U.S. business and economic developments. The Dow Jones Energy Service is a specialized source of news relating to the global energy industry, with coverage ranging from market information and significant firm-specific news to geopolitical events and energy policy. Since both are professional services, they emphasize timeliness of coverage and are usually among the first to break the story. Unlike the newspaper coverage, newswire releases tend to be highly-condensed and factual, making interpretation easier in most cases. They also contain few journalistic opinions, which substantially reduces political bias of economic coverage that has been found to exist in newspaper stories (e.g. see [Mullainathan and Shleifer \(2005\)](#), [Grosche and Milyo \(2005\)](#), [Dyck and Zingales \(2003\)](#) and [Lott and Hassett \(2004\)](#)). Their position at the top of the news chain, breadth of coverage and unambiguous format make the newswires an excellent source of information for indexing that is comprehensive, reduces the chance of misinterpretation, and contains little noise arising from the repetition of news by multiple outlets.

Since our aim is to capture and quantify the inflow of news relating to U.S. macroeconomic conditions, we restrict attention to releases that follow five key themes usually associated with economic activity. In particular, we focus on stories covering U.S. industrial production, national and regional labor markets, housing markets and construction industry, the energy policy and markets, and monetary conditions. Industrial production, employment, and construction activity are often viewed as important indicators that carry signals about aggregate output and consumption. Monetary conditions such as, for example, the money supply and the state of bond markets have implications for the cost of capital. Energy costs can affect factor productivity, corporate profitability, and return to capital which motivates our choice of energy news as another index component.

We use the Dow Jones Factiva as the source of all historical newswire releases. Factiva captures and stores all messages carried by TRN and DJES in full, exactly as they appeared at the time of the release, without edits or revisions that may have been made to the content at a later date. Updates and corrections to earlier releases are typically issued by TRN and DJES separately, and are also included into the index.

The overall pool of stories transmitted during our sample period is extremely large, and only a minority of wires are related to U.S. macroeconomic conditions. We utilize the Dow Jones Intelligent Indexing (DJII) service to identify relevant releases that fit one of our five selected themes.

2.2. Indexing methodology

For every month in our sample, the construction of the index proceeds as follows. First, we collect all economic stories that were carried by TRN and DJES during the month and sort them into one of the five groups based on economic theme. For example, during April 2014 DJII search yields 27 newswires relating to U.S. employment, 17 wires covering U.S. industrial production, 7 wires on housing markets and construction industry, 27 stories on energy markets and policy, and a further 15 releases focusing on monetary conditions that were carried by TRN and DJES. Once the relevant stories are identified, we review the content of every story in full and classify the release either as a "positive", a "negative", or a "neutral". A story is viewed as "positive" if it contains information indicating improvement in current, or a likely improvement in

future macroeconomic conditions, which for energy news is interpreted as easing of market conditions and a likely decline in price of key carriers such as oil or liquefied natural gas, and for monetary conditions as monetary easing likely to result in lower cost of funds. “Neutral” stories are those that signal neither deterioration nor improvement.

A large portion of industrial production, employment, and housing and construction-related newswires are driven by scheduled releases of macroeconomic statistics issued, among others, by U. S. Department of Commerce, the Bureau of Labor Statistics and Federal Reserve Banks, or by revisions to their previously-released figures. When interpreting such releases, it becomes important to account for prior expectations since, for example, a sound gain of 50,000 in non-farm payrolls may in fact be viewed as negative news in times when higher growth was expected. Fortunately, in addition to the headline number, most data-related TRN releases also include a measure of expectations based on the most recent Reuters poll of forecasters. We therefore classify such releases in relation to expectations and treat the release as “positive” if it exceeds expectations, “negative” if it falls short of expectations, and “neutral” if it meets the expectations. The part of the index that is driven by scheduled releases of core macroeconomic data therefore captures “economic surprises”, or the unexpected component in macroeconomic data.

Revisions to past economic data are another major component of data-driven news. For example, growth estimates issued by the U.S. Bureau of Economic analysis tend to be revised multiple times, and revisions can be substantial and occur several months after initial issue. Many historical macroeconomic data that are available today are therefore different from what was reported at the time of the release. The flow of such revisions represents important information that is absent from many available data, and we include all news relating to revisions into the index.

The remaining, or non data-driven industrial production, employment, and housing and construction-related stories, along with the bulk of stories covering the energy markets and monetary conditions are qualitative in nature and include comments made by senior officials and policy-makers such as, for example, members of the board of governors of the Federal Reserve System, U.S. Secretary of Commerce or the Secretary of Energy, important geo-political developments such as sanctions or energy cartel quota decisions, as well as natural disasters with potential for economic impact. We describe the content of TRN and DJES economic releases along with specific classification guidelines in detail in the rest of this section. The total number of newswire releases reviewed during the construction of the index across the five news groups is presented in Table 1.

Since our classification is similar to the grouping of responses to the University of Michigan Consumer Sentiment Index, we adopt its methodology and use the difference in percentage of positive and negative stories as the basis for the index. An analogous indexing approach is used in Birz and Lott (2011). To calculate the monthly value of the macroeconomic news index we first find the ratios of positive and negative stories for each of the four news groups, and then take their difference to find corresponding sub-index for that group. For example, Table 2 shows the raw news counts and the resulting four sub-indexes for April 2014. This yields a set of five indexes capturing polarity of U.S. employment, housing, industrial production, monetary, and energy-related news that are interesting in their own right, and are reviewed in more detail in Sections 2.3–2.7. The final value of the macroeconomic news index for the month is calculated by finding the average of the four sub-indexes, which amounts to -0.12 during April 2014. It is evident that positive or negative readings of the final index indicate whether the month was dominated by positive or negative news respectively, while the magnitude of the reading shows

Table 1

Number of Reuters and Dow Jones Energy Service newswires by category, January 1999 to April 2014.

News group	Positive	Negative	Neutral	Total
Employment	3328	3220	479	7027
Housing	982	830	126	1938
Industry	1407	946	107	2460
Energy	3830	3203	1281	8314
Monetary	334	441	1050	1827
Total	9881	8640	3043	21566

Table 2

Raw news counts and resulting news sub-indexes, April 2014.

	Positive	Negative	Neutral	Sub-index
Employment	17	10	0	0.26
Housing	0	5	2	-0.71
Industry	12	3	2	0.53
Energy	13	13	1	0
Monetary	0	2	1	-0.66

prevalence of certain type of news, with 1 and -1 representing entirely positive and negative news-months. To this end, macroeconomic news during April 2014 appears mixed but somewhat dominated by negative news.

The indexing methodology adopted here, as arguably other approaches to the building of such index, has some limitations. Here, the averaging of the four sub-indexes places equal weight on employment, housing, industry, monetary conditions, and energy-related news. Alternative weighting is clearly possible. To allow for alternative index definitions, we make our disaggregated classification data available as online appendix in addition to the final index series. Next, we review the four sub-indexes and the resulting macroeconomic news index in more detail.

2.3. Employment news sub-index

Nearly two thirds of employment-related wires cover scheduled releases and revisions to economic statistics by the agencies of the U.S. Department of Labor, with a large share of releases issued by the Bureau of Labor Statistics. These include statistics on national labor force, participation rates, employment and unemployment rates, non-farm payrolls, job openings and labor turnover, as well as jobless claims reports. State-level statistical releases also make a substantial part of the labor news flow and are included into the index, but their share relative to the national stories declines substantially closer to the end of our sample. Such data-driven releases contain least ambiguity, and interpretation is straightforward in most cases. For example, on August 1, 2014 Reuters wrote:

“U.S. job growth slowed a bit in July and the unemployment rate unexpectedly rose, pointing to slack in the labor market ... Nonfarm payrolls increased 209,000 last month after surging by 298,000 in June, the Labor Department said on Friday. Economists had expected a 233,000 job gain”,

which we recorded as “negative” due to indication of raising unemployment and lower than expected job growth.

Most non data-driven employment-related releases contain comments by senior officials on the state of the U.S. labor market. For example, on July 15, 2014, Reuters issued a release citing the Chair of the Federal Reserve:

“Labor force participation appears weaker than one would expect based on the ageing of the population and the level of unemployment. These and other indications that significant slack remains in labor markets are corroborated by the

continued slow pace of growth in most measures of hourly compensation”,

which we also classify as “negative”. While such comments clearly indicate a negative view of the labor market, they may be perceived as good news in other context. For example, financial markets may view this as signal suggesting greater likelihood of monetary easing. Interaction between market impact of employment news and other economic variables is documented in, for example, [Boyd et al. \(2005\)](#), where negative unemployment news is found to have a negative effect on equity prices during economic contractions, but a positive effect during expansions. Such non-linear effects can be captured using appropriate econometric models and controls, as we do in Section 4, rather than by contextual indexing of news. Here, we make particular effort to classify releases from the standpoint of underlying real economic signals, rather than its market interpretation or impact.

[Fig. 1](#) of the Appendix shows the monthly values of employment news sub-index and the total number of employment-related news releases carried by Reuters between January 1999 and April 2014. While the index remained positive during most of the past decade and a half, the two periods of time dominated by persistent negative news coincide with 2001–2002 and 2007–2009 U.S. NBER recessions. The volume of labor market news varies substantially during our sample period reaching a peak of 83 releases in October 2002, with peak volume occurring roughly in the aftermath of both recessions, and on average amounts to 38 releases per month.

2.4. Housing and construction news sub-index

As with labor market news, most housing and construction releases are data-driven, and cover statistics by the U.S. Department of Commerce, National Association of Home Builders, National Association of Realtors, the American Institute of Architecture as well as the U.S. Department of Housing and Urban Development. Such releases typically include data on new and existing home sales, new home completions, building permits and housing starts, home financing costs, mortgage issue and refinancing rates, home affordability and rents, and even architectural billings. Some data, such as home sales, building permits and completions are periodically revised, and we include news of revisions into the index. A substantial number of releases cover related commodity-market news such as, for example, significant changes in the price of construction timber. The remaining, non-data driven releases include news about major policy initiatives aimed at stimulating the construction industry and occasional extreme weather events that adversely affect home building.

The monthly values of the housing and construction news sub-index and the volume of housing-related news releases that appear in our sample are shown in [Fig. 3](#). As with the labor market news, the 1999–2014 period was dominated by generally positive stories, with the exception of the five year span surrounding the U.S. housing crisis. The number of housing and construction-related releases carried by Reuters declines steadily and on average amounts to only 10 releases per month, which is the lowest among the four news groups in the sample.

2.5. Industry news sub-index

The majority of signals about the U.S. industrial activity that receive news coverage are in the form of commentary, special reports, and statistical releases issued by the Federal Reserve banks, mainly of Chicago, Philadelphia and Richmond, industry associations such as the Institute of Supply Management (ISM) and the Manufacturers Alliance, as well as research circulated by

major financial firms. These include data on industrial output, durable goods orders and non-farm productivity, along with a range of indexes of national and state-level manufacturing activity such as, for example, the Chicago Fed Midwest Manufacturing Index or the ISM Purchasing Managers' Index. Periodic polls of analysts expectations by Reuters as well as data revisions also receive significant attention and are frequently mentioned in the news. As with employment and construction-related news, non-data driven industry releases mostly contain commentary by senior officials on the state of U.S. manufacturing and other industrial indicators.

The number of industry-related Reuters releases and the monthly values of the industry news sub-index are shown in [Fig. 2](#). As with employment news, periods of persistently-negative industry news appear to roughly coincide with the two most recent NBER recessions. Interestingly, the most recent span of negative industry news occurred in late 2011 and early 2012 – well past the June 2009 NBER recession end date, which supports the “double-dip” view of the latest U.S. recession.

2.6. Energy news sub-index

Among the five groups of news included into the index, energy news contains the greatest number and by far the widest range of stories. Data-driven releases represent a minority of energy news and, in addition to announcements of major price changes for energy carriers such as crude oil or liquefied natural gas, include production figures, quota assignment and compliance rates by members of the OPEC, statistics on U.S. Strategic Petroleum Reserves, petroleum balances and other items tracked by the U.S. Energy Information Administration, as well as data released by the International Energy Agency. Non-data component of energy news is also very broad and contains news of natural and man-made disasters that adversely affect energy supply such as, for example, a major hurricane in the Gulf of Mexico, oil spill, or pipeline breakdown that interrupts oil production and refining, international and regional conflicts, as well as policy developments that lead to supply restrictions or easing such as sanctions or rules that permit new extraction.

[Fig. 4](#) shows the number of energy-related DJES releases along with the values of the energy news sub-index. Set against the backdrop of steadily raising energy prices during 1999–2014, combined with political turmoil and military action that involved some of the largest energy producers in the world, energy news sub-index remained negative throughout most of this period, reflecting both growing supply risks and global energy demand.

2.7. Monetary conditions news sub-index

Majority of Reuters releases relating to U.S. monetary conditions cover comments and guidance issued by the U.S. Federal Reserve System officials, staffing changes, releases of minutes, as well as significant bond market developments such as major debt issues or repurchase initiatives. Data-driven releases mostly report on money stock figures and depositary reserves. Over one third of money-related releases cover the search for the new Chairman of the Federal Reserve that dominated coverage throughout much of 2006.

The total number of Reuters releases relating to monetary conditions along with the values of the monetary news sub-index is shown in [Fig. 5](#). The two rounds of monetary easing during 2001–2002 and from 2007 and on can be clearly seen, along with the periods of tightening in between. Interestingly, the index also seems to correctly reflect persistent talk of monetary tightening that began around the start of 2013 and presently persists.

2.8. Combined index

Final values of the macroeconomic news index, as well as the combined number of processed Reuters and DJES releases, are shown in Fig. 6. The index appears to correctly reflect the inflow of poor economic news during the two NBER recessions during 1999–2014 and the prevalence of good news indicating periods of growth in between.

3. Our methodology: the conditional copula approach

3.1. A copula approach

To gain a deeper understanding of the relationship between macroeconomic news and equity returns, we adopt a relatively-new statistical approach that is based on the theory of copulas. Consider a pair of random variables X and Y , and let $F(x; \theta_x)$ and $G(y; \theta_y)$ represent their marginal distribution functions with parameters θ_x and θ_y , and $H(x, y)$ be the joint CDF. Following a result by Sklar (1959), the joint CDF can be expressed as

$$H(x, y) = C[F(x; \theta_x), G(y; \theta_y); \theta_c], (x, y) \in \mathbb{R}^2, \quad (1)$$

where $C: [0, 1]^2 \rightarrow [0, 1]$ is the so-called copula of X and Y , and θ_c is a vector containing copula parameters. Letting $u = F(x; \theta_x)$ and $v = G(y; \theta_y)$, it is evident that the copula is simply the joint CDF of (u, v) which we can write as $C(u, v; \theta_c) = H[F^{-1}(u; \theta_x), G^{-1}(v; \theta_y)]$.

Copulas are becoming central to the analysis of dependence as they provide a complete description of the association between X and Y that is also unique in the case that the variables are continuous. Different families of copulas represent a variety of dependence structures, with parameters in θ_c measuring the strength of association. For example, some of the better-known copula families include the Gaussian copula that captures linear correlation, Gumbel and Clayton copulas that measure asymmetric dependence that may be stronger among larger or smaller values of the data, as well as t and Symmetrized Joe-Clayton (SJC) copulas that allow for tail dependence, or dependence among data extremes.

Many well-known measures of association can be represented in terms of the copula. For example, rank-correlation measures such as Kendall's τ and Spearman's ρ can be expressed in terms of C as

$$\tau = 4 \int_0^1 \int_0^1 C(u, v) dC(u, v) - 1 \quad (2)$$

and

$$\rho = 12 \int_0^1 \int_0^1 C(u, v) du dv - 3. \quad (3)$$

A major advantage of the copula approach is that it enables the separate modelling of the marginal behaviour of X and Y and of the dependence structure embedded in C , meaning that a rich model of association that is free from limitations imposed by marginals F and G can be specified. For an introduction to copulas see Joe (1997), Nelsen (2006) and Cherubini et al. (2004) and Patton (2009) for applications of copulas in finance. When the marginal models include other control variables, this amounts to the *conditional copula* approach of Patton (2006). In this case, the copula captures dependence after “netting out” the effects of variables included into the marginals as controls.

Our aim here is to explore the nature of dependence between our macroeconomic news variable and aggregate equity returns by specifying and fitting an accurate copula model to our data. While much work has been done to assess the impact of economic news on equity returns, our particular interest is in probing for non-linearities in this relationship such as tail dependence, which

refers to dependence among extremes, or the tendency of very-large (or small) values of one variable to be associated with very-large (or small) values of another. In other words, in addition to gaining a better understanding of the overall association between macroeconomic news and security returns using the copula approach, our goal is to understand whether market impact varies with severity of news, with focus on extreme events. Such extreme dependence is usually studied through the so-called upper- and lower-tail dependence coefficients denoted λ_u and λ_l respectively and defined as

$$\lambda_u = \lim_{u \rightarrow 1^-} \Pr[F(x) \geq u | G(y) \geq u] = \lim_{u \rightarrow 1^-} \frac{1 - 2u + C(u, u)}{1 - u}, \quad (4)$$

$$\lambda_l = \lim_{u \rightarrow 0^+} \Pr[F(x) \leq u | G(y) \leq u] = \lim_{u \rightarrow 0^+} \frac{C(u, u)}{u}. \quad (5)$$

Greater values of λ_u (λ_l) indicate stronger tendency of large (small) extremes of the variables to co-occur. One of our objectives is therefore to obtain estimates of coefficients λ_u and λ_l between our economic news variable and security market returns.

3.2. Estimation

Differentiating Eq. (1) will reveal that the joint PDF of X and Y can be represented as

$$f(x, y; \theta_x, \theta_y, \theta_c) = f(x; \theta_x)g(y; \theta_y)c(u, v; \theta_c), \quad (6)$$

where $f(x; \theta_x)$ and $g(y; \theta_y)$ are the marginal densities and $c(u, v; \theta_c)$ is the so-called *copula density* defined as

$$c(u, v; \theta_c) = \frac{\partial^2 C(u, v; \theta_c)}{\partial u \partial v}. \quad (7)$$

Parameter estimates $\hat{\theta}_x$, $\hat{\theta}_y$ and $\hat{\theta}_c$ can therefore be obtained by maximizing the corresponding log-likelihood function

$$\log(f(x, y; \theta_x, \theta_y, \theta_c)) = \log(f(x; \theta_x)) + \log(g(y; \theta_y)) + \log(c(u, v; \theta_c)), \quad (8)$$

where $l_x = \log(f(x; \theta_x))$ and $l_y = \log(g(y; \theta_y))$ are the log-likelihoods for the marginal models and $l_c = \log(c(u, v; \theta_c))$ is the *copula log-likelihood*.

Joe and Xu (1996) propose a two-step method where marginal models are first estimated independently using maximum likelihood so that to obtain the values for u and v , and estimates of copula parameters are obtained second by maximizing l_c , given the marginal estimates. When the marginals are specified parametrically, this method is known as Inference Functions for the Margins (IFM). When the marginals are non-parametric, this procedure is known as Canonical Maximum Likelihood (CML). Consistency and asymptotic normality of the IFM estimator under a set of regularity conditions is shown in Joe (1997). The estimator is also known to be highly-efficient (for example, see Michelis and Ning (2010)), and we use it as the main estimation method here along with delete-one jack-knife procedure for estimating coefficient variances, as in Joe and Xu (1996).

4. Empirical results

We use the monthly return to the S&P 500 index as our measure of aggregate U.S. equity returns, with all data taken from the Center for Research in Security Prices (CRSP) monthly stock files. Next, we specify and estimate the marginal models for security returns and the macroeconomic news index, and the copula model of dependence.

4.1. Series diagnostic tests

Our estimation approach requires that all series be stationary. In addition, to ensure validity of copula estimates, the marginal models must accurately capture any serial dependence that may be present in the series. We therefore begin our analysis by conducting diagnostic tests of our news variable MNI_t , market returns R_t , employment news sub-index ENI_t , industry news sub-index INI_t , energy news sub-index $ENNI_t$, monetary conditions news sub-index $MCNI_t$ and housing and construction news sub-index series HNI_t . Table 3 shows rejection decisions for the null-hypotheses of unit root based on the ADF test, conditional heteroskedasticity obtained with the ARCH test of Engle (1982), and serial correlation based on the Ljung-Box Q-test, for 12 monthly lags of the series, all carried out at 5% significance level. We also collect the summary statistics for all series in Table 4 and examine our data for unconditional skewness and excess kurtosis.

We find that while none of the series appear to have a unit root, with the exception of INI_t , conditional heteroskedasticity is present in all series, and with the exception of R_t , all series are serially-correlated. In addition, a degree of skewness is present in most variables and will need to be accounted for during the specification of marginal models.

4.2. The marginal models

We begin the construction of the marginals with the model for security returns. Similar to Birz and Lott (2011), we include an economic surprise variable to control for the effect of surprises associated with releases of economic statistics. Since the impact of news can depend on the current economic conditions, we also include the current unemployment rate to control for such interactions. As the returns are not serially-correlated, we do not include any lags. Our marginal model for security returns is then specified as follows:

$$R_t = \beta_0 + \beta_1 X_t + \beta_2 L_t + \epsilon_{r,t}, \sqrt{\frac{1}{\sigma_{r,t}^2}} \epsilon_{r,t} \sim N(0, 1), \quad (9)$$

$$\sigma_{r,t}^2 = \theta_0 + \theta_1 \sigma_{r,t-1}^2 + \theta_2 \epsilon_{r,t-1}^2 + \theta_3 \mathbb{I}[\epsilon_{r,t-1} < 0] \epsilon_{r,t-1}^2, \quad (10)$$

where R_t is the market return during month t , X_t is a measure of economic data surprises, L_t is the current U.S. unemployment rate, and $\epsilon_{r,t}$ is the error term with time-varying variance $\sigma_{r,t}^2$ where \mathbb{I} is the indicator function such that $\mathbb{I}[\epsilon_{r,t-1} < 0] = 1$ whenever $\epsilon_{r,t-1} < 0$ and $\mathbb{I}[\epsilon_{r,t-1} < 0] = 0$ otherwise. We therefore model R_t as conditionally-normal, with time-varying mean that depends on the current economic conditions and real surprises, and variance that follows a GJR – GARCH(1, 1) process as in Glosten et al. (1993). The inclusion of the indicator and the so-called leverage term θ_3 into the variance model allows us to address the sign bias often present in security returns by enabling asymmetric volatility clusters that are skewed toward negative return shocks. For additional discussion see, for example, Engle and Ng (1993). We use the U.S. economic surprise index of Scotti and Yue (2013), which shows accumulated differences between expected and actual economic data releases, as our measure of X_t . Controls for economic data surprises and current economic conditions here imply that our analysis of association between market returns and our economic news variable will be net of market reactions to surprises in statistical releases, and will also not be driven by interaction between the markets and the different stages of the business cycle. In other words, the dependence between equity markets and economic news that we assess in the next section is not driven by the data-revealing component of economic news, and is not due

Table 3

Diagnostic tests for news variables and security returns.

	Reject null at 5%		
	Unit Root	Heteroskedasticity	Autocorrelation
R_t	Reject	Do not reject	Reject
MNI_t	Reject	Do not reject	Do not reject
ENI_t	Reject	Do not reject	Do not reject
INI_t	Reject	Reject	Do not reject
$ENNI_t$	Reject	Do not reject	Do not reject
HNI_t	Reject	Do not reject	Do not reject
$MCNI_t$	Reject	Do not reject	Do not reject

Table 4

Monthly summary statistics for news variables and security returns, January 1999–December 2013.

	Average	St. Dev.	Max.	Min.	Skew.	Kurt.
R_t	0.00	0.04	0.11	−0.17	−0.55	3.78
MNI_t	0.04	0.24	0.60	−0.63	−0.24	2.96
ENI_t	0.03	0.34	0.70	−0.92	−0.43	3.01
INI_t	0.17	0.55	1.00	−1.00	−0.34	2.17
$ENNI_t$	−0.09	0.28	0.85	−1.00	−0.05	3.87
HNI_t	0.06	0.53	1.00	−1.00	−0.22	2.16
$MCNI_t$	−0.01	0.26	0.67	−1.00	−0.74	6.15

Table 5

Maximum likelihood estimates of returns marginal model. Bold indicates significance at 5 s.l.

	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\theta}_0$	$\hat{\theta}_1$	$\hat{\theta}_2$	$\hat{\theta}_3$	R^2
Estimate	0.002	0.008	0.001	0.001	0.770	0.001	0.319	0.011
t-Ratio	(0.17)	(1.28)	(0.46)	(1.37)	(9.84)	(0.10)	(2.33)	–

to the market effects of real economic fluctuations, but represents short-term market reactions to the various news-wire signals that we index.

Maximum likelihood estimates of the marginal model in (9) are shown in Table 5. The conditional variance terms appear highly-significant, indicating the presence of conditional heteroskedasticity in the return series, and the positive and significant estimate of the leverage term θ_3 suggests skewness toward negative return shocks. Much in line with previous literature, economic data surprises and unemployment are borderline-significant but still improve the overall model fit and therefore remain.

The marginal model for our economic news variable is specified as follows:

$$MNI_t = \alpha_0 + \alpha_1 MNI_{t-1} + \alpha_2 MNI_{t-2} + \epsilon_{m,t}, \quad (11)$$

where MNI_{t-j} are the lagged monthly values of the macroeconomic news index and $\epsilon_{m,t}$ is the error term. The number of lagged months of the news variable included into the model was determined first by estimating autoregressive model of order 6 and then eliminating insignificant lags. Parameter estimates for model (11) are collected in Table 6.

Highly-significant estimates of auto-regressive coefficients indicate a substantial degree of persistence in our news variable which is perhaps unsurprising given the persistent nature of the business cycles.

4.3. Goodness of fit tests for marginal models

Before we construct and estimate the copula model, we need to ensure that the marginals are specified well. To this end, we use the $K-S$, $ARCH$ and LBQ tests to probe for normality, homoskedasticity and absence of serial correlation of the residuals from models (9) and (11) and find that we cannot reject any of the nulls at 5%

Table 6

Maximum likelihood estimates of the marginal model for the macroeconomic news index. Bold indicates significance at 5% s.l.

	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	R^2
Estimate	0.019	0.176	0.278	0.13
t-Ratio	(1.56)	(2.78)	(3.81)	-

significance level for both models, indicating a good fit for our return and news index series and appropriate capture of features of the data highlighted in Tables 3 and 4.

Note also that probability transforms $u = F(x; \theta_x)$ and $v = G(y; \theta_y)$ are uniformly distributed on $[0, 1]$. Following Patton (2006), we calculate the transforms corresponding to R_t and MNI_t as $\hat{u}_t = \Phi(\hat{\epsilon}_{r,t}/\hat{\sigma}_{r,t})$ and $\hat{v}_t = \Phi(\hat{\epsilon}_{m,t}/\hat{\sigma}_{m,t})$, where $\Phi(\cdot)$ is the standard normal CDF and $\hat{\epsilon}_{r,t}/\hat{\sigma}_{r,t}$ and $\hat{\epsilon}_{m,t}/\hat{\sigma}_{m,t}$ are the standardized residuals from the marginal models. When the marginals are specified correctly, the empirical transforms \hat{u}_t and \hat{v}_t should also be uniform on $[0, 1]$. As an additional goodness of fit check, we test the transforms for uniformity using the $K-S$ test, and find that we cannot reject the null in both cases, with p -values being close to one.

4.4. Empirical copula table

To gain an initial understanding of the nature of association between security returns and economic news in our data, we construct the so-called *empirical copula table* (for other examples see Knight et al. (2005) and Ning (2010)). The copula table gives an overview of the structure of dependence, and is often used as the first step of the copula model selection process. First, we arrange the probability transforms \hat{u}_t and \hat{v}_t of the return and news index series in ascending order and then sort them evenly into four bins. In each case, the first bin contains the bottom 25% smallest observations, and the fourth bin contains the top 25% largest observations in the sample. We then construct a frequency table with four rows and four columns, where the j row and i column shows the total number of elements in j 'th bin of the news index series and i 'th bin of the security return series. For example, the number in cell (4,4) of this table shows the total number of observation pairs in the sample that are in top 25% for both variables. It should be evident that such table represents the joint frequency distribution of probability transforms \hat{u}_t and \hat{v}_t , and since these are uniform, our frequency counts should also be evenly distributed among the table cells when the variables are independent. That is, if security returns are independent from economic news, conditional on our controls, we should expect to see 11 observations in each of the 16 bins, since our monthly series spanning January-1999 to December-2013 contain a total of 180 observations. A number greater than 11 indicates a tendency of our variables to "cluster" together in a particular bin. For example, a number in cell (4,4) of this table that is substantially larger than 11 would indicate that largest 25% values of the news index tend to be associated with largest 25% of market returns, and so on.

We present the empirical copula table for our news variable and security market returns in Table 7, with the largest deviation from independence count highlighted in bold. Interestingly, greatest deviation from expected count occurs among the bottom 25% of news-return pairs where observed count exceeds expected by almost 40%, indicating that dependence between returns and economic news appears to be heavily skewed toward the lower tail of the joint distribution. The count in bin (4,4) showing clustering of observations in top 25% for both variables nearly equals to that expected under independence, suggesting that little association exists among largest returns and news index values. In other words, the empirical copula table appears to suggest that

Table 7

Empirical copula for security returns and macroeconomic news index.

Bin	1	2	3	4
1	15	6	12	12
2	15	4	13	13
3	14	7	13	13
4	8	12	11	12

unusually-bad macroeconomic news tends to lead to substantial market declines, while equally unusually-good news has little market effect.

4.5. Copula model selection, estimation, and main result

Asymmetric tail and nonlinear dependence between financial series has attracted some recent attention. For example, Patton (2006) and Michelis and Ning (2010) use copulas to study asymmetries in exchange rate dependence, and Ning and Wirjanto (2009) use a copula model to probe for tail dependence among security returns and trading volume. Here, since our marginal models include controls, our modelling approach is similar to the conditional copula models of Patton (2006) and Michelis and Ning (2010).

While our initial results indicate dependence that is skewed toward the lower distribution tail, we begin formal model selection by fitting several bi-variate copulas representing a variety of dependence structures to the news index and market returns using the IFM method and assess their fit. We find that among Gaussian, Gumbel, Clayton, t and SJC coupla families, the one-parameter Clayton copula yields the superior fit on the basis of Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The bi-variate Clayton copula is defined as

$$C(u, v; \theta) = [\max(u^{-\theta} + v^{-\theta} - 1, 0)]^{-1/\theta}, (u, v) \in [0, 1]^2, \quad (12)$$

where $\theta \geq 0$ is the dependence parameter such that greater values of θ indicate stronger association between the variables, and the case of $\theta = 0$ corresponds to independence. The Clayton copula features lower, but not upper-tail dependence, with tail-dependence coefficients given by $\lambda_l = 2^{-1/\theta}$ and $\lambda_u = 0$. Significant positive values of θ therefore also indicate the presence of asymmetric tail dependence skewed toward the lower tail. The superior fit of the Clayton copula here supports our findings from the empirical copula table.

IFM estimation results of the conditional Clayton copula model using our macroeconomic news index, aggregate stock market returns, and the marginal model specifications from Section 4.2 are shown in Table 8. The estimate of the Clayton dependence parameter is significant at 5% s. l. indicating that, controlling for economic data surprises and current economic conditions, macroeconomic news has a significant effect on security returns, and that this effect is skewed toward the lower distribution tail. In other words, we find that markets react strongly and negatively to extremely-poor economic news, but show no similar tendency to respond to good news, and that this relationship is not driven by the data-revealing component of economic news, or the changing interpretation of news in different economic conditions.

4.6. Robustness checks

In this section we perform several robustness checks to our result in Table 8. Firstly, since our macroeconomic news index is calculated at monthly frequency, journalists writing the news-wire releases can observe market returns during the month, which may affect the tone of their reporting and create potential for

Table 8

IFM estimate of bi-variate conditional Clayton copula model of dependence between R_t and MNI_t . Bold indicates significance at 5% s.l. Monthly observations, January 1999–December 2013.

	Estimate	t-ratio	AIC	BIC	LogL
$\hat{\theta}$	0.101	(1.77)	-0.384	2.787	1.203

reverse causation. Fortunately, TRN and DJES economy-related news-wires tend to be condensed and factual and contain little in terms of journalistic opinion, subjective reporting, or market commentary. Classification of news-wires is therefore hardly affected by the reporter's tone. The index, however, reflects comments made by policy officials, which represents greater potential for reverse causation since such comments may be induced by market events in the first place. In other words, officials may issue commentary in response to market movements, which then gets objectively reported on by the TRN or DJES and reflected in the index. Following [Birz and Lott \(2011\)](#), we note that if news is indeed driven by market activity, we should see more news releases during the high-activity months. To test this, we regress the absolute values of market returns on de-trended volume of news measured by the total number of news-wire releases in a given month and find the coefficient on news volume to be insignificant, with p -value close to one. Market activity is therefore not associated with volume of news. As a further test, we also re-estimate the marginal model for market returns given in (9), but include the number of news releases as an additional control. As before, we find the news volume to be insignificant. As a final check, we keep the de-trended news volume in (9) and re-estimate the entire Clayton copula model with IFM. Unsurprisingly, our estimation results change very little, and the Clayton dependence parameter remains significant. We therefore conclude that reverse causation between market returns and economic news is highly unlikely.

Another factor that may potentially affect our result is the choice of the market return composite. To test for robustness against the choice of market benchmark, we re-estimate the model using both value-weighted and equal-weighted returns to a portfolio of all NYSE, NASDAQ, and NYSE Arca-listed securities as measures of U.S. aggregate stock market performance. We find that the choice of the market composite has little effect on our results, with Clayton dependence parameter remaining significant in all cases and its estimate roughly unchanged.

Lastly, to ensure that the result is not solely driven by our choice of modelling approach, we repeat our analysis using the same methodology but different measures of news that have been used in the literature to date. Specifically, we focus on initial statistical announcements for 13 key macroeconomic variables and following [Flannery and Protopapadakis \(2002\)](#), among others, define news as the difference between the headline number and the median expectation at the time, with all data taken from Bloomberg. For each of the variables that we consider, we follow the same conditional copula approach as in Sections 3 and 4 to assess their impact on stock returns. That is, we first construct appropriate marginal models where unemployment rate is retained as control, and test for their goodness of fit. We then use the empirical copula table in combination with IFM AIC and BIC to select the copula family that best captures the market effect of each news measure, and collect our findings in Table 9. The estimates of copula parameters along with corresponding p -values indicate whether a statistically-meaningful relationship between each measure of news and the market returns exists.

In line with much of the previous literature, we find that when controlling for current economic conditions, most, but not all macroeconomic data surprises seem to have no effect on market

Table 9

IFM estimation results using alternative measures of news. Monthly data, January 1999–December 2013. *Conditioning on unemployment rate removed from marginal model for unemployment announcements. **Output analysis done at quarterly frequency, in accordance with the schedule of BEA releases. Bold indicates significance at 5% s.l.

Economic variable	Copula family	Market effect	Estimate	P-val.
Trade balance	Clayton	Lower tail	0.067	0.08
Consumer credit	Gaussian	Linear	-0.118	0.04
Construction spending	Gaussian	Linear	0.009	0.14
CPI inflation	Gaussian	Linear	-0.096	0.21
Nonfarm payrolls	Gaussian	Linear	0.137	0.01
Unemployment rate*	Gaussian	Linear	-0.033	0.56
New home sales	Gaussian	Linear	-0.023	0.99
Retail sales	Clayton	Lower tail	0.149	0.02
House starts	Gaussian	Linear	-0.105	0.17
Industrial production	Gaussian	Linear	-0.012	0.59
Personal income	Clayton	Lower tail	0.010	0.92
Producer price index	Gaussian	Linear	-0.056	0.45
Output**	Gumbel	Upper tail	1.047	0.45

returns, even once the conditional copula approach is adopted. To this end, our result in Section 4 appears to represent a genuine, asymmetric market reaction to broad economic news that is revealed, but is not driven by the copula model.

Interestingly, for most economic variables, our approach selects the Gaussian copula and hence a linear dependence structure as one that best captures the underlying market effect, suggesting that linear or piecewise linear model specification adopted in much of the earlier literature is generally suitable². It is not always so, however, as the case of retail sales demonstrates where a significant Clayton parameter represents the presence of a non-linear, skewed market effect. It therefore appears that the conditional copula approach can detect nonlinearities that may have been missed in previous studies, which is something that future research should investigate.

4.7. Component analysis

The five components of the macroeconomic news index outlined in Sections 2.3–2.7 may be interesting in their own right. Moreover, the asymmetry that we document in Table 7 and formally in Table 8 may be due to disproportional market reaction to a single index component. To gain a better understanding of the contribution of each component to our result, we once again repeat the analysis but now focus on individual news sub-indexes. We follow the same Box–Jenkins approach and construct separate marginal models for employment news sub-index, housing and construction news sub-index, industry news sub-index, energy news sub-index, and monetary conditions news sub-index, and then use empirical copula table and IFM AIC and BIC to select and estimate a copula model of dependence that best captures their individual market effects, with results summarized in Table 10.

With the exception of energy-related news, there appears to be no significant market reaction to individual index components. As for Energy News Sub-Index, the two-parameter Student copula yields superior fit, and while the correlation coefficient between energy news and market returns is not statistically-different from zero, significant tail dependence parameter indicates presence of nonlinear market response that is not captured by the correlation estimate. Specifically, tail dependence estimate implies that unusual energy news on both ends of the spectrum tends to be associated with extreme market returns. Several previous studies have

² Note that when the copula is Gaussian, IFM parameter estimate is the conditional correlation between the news measures and stock returns.

Table 10

Copula model estimates for individual news sub-indexes. Monthly observations, January 1999–December 2013. Student copula is parametrized by linear correlation coefficient ρ and tail-dependence parameter k . For energy news, correlation parameter is not significant (with estimate $\hat{\rho} = -0.016$, p -value 0.864), and we only include the significant estimate of Student tail dependence parameter above. Bold indicates significance at 5% s.l.

News sub-index	Copula family	Market effect	Estimate	P-Val.
Employment	Clayton	Lower-tail	0.073	0.19
Housing	Clayton	Lower-tail	0.050	0.25
Energy	Student	Symmetric tail	6.991	0.00
Industry	Clayton	Lower-tail	0.091	0.11
Monetary	Gaussian	Linear	-0.043	0.65

found that energy news tends to affect the market asymmetrically, depending on whether news represents a demand or a supply shock, for example (see Kilian and Park (2009) for effects on the U.S. stock market, and Kang et al. (2014) on the bond markets). Our finding here is different in that it suggests that market impact of energy news also varies with news severity.

To ensure that our findings in Section 4.5 are not solely driven by market reaction to energy news, we re-estimate the Clayton copula model one final time but now using a version of the macroeconomic news index that excludes energy news. Table 11 shows the resulting IFM model estimate.

As before, we find the Clayton parameter to be positive and significant, suggesting that our main result is not driven by energy news, and due to lack of significance for other sub-indexes in Table 10 – not by any other index component individually. The asymmetric negative market response to macroeconomic news that we document in Section 4.5 is therefore due to simultaneous occurrence of unfavorable news on all fronts. Plainly speaking, the market tends to substantially fall when all news is bad, but fails to similarly respond when news surprises on the upside.

4.8. Trading rule based on information revelation

Given the relationship between news and returns that we document in Table 7 and formally in Table 8, it is natural to ask whether a trading rule based on information revelation is possible. Since our marginal estimates indicate the presence of temporal correlation in the news variable, we reason that strongly-unfavorable economic news may also induce a price drift and signal a higher likelihood of an unusually-low market return in the future. We consider a simple monthly trading strategy which involves holding a long-only value-weighted portfolio of all S&P 500 stocks during all months, except following the release of sufficiently-poor economic news. When this happens, we sell short the same portfolio during the next month. We rebalance at the end of every month, when the past month's news index becomes available.

We treat the value of MNI_t as “sufficiently-poor” if it falls below the bottom quartile of all index values observed up until trade date, therefore ensuring that only information available at trade time is used. We adopt the S&P 500 index as the benchmark, and it should be evident that during any given month t the strategy return equals to that of the S&P 500 if $MNI_{t-1} > \hat{F}_{t-1}^{-1}(0.25)$, where $\hat{F}_k(x)$ is the empirical CDF of MNI_1, \dots, MNI_k , and to the negative of benchmark return if $MNI_{t-1} \leq \hat{F}_{t-1}^{-1}(0.25)$. In what follows, we refer to this as the *baseline strategy*. We begin our trading following this strategy in January 2004, using the years 1999–2003 to obtain initial estimate $\hat{F}_k(x)$.

Lastly, to obtain the longest possible history, we dispose of percentile rule and modify the strategy so that a long position is open during month t simply if $MNI_{t-1} > 0$, and a short position if

Table 11

IFM estimate of bi-variate conditional Clayton copula model of dependence between R_t and MNI_t , excluding energy news. Bold indicates significance at 5% s.l. Monthly observations, January 1999–December 2013.

	Estimate	t-ratio	AIC	BIC	Log L
$\hat{\theta}$	0.124	(1.94)	-1.526	1.644	1.203

Table 12

Performance statistics for the S&P 500 index, benchmark, and naive news-based trading strategies.

Strategy	Jan. 2004–Dec. 2014		Feb. 1999–Dec. 2014	
	Baseline	S&P 500	Naive	S&P 500
Cumulative return	183.08%	85.51%	181.00%	73.20%
Annualized return	10.32%	6.13%	6.89%	3.66%
St. deviation	14.43%	14.63%	15.41%	15.50%
Sharpe ratio	0.71	0.42	0.44	0.23
Max. drawdown	20.75%	50.48%	20.75%	50.48%
MM alpha	0.36%	–	0.27%	–
CAPM alpha	0.73%	–	0.42%	–
CAPM t-ratio	(1.91)	–	(1.25)	–

otherwise. We refer to this version of the baseline strategy as the *naive strategy*, which now begins in February 1999, immediately after our index becomes available.

We collect a number of performance statistics for the benchmark, the baseline, and the naive strategy in Table 12. Annualized return is the equivalent annual continuously-compounded rate of return that each of the strategies delivers. The standard deviation shows annualized volatility of monthly returns, while the maximum drawdown is the greatest peak-to-trough percentage loss throughout entire trading history. We use the risk-adjusted excess return measure of Modigliani and Modigliani (1997) which we denote MM alpha along with the usual CAPM alpha of Jensen (1968) to draw inference about abnormal return. Bold indicates CAPM alpha that is significantly positive, at 5% s.l.

Both the baseline and the naive strategy substantially outperform the benchmark on both net return and risk-adjusted basis, with the annualized excess return to the baseline strategy between 4.41% and 9.12% based on MM and CAPM alpha estimates, respectively. Since our news variable is constructed using generally-available sources, this appears to contradict the weak form of market efficiency which precludes the possibility of obtaining such superior returns on the basis of public information.

The top panel of Fig. 7 shows the cumulative return to the baseline strategy and the S&P 500 index, and the bottom panel shows cumulative return profile for naive strategy, with highlighting indicating months during which short-selling has occurred. For both strategies, most active short-selling appears to have happened in the lead up to and during financial crises, that is, in the periods 2001–2002 and 2007–2008. Large excess return was realized during these periods due to robust loss avoidance by both strategies, which also explains the substantial difference in draw-downs between the strategies and the benchmark seen in Table 12.

While our trading strategy is simple, trading results may still be affected by the choice of parameter values, which here are the news percentile cutoff currently set at 25% and the initial trade date set to January 2004. To check the estimates in Table 12 for robustness, we vary the bad news percentile cutoff from 15% to 45%, in 10% increments, and the trade starting date from March 2003 to March 2007 in 12 month increments, and repeat the simulation for every combination of parameters. We find that in all twenty cases that we consider, the strategy continues to outperform the benchmark on risk-adjusted basis, with CAPM alpha remaining positive and significant, and in 18 out of 20 cases the

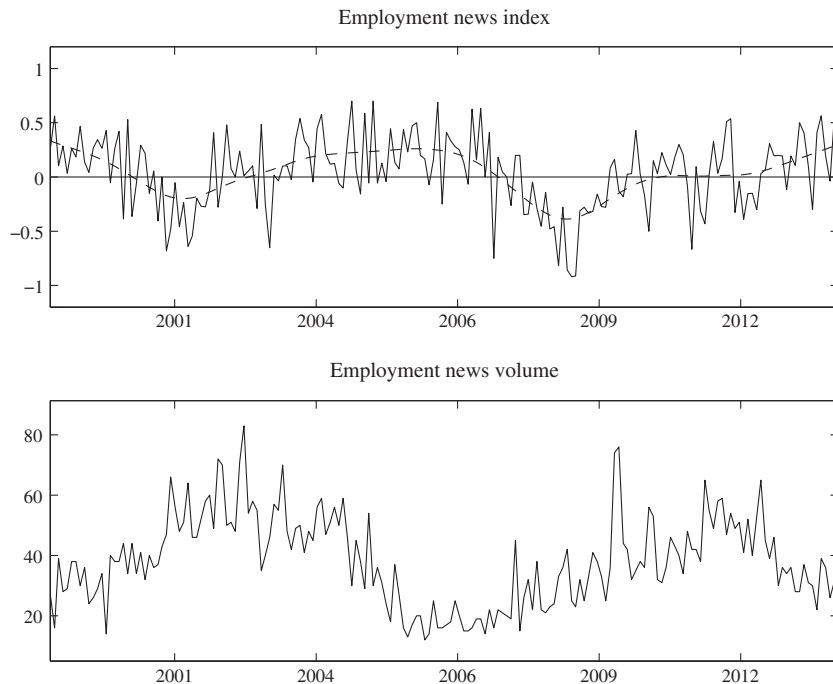


Fig. 1. Monthly values of employment news index and total number of employment-related news releases carried by Reuters, January 1999 to April 2014. Dashed line shows HP-filtered trend.

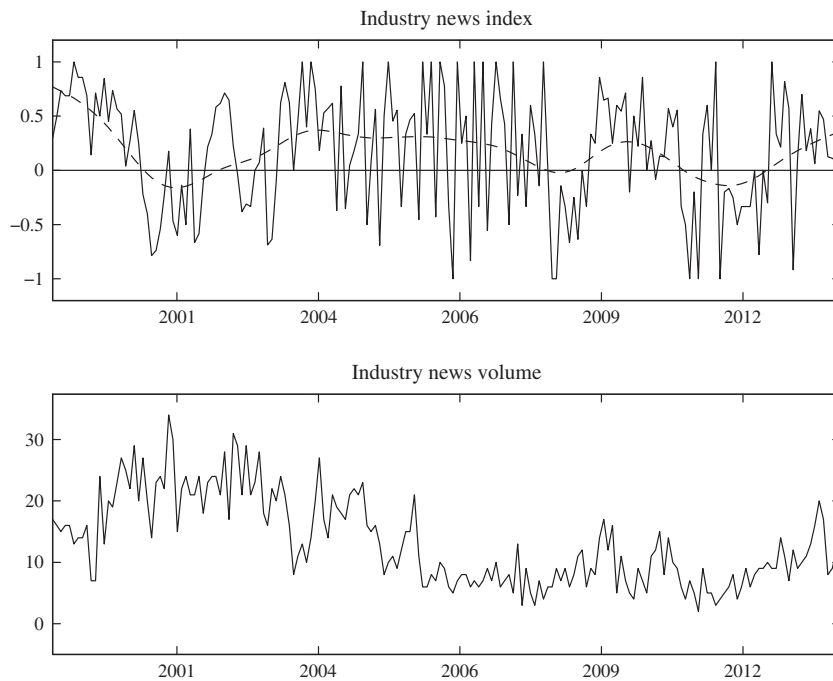


Fig. 2. Monthly values of the industry news index and total number of industry-related news releases carried by Reuters, January 1999 to April 2014. Dashed line shows HP-filtered trend.

strategy continues to substantially outperform on the basis of net return as well. We therefore conclude that abnormal returns that we document in this section are not driven by favorable choice of parameters, but represent genuine opportunities.

It is also important to note that our aim here is only to demonstrate that information revelation strategy that utilizes the index is possible and can lead to superior investment returns. Many alternative strategies involving the index are possible and may improve

upon ours. We do not explore such alternatives here, as our focus is the contemporaneous clustering between news and returns that we document in [Table 8](#).

5. Discussion

It is interesting to note that since the probability transforms \hat{u}_t and \hat{v}_t are serially uncorrelated, the asymmetric relationship

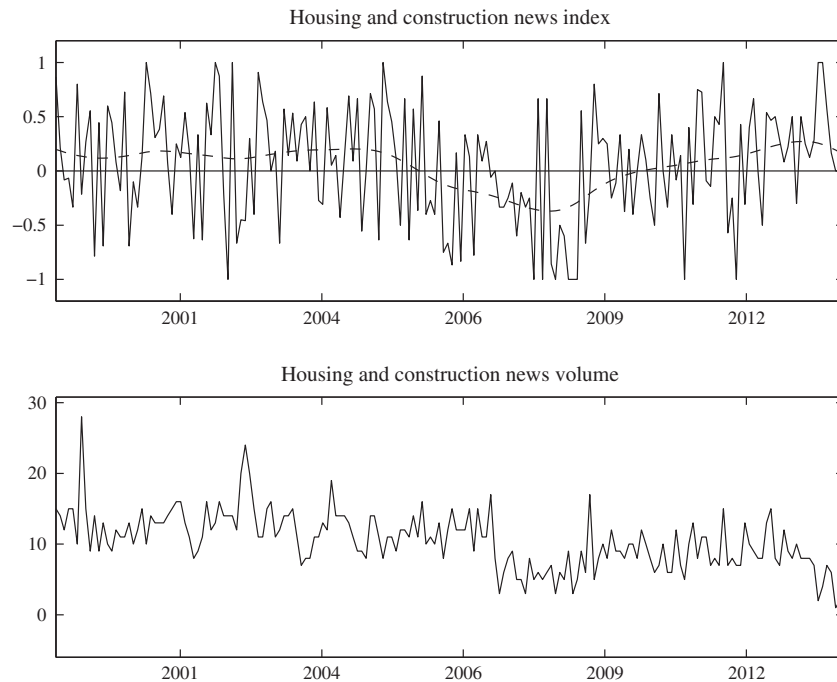


Fig. 3. Monthly values of housing and construction news index and total number of housing-related news releases carried by Reuters, January 1999 to April 2014. Dashed line shows HP-filtered trend.

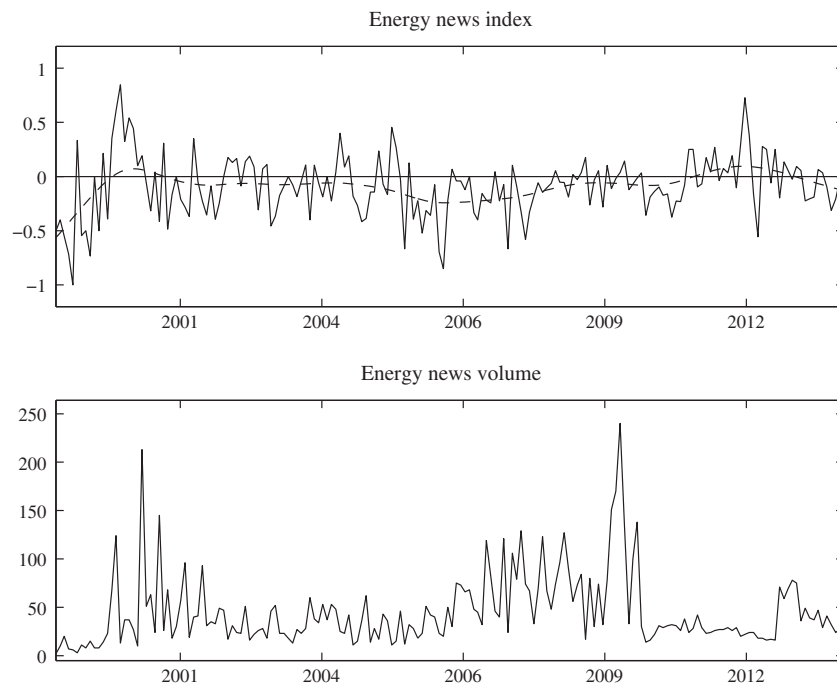


Fig. 4. Monthly values of the energy news index and total number of energy-related news releases carried by Reuters, January 1999 to April 2014. Dashed line shows HP-filtered trend.

between news and returns that we document here is not driven by any particular period of time such as, for example, the two NBER recessions in our sample, but is persistent throughout the business cycle. This may have implications for policy makers that have the potential to issue financially-disruptive comments. From the stock market standpoint, upbeat talk seems cheap, while economic pessimism can be costly at all times, not only during crises.

The copula methodology adopted here provides a statistical setup that is particularly well-suited for controlling for conditions that may influence investors' interpretation of economic news as well as capturing nonlinearities in market reaction, and may represent scope for future research in this area. Additionally, individual news sub-indexes along with our data on news volume may be interesting in their own right and their effect on the market should be investigated further.

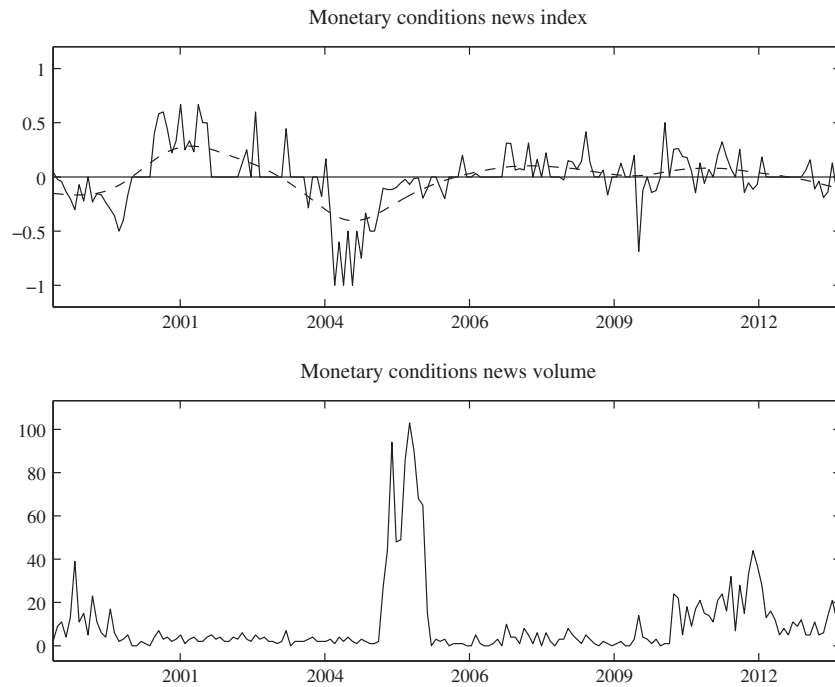


Fig. 5. Monthly values of the monetary conditions news index and total number of news releases related to U.S. monetary conditions carried by Reuters, January 1999 to April 2014. Dashed line shows HP-filtered trend.

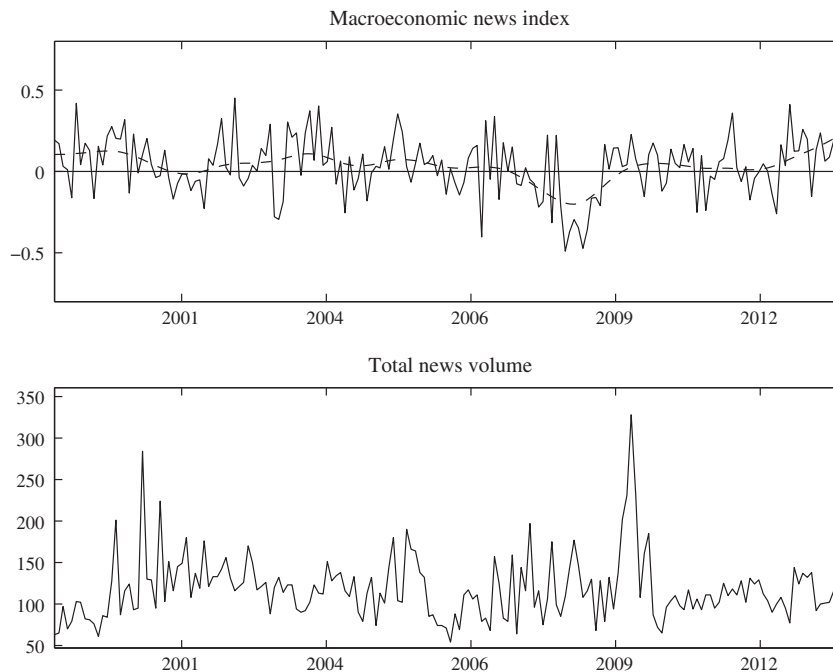


Fig. 6. Monthly values of the macroeconomic news index and total number of treated news releases carried by Reuters and Dow Jones Energy Service during January 1999–April 2014. Dashed line shows HP-filtered trend.

The news variable that we construct here may have some broader applications. For example, [Engle and Rangel \(2008\)](#) develop a model for low-frequency volatility that is driven by macroeconomic causes. Our news index may simplify the estimation of such models since it provides quantitative estimate of broader economic news that is available at a higher frequency than many scheduled statistical releases.

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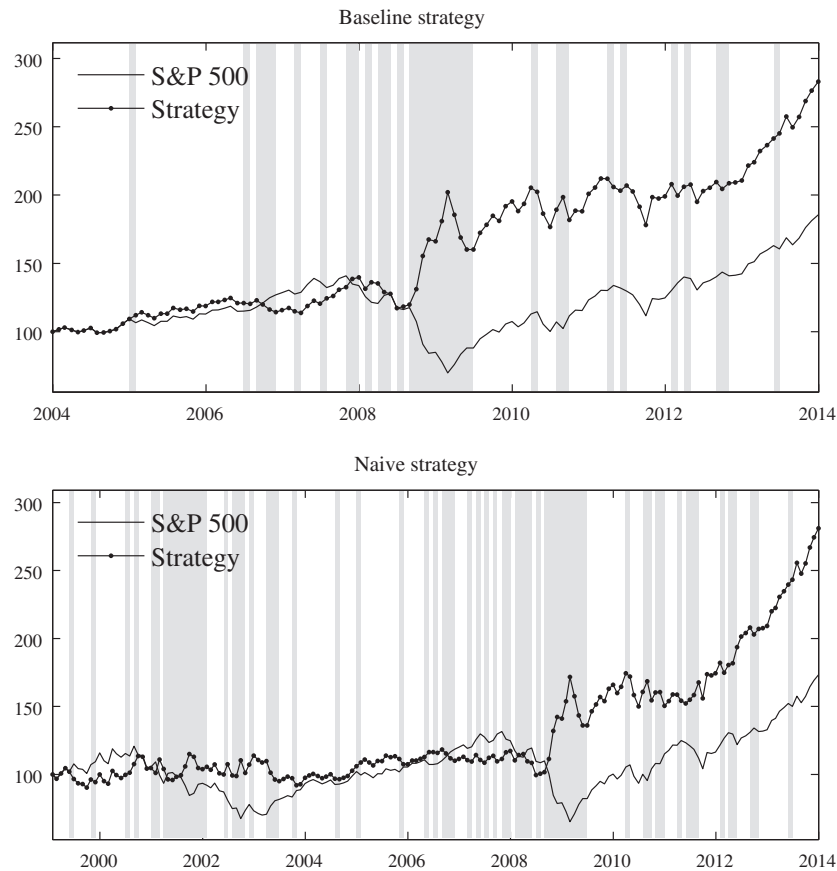


Fig. 7. Monthly cumulative return profiles of baseline, naive, and benchmark strategies. Gray shading indicates months during which short-selling occurred.

Appendix A

See Figs. 1–7

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.jbankfin.2016.01.004>.

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