Essays in Financial Economics

by

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This thesis is dedicated to my father Tongchun Wang, to my mother Jianrong Chen, and to my husband Robert Yhap, without whom it would never have been accomplished.

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LIST OF ABBREVIATIONS

IJC	Initial Jobless Claims
ERC	Earnings Response Coefficient
SUE	Standardized Unexpected Earnings
PEAD	Post Earnings Announcement Drift

SUMMARY

Financial Economics is a field of study which concerns the interrelation between financial market and real economy. My dissertation tries to understand this interrelation from two perspectives: The first perspective goes from real economy to financial market, and specifically looks at how the information about real economy is incorporated into financial market. The second perspective goes from financial market to real economy, and studies how the design and enforcement of financial market rules affects the real economy development.

Chapter 1 and Chapter 2 take the first perspective, to look at how the stock market responds to the macroeconomic news announcements. Information about the state of the economy is mostly communicated to the public through macroeconomic news announcements. Financial market responds to this new piece of information. However, there are yet no universal conclusions on WHAT and HOW the macroeconomic news announcements move the financial market. The first two chapters contribute to this field of study.

Chapter 1 is titled as "Post Macroeconomic Announcement Drift". This chapter is studying how the stock market responds to the macroeconomic news announcements, especially the Initial Jobless Claims report released by the Department of Labor every week. Motivated by the widely documented investors' underreaction behavior to firm-specific news announcements, this chapter is examing whether investors may also underreact to macroeconomic news announcement as well. Surprisingly, I find that investors do underreact to the Initial Jobless Claims (IJC) announcements. The stock market continues to go up following good IJC news and down following bad IJC news for several months. Furthermore, a trading strategy which simply buys S&P500 index after good IJC news and shorts S&P 500 index after bad IJC news can earn significant abnormal return, after controlling for the standard risk factors. The study also shows that the underreaction to IJC news may help to explain the time series momentum and cross sectional momentum phenomena documented in existing literature. To my knowledge, this is the first study which documents investors' underreaction behavior to macroeconomic news announcements.

Chapter 2 is titled as "Concordant News or Discordant Noise: Does Concurrent Macro News Affect Reaction to Earnings News?". Similarly as Chapter 1, this chapter continues to study how the macroeconomic news announcements affect stock returns. However, different from Chapter 1 which focuses on the systematic reaction by looking at the equity index's response to macro announcements, this chapter examines how the macroeconomic news announcements affect a single stock's return, especially on the days when the firm is concurrently announcing its quarterly earnings. Essentially, this chapter is studying the implication of a concurrent macroeconomic news announcement and a firm-specific earnings announcement. I find that a concurrent macroeconomic news announcement changes a stock's response to its earnings news: investors react strongly to firm-specific news when the macro news and firm-specific news are concordant, i.e., when the macro news and earnings news are both positive or both negative. I also find that the drift following positive earnings announcements is only seen when the concurrent macro news is negative. Those results suggest that investors underreact to discordant positive earnings news.

Differently from the previous chapters, Chapter 3 takes the second perspective, which studies how the financial market, on the other hand, shapes the real economy. Financial market acts as an intermediary in the real economy, to facilitate money flow from the lenders to the borrowers. Regulators enforced various rules within the financial market, normally referred to as market design, aiming to allocate capital more efficiently. This chapter thus looks at how the different stock market designs across the world may affect the real economy development, using cost of capital, market capitalization ratio as well as allocative efficiency measure as dependent variables. I collect data on 26 stock trading rules from 42 countries since 1980s, and creates five categorical indices from those rules. Each of the indices captures a different aspect of the market's quality, including: competition, financial disclosure, information access, market dynamics and market stability. To my knowledge, this is one of the most complete dataset of trading rules, and allows us to further understand the economic effect of financial market designs.

In conclusion, my thesis is working to understand the interrelation between the financial market and the real economy. Financial market as part of the whole economy is affected, as well as affects the real economy. My thesis essentially touches base on the two direction around this loop. In the direction from the real economy to financial market, I focus on the information transmission channel ,and unfold some interesting investors trading behaviors to macro news announcements. In the direction from the financial market to the real economy, I focus on the high level regulatory perspective, and find that a well-designed stock market can help to decrease the economy's funding cost and allocative efficiency.

CHAPTER 1

POST MACRO ANNOUNCEMENT DRIFT

I find that the U.S. stock market underreacts to macroeconomic news, particularly the Initial Jobless Claims (IJC) news released by the U.S. Department of Labor. The stock market continues to drift in the same direction as the IJC news several months after the release of the news. A *news momentum strategy* that buys the market after good IJC news and shorts the market after bad IJC news beats the passive buy-and-hold strategy on the SPX index. Standard risk factors fail to explain the news momentum strategy: the abnormal return is about 8.4% per annum after controlling for these factors. News momentum returns are highly correlated with cross-sectional and time series momentum returns, suggesting that underreaction to macro news can potentially explain these price momentum phenomena. The drift following U.S. IJC news is also evident in other international equity markets. A diversified IJC news momentum strategy based on nine international equity indices partially explains globally diversified cross-sectional and time series momentum returns. This suggests that the global underreaction to U.S. macro news might be a potential common factor that drives the strong comovement between momentum returns across countries.

1.1 Introduction

Underreaction to news has been widely documented in finance literature. Studies show that investors underreact to various firm-specific news, including quarterly earnings announcements ((Ball and Brown, 1968a), (Bernard and Thomas, 1989)), stock splits ((Ikenberry et al., 1996)), analysts' recommendations ((Womack, 1996)), and dividend reductions and omissions ((Michaely et al., 1995)), causing the stock price to drift following those announcements. Recent paper ((Chordia et al., 2009)) suggests that investors' underreaction to firm-specific news contributes to the price momentum found by (Jegadeesh and Titman, 1993).

This paper provides the first evidence that investors also underreact to U.S. macroeconomic news announcements that are informative about future economic activities. Specifically, I find that the U.S. stock market continues to rise for several months following unexpectedly low Initial Jobless Claims news (good IJC news) and fall following unexpectedly high Initial Jobless Claims news (bad IJC news). A *news momentum strategy* that longs the market following good IJC news and shorts the market following bad IJC news generates significant abnormal returns after controlling for the Fama–French four factors and liquidity factor.

I argue that investors' underreaction to macro news is closely related to time series momentum documented by (Moskowitz et al., 2012). Time series momentum refers to the fact that a security's past returns positively predict its future returns. It is different from the well-documented cross-sectional momentum because it focuses on a security's own past return rather than the relative returns between securities. I find that time series momentum returns are significantly correlated with news momentum returns. News momentum subsumes the abnormal returns generated from time series momentum. These results suggest that news momentum has significant explanatory power for time series momentum.

The stock market drift following IJC news lasts up to six months. By varying the look-back period (K) and the holding period (H), I find that the news momentum strategy beats the passive buy-and-hold strategy when K and H range from one to nine months. For example, when $K = 6$ and $H = 1$, a news momentum strategy based on the S&P 500 (SPX) index from 1999 to 2014 generates an annualized excess return of 5.89% and a Sharpe ratio of 0.39, compared with 3.68% and 0.24 for the passive strategy. Standard risk factors fail to explain the return variations of this strategy. Specifically, I find that the strategy loads negatively on the market and positively on the momentum factor, and generates an abnormal return close to 8.4% per annum.

Interestingly, equity markets outside the U.S. also exhibit drift following U.S. IJC news. A news momentum strategy that trades a foreign stock market index following U.S. IJC news beats the passive buy-and-hold strategy on the foreign index in eight developed countries. In some cases, the news momentum strategy in other countries even outperforms the news momentum strategy within the U.S. For example, the news momentum strategy generates an annualized excess return of 11.09% using France's CAC 40 index and 11.54% using Japan's TOPIX index, while its passive benchmark generates annualized excess returns of only -0.62% and -0.39%, respectively. A globally diversified news momentum strategy that trades all nine equity indices delivers a 7.38% excess return annually. After controlling for the MSCI world index, and the globally diversified value and momentum factors as in the study by (Asness et al., 2013), the abnormal return still stands at 7.80% per annum.

Further investigation shows that news momentum is highly correlated with existing cross-sectional and time series momentum. The intercept from a regression of cross-sectional momentum on news momentum is not statistically different from zero. The correlation between news momentum and time series momentum is 0.57 for the U.S. equity market and 0.67 for the international equity market. While time series momentum generates significant abnormal returns after controlling for standard risk factors, as shown by (Moskowitz et al., 2012), the abnormal returns become insignificant after controlling for news momentum. This is true for both domestic and globally diversified momentum strategies. These results suggest that under-reaction to U.S. IJC news may provide a potential explanation for momentum both in the U.S. and international market. The U.S. IJC news, which predicts future U.S. equity market returns, is also a positive predictor of global equity market returns. This is consistent with the study by (Rapach et al., 2013), which shows that U.S. stock returns have significant predictability for international stock returns.

News momentum generates higher returns when the market is volatile, especially when the market is experiencing large downward movements. In a regression of news momentum returns on each of a set of market volatility indicators, including the squared returns of the market index, VIX, and the change of the VIX, the coefficients are all positive and statistically significant. This is true for both the news momentum strategy within the U.S. market and international market. During the period when the economy is going from good to bad, the negative IJC news induces the news momentum strategy to take a short position in the market index. As the economy is going from bad to worse, news momentum generates profits. The results suggest that returns from news momentum might be compensation for tail events.

This paper contributes to several aspects of the literature. To the best of my knowledge, this is the first paper to document investors' underreaction to macroeconomic news announcements. This can help to model how macro news information diffuses through financial markets and furthers our understanding of how the real economy is connected with financial markets. Existing studies that examine market response to macro announcements mostly focus on the initial response on the event day, assuming the market incorporates all the information fully and quickly ((Savor and Wilson, 2013), (Flannery and Protopapadakis, 2002), (Bernanke and Kuttner, 2005), (Grkaynak et al., 2005), (Andersen et al., 2007)). Ignoring the slow diffusion process can blur the true market reaction to a certain type of macro news, which could prevent us from finding the true macroeconomic risk factor.

This paper also contributes to the momentum literature. In an earlier paper, (Hong et al., 2000) state that "momentum is a symptom of underreaction — prices adjust too slowly to news." (Moskowitz et al., 2012) also suggest that their time series momentum could be due to underreaction to news and propose the presence of a common factor which could drive the strong comovement of momentum across asset classes. (Chordia and Shivakumar, 2006) find that price momentum and earnings momentum are related. However, it is less clear how underreaction to firm-specific news could drive price momentum at the aggregated market level.

My paper provides further evidence that momentum observed in different countries could be related to global underreaction to U.S. macro news announcements.

The remainder of the paper is organized as follows: Section 2 contains the descriptions of the dataset and the methodology to construct news momentum. Section 3 contains the empirical results on the performance of news momentum. Section 4 shows the relationship between news momentum, and time series and cross-sectional momentums. Section 5 looks at the time varying feature of the news momentum. Finally, Section 6 concludes.

1.2 Data and News Momentum Strategy

1.2.1 Macroeconomic data

In this paper, I analyze macroeconomic news announcements in the U.S. from January 1999 to December 2014. The main dataset used in this paper is the macroeconomic news dataset from Bloomberg. When testing the market response to a piece of news, the news is typically defined as the unexpected component of the announcement. The expected part of the announcement should have already been incorporated into prices under the efficient market hypothesis. In this paper, analyst forecast data for macro announcements is collected from Bloomberg. As in the work of (Flannery and Protopapadakis, 2002) and (Green, 2004), macro news is defined as:

$$News_{i,t} = \frac{Actual_{i,t} - Median(Forecast)_{i,t}}{\sigma(Forecast)_{i,t}}, \tag{1.1}$$

where i indexes a type of macro news and t indexes one announcement of the news.

Bloomberg started to collect analyst forecasts for macroeconomic announcements in 1997. Data before 1999 are not included in this study because the time series data are incomplete for the first two years. Forecasters are normally professional analysts from banks, asset management firms, and investment funds. Compared with other datasets on macro news forecasts, the data from Bloomberg have several advantages: First, the forecasts are made at the same frequency as the announcements, and thus convey more timely information about market expectations for the macro economy. Second, the forecasts in Bloomberg are provided by market participants, whose opinions are more relevant to the market. Finally, the information is easily accessible and understandable by investors[1]. On macro news announcements days, Bloomberg publishes the actual announcements together with analyst forecasts on its website. Thus, it is easy for investors to understand whether the actual announcements exceed or miss market expectations.

The Bloomberg forecast data provide expectations from a wide pool of professional analysts. From 1999 to 2014, the average number of forecasts for a GDP report is about 70. For the IJC report, the average number of forecasts is about 37. In my analysis, I exclude any announcement if the number of forecasts for the announcement is less than three. This has little effect on the data because most important macro news announcements have more than three analyst forecasts. I also move any macro announcements that occur after-hours or on non-trading days to the next trading day[2].

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[1]Bloomberg Economic Calander: http://www.bloomberg.com/markets/economic-calendar

[2]Recent papers that use Bloomberg analyst forecast data include those by (Gilbert et al., 2015), (Jan Hanousek and Evzen Kocenda, 2011), and (Rui Albuquerque and Clara Vega, 2009).

1.2.2 Initial Jobless Claims

In this paper, I focus on one particular news announcements: the Initial Jobless Claims (IJC) report released by the U.S. department of Labor. It is a weekly report released at 8:30 A.M. most Thursdays and contains the number of people who file for unemployment insurance for the first time during the previous week period. A high IJC number indicates higher unemployment and a low IJC number indicates lower unemployment.

In the U.S., there are hundreds of macro news announcements. I pick IJC based on several criteria. First, the news should be relevant to the stock market. Based on the Bloomberg relevance score, which is a rank based on the number of people who subscribe to news alerts, IJC is the second most important news. More importantly, in several regression analyses that examine the contemporaneous effect of macro news announcements on stock market returns, IJC news is the only news that moves the stock market during both expansion and recession.

Second, if the market underreacts to the news, the news should have positive predictive power in future market returns. I start with a simple regression analysis that includes four important macro news announcements, using three lags for each:

$$ret_t = \alpha_t + \sum_{i=1}^{I}\sum_{l=0}^{3}\beta_{i,t-l} * news_{i,t-l} + \epsilon_t, \tag{1.2}$$

where ret_t is the monthly return on the SPX index, t indexes the month, i indexes the news announcements, and l indexes lags in months. Four news announcements are included: Change in Nonfarm Payrolls, Initial Jobless Claims report, GDP report, and ISM Manufacturing. Those four news announcements are included because they have the highest relevance scores. If the market underreacts to any macro news, then news released in previous months should have predictive power in the current month return.

Note that all four macro news announcements are made monthly except for the IJC reports, which are released weekly. Therefore, I aggregate weekly IJC news into monthly IJC news by taking the mean of weekly IJC news released during that month. Throughout this paper, I use this methodology to aggregate weekly IJC news into monthly IJC news.

Table I contains the monthly time series regression of the SPX index returns on the four macro news announcements. Models 1–4 are regressions using one of the four macro news announcements. The independent variables include the current month news and their three lagged values. From the data, IJC is the only news announcement that has a significant coefficient on current month news. Positive (Negative) IJC news indicates the actual number of people who filed for jobless insurance was higher (lower) than the market expectation, indicating a bad (good) employment situation. From the regression, a month with positive IJC news (bad employment situation) has a lower market return. The R^2 is also highest for IJC news. The IJC news and its lags can explain up to 13% of monthly return variation, compared with 3% for other news announcements. More importantly, the coefficient for lagged IJC news is statistically significant at the 1% level. IJC news released three months previously is negatively and significantly related to the market return in the current month. The coefficient for IJC_{t-3} is even higher than that for IJC_t in absolute value, indicating that IJC is predictive. When including all four macro news announcements in Model 5, the pattern persists. The coefficients on IJC_t

and IJC_{t-3} are the only ones that remain statistically significant in the regression. Change in Nonfarm Payrolls, although normally referred to as the "king of the macro announcements," does not exhibit any statistical power for current or lagged months. The lack of predictive power is also found for GDP announcements.

As a robust check, I run regressions that include IJC news and one other macro news announcement with their three lags. The other macro news tested in these regressions are the 19 other news announcements that place in the top 20 of the Bloomberg relevance score, including: Change in Nonfarm Payrolls, FOMC rate decision, GDP change, ISM Manufacturing, Consumer Confidence Index, CPI, University of Michigan Sentiment, Durable Goods Orders, New Home Sales, Retail Sales, Housing Starts, Unemployment Rate, Industrial Production, Existing Home Sale, Factory Orders, Personal Income, Personal Spending, Trade Balance, and Leading Index. For all regressions, IJC_t and IJC_{t-3} remain significant. IJC_{t-1} is marginally significant in some of the regressions. Therefore, the robust check shows that the results for IJC news in Table 1 are not driven by omitted variables.

To make good news good for the market, I reverse the signs of the IJC news surprises such that good IJC news announcements occur when jobless claims are unexpectedly low and bad IJC news announcements occur when they are unexpectedly high. In the final dataset, there are 833 weekly IJC news announcements from 1999 to 2014, which is aggregated into 192 monthly IJC observations. Figure 1 shows the plot of the time series weekly and monthly IJC news. Both weekly and monthly IJC news oscillate around zero during the time period. There is no strong persistence of the news in any period. Figure 2 shows the plot of the news autocorrelations. Both weekly and monthly IJC news are not strongly autocorrelated. Table II reports the summary statistics and the initial market response to IJC news. Panel A of Table II shows that good and bad news are quite balanced throughout the period: there are 409 good IJC news announcements and 405 bad IJC news announcements. After the weekly news is aggregated into monthly IJC news observations, there are 98 months with good news and 94 months with bad news. The means are similar in absolute values for the good and bad samples. Panel B reports the regressions of daily SPX index returns and monthly SPX index returns on the IJC news; the coefficients are all statistically significant, again indicating that IJC news is significantly related to stock market returns.

1.2.3 News Momentum Strategy

Market underreaction to news implies that prices will drift in the direction of the news following the announcement. For example, underreaction to earnings announcements has led to the widely documented post earnings announcement drift (PEAD) phenomenon. A trading strategy that buys firms with good earnings surprises and sells firms with bad earnings surprises can earn significant abnormal returns over the 60 days following the earnings announcements ((Bernard and Thomas, 1990)). Similarly if the market underreacts to macro news, it will continue to move up following good macro news announcements and down following bad macro news announcements. Based on this idea, I construct a market timing strategy, which I call the "news momentum strategy."

The methodology for constructing the news momentum strategy is motivated by (Moskowitz et al., 2012). It is a monthly trading strategy.[1] First, for each month, I calculate a trading signal based on IJC news released in the past months. The number of months used to calculate the trading signal is defined as the K. The trading signal is simply the average of the monthly IJC news (after taking the opposite) released in the past K months. Second, if the trading signal is positive, I short the risk-free asset to initiate a long position in the stock market. If the trading signal is negative, I short the stock market and invest in the risk-free asset. I hold the market positions for H months, where H is defined as the holding period. The position size invested in the stock market is scaled by the inverse of the ex-ante volatility of the market. When the holding period is more than one month, there will be a total of H positions in any month t that are initiated at the beginning of month t, $t-1$, and until $t-H-1$. These H positions will be either long or short the market, depending on the trading signals. Thus, the return in month t will be the portfolio return for those H positions. The strategy is constructed as a zero-cost strategy; thus, the returns are excess returns.

Similar to the methodology of (Moskowitz et al., 2012), I calculate ex-ante volatility for the market index as follows:

$$\sigma_t^2 = 261 * \sum_{i=0}^{\infty} w_i * (r_{t-1-i} - \bar{r_t})^2, \tag{1.3}$$

[1]The reason I construct the strategy in monthly frequency is to easily compare to existing momentum strategies, which are constructed monthly. In section 3.2, I present the results for the weekly traded news momentum strategy.

where $1/\sigma$ is annualized volatility, t indexes the day, r is the return of the index, $\bar{r}$ is the weighted average return, and w_i is the weight. The weight varies exponentially across days and is chosen so that the average time is 60 days: $\sum_{i=0}^{\infty}(1-\delta) * \delta^i * i = \delta/(1-\delta) = 60$. $\bar{r_t}$ is the exponentially weighted average return using the same weight: $\bar{r_t} = \sum_{i=0}^{\infty} w_i * r_{t-1-i}$.

In related studies, market timing strategies are constructed similarly, but usually fix the holding period at one month. For example, (Shen, 2002) uses the spread between the price-to-earnings ratio of the S&P 500 index and interest rates as a trading signal. (Lander et al., 1997) use earning yields on common stocks and yields on treasury bonds as trading signals. In a similar manner to the study by (Moskowitz et al., 2012), the news momentum strategy allows us to study returns when the holding period is greater than one month.

1.3 IJC News Momentum Strategy

As shown in the previous section, IJC news surprises can predict future U.S. stock market returns, suggesting that the stock market may underreact to IJC news. Thus, I construct the news momentum strategy by following IJC news. The news momentum strategy buys the SPX index following good IJC news and shorts the SPX index following bad IJC news.

1.3.1 Performance of the IJC News Momentum Strategy

Table III shows the performance of the IJC news momentum strategy constructed on the SPX index for different look-back periods (K) and holding periods (H). K and H range from one to twelve months. As a benchmark, the passive buy-and-hold strategy on the SPX index from January 1999 to December 2014 yielded an average monthly excess return of 0.34% and a Sharpe ratio of 0.08.

Panel A in Table III shows the average monthly excess returns for the news momentum strategy. Returns for multiple (K, H) pairs are higher than those for the passive buy-and-hold strategy. For example, when $K = 1$, the returns for the news momentum strategy are higher than those for the passive strategy when H ranges from three to nine months, which suggests that there is a drift following past IJC news announcements. When $K = 1$ and $H = 3$, the excess return is 0.68% and Sharpe ratio is 0.16, which doubles the values for the passive strategy. The drift starts to reverse when H is more than four months. When $H = 6$, the excess return decreases to 0.46% and Sharpe ratio decreases to 0.13. As K increases, H needs to decrease for the strategy to beat the passive buy-and-hold strategy. For example, when K increases to nine months, the strategy beats the passive strategy only when H equals one month. Finally, when K increases to twelve months or above, the strategy is less profitable than the passive strategy. The highest return in this table is realized when $K = 1$ and $H = 4$, the excess return is 0.82%, and the Sharpe ratio is 0.24.

To account for the risk exposure of the news momentum strategy with different look-back and holding periods, Table IV shows the risk-adjusted performance. The table contains the coefficients and t-statistics of the intercept from a time series regression, which regresses the monthly excess returns on the monthly Fama–French three factors. The intercept is the monthly abnormal returns for the news momentum strategy. The abnormal returns are all positive and statistically significant for multiple (K,H) pairs. Similar to the results in Table III, when K is one month, the abnormal returns increase with H initially and start to decrease when H is more than four months, suggesting that the drift following IJC news lasts for several months before disappearing. The abnormal return when H equals six months is 0.65%, with t-statistics at 2.40, which is even higher than the excess return. Unlike Table III, some (K,H) pairs that do not yield high excess returns actually generate significant abnormal returns, such as when $K = 12$ and $H = 1$. Abnormal returns are higher than excess returns because the news momentum strategy loads negatively on some risk factors and provide a hedge to the systematic risk.

To conduct a more in-depth analysis on the news momentum strategy, I focus on a single news momentum strategy. Specifically, I choose $K = 6$ and $H = 1$ to easily related to the existing momentum strategy. As shown in the previous tables, this strategy is a relatively conservative strategy; thus, the following results are not driven by selecting the most favorable strategy.

Table V contains the factor loadings of the news momentum strategy. I regress the monthly excess returns of the news momentum strategy on the standard risk factors. The risk factors include: Fama–French three factors (MktRf, HML, SMB), the cross-sectional momentum factor (UMD), and the liquidity factor. MktRf, HML, SMB, and UMD are obtained from the Kenneth Data Library. The liquidity factor (LIQ) is a traded liquidity factor based on the work of (Pastor and Stambaugh, 2003). Table V shows that the strategy loads negatively on the MktRf factor, which is why the abnormal returns are higher than the excess returns. The strategy does not have a significant loading on the liquidity factor, which indicates that the returns in news momentum are not compensation for illiquidity. However, the strategy is significantly correlated with the UMD factor, which I examine in more detail in Section 4. Table V shows that after controlling for UMD and LIQ, the abnormal returns are still positive and statistically significant. The abnormal monthly return after controlling for all five factors is a significant 0.70% (8.4% annualized); that is, I find that existing risk factors fail to fully explain the news momentum strategy.

1.3.2 Weekly IJC News Momentum Strategy

The news momentum strategy presented above is constructed monthly. Constructing the strategy monthly allows us to easily relate news momentum to existing momentum strategies, which are usually constructed monthly as well. However, because the IJC news is announced weekly, aggregating the weekly news into monthly news may induce biases or information loss. As a robustness check, I construct news momentum in weekly frequency.

The weekly news momentum strategy forms a new position weekly. Each week, two days after the IJC news announcement, I long or short the market depending on the sign of the IJC news announced two days previously. I skip one day after the announcement to avoid possible next day reversal. If the IJC news announced two days previously is positive, I invest in the SPX index while shorting the risk-free asset; if negative, I short the SPX index and invest in the risk-free asset. The position is scaled by the inverse of SPX index volatility on the day prior to position formation day. The position is held for H trading days. When the holding period is more than one day, the return on the current day will depend on the total positions initiated in the past $H-1$ days.

Table VI contains the performance of the weekly news momentum strategy constructed on the SPX index. The holding days H ranges from 5 to 120 trading days, which roughly corresponds to six months. The abnormal returns are the intercept from the regression, which regresses the daily excess returns of the news momentum strategy on the daily Fama–French three factors. As a comparison, the passive buy-and-hold strategy yielded an average daily excess return of 0.019% and a daily Sharpe ratio of 0.015. As shown in the table, the daily excess returns and Sharpe ratio all beat that for the passive buy-and-hold strategy. The daily abnormal returns are all positive. Most of the t-statistics for the intercepts are close to or above 2. The abnormal returns in Table VI are consistent to what observed in Table IV. The highest abnormal return is achieved when the holding period is around 70 days, which roughly corresponds to four months as in Table IV. For example, when the holding days are 80 days, the daily abnormal return is 0.044%, compared with 0.97% when $K = 1, H = 4$ in Table IV. Table VI also shows that there is a drift following IJC news even when the holding period is less than one month. For example, when the holding period is five days, the daily excess return is 0.038% and the abnormal return is 0.041%.

1.4 Can Underreaction to Macro News Explain Momentum?

The previous sections show that the stock market underreacts to IJC news, which makes returns predictable using IJC news. Another widely documented anomaly in the finance literature concerning return predictability is momentum. Studies have suggested that momentum may be due to investors' underreaction to some type of news ((Hong et al., 2000), (Moskowitz et al., 2012)). In this section, I consider whether underreaction to IJC news may explain the documented momentums: both cross-sectional momentum and time series momentum.

Cross-sectional momentum was first documented by (Jegadeesh and Titman, 1993) and finds that if stocks are ranked on their past returns, the winners keep winning and losers keep losing for the next few months. A strategy that buys stocks with high relative returns over the past three to twelve months and sells stocks with low relative returns over the same period, and holds the position for the next three to twelve months generates a return of 1% per month. The returns from this strategy cannot be fully explained by current asset pricing models. Subsequent papers find cross-sectional momentum in international equity markets as well. In a recent paper, (Asness et al., 2013) examine four stock markets (U.S., U.K., E.U. and Japan) and find consistent momentum returns in all markets. They also find that the momentum strategies across those markets are more correlated compared with their passive strategies.

Time series momentum was first documented by (Moskowitz et al., 2012) and suggests that an asset's return is predictable from its own past returns: if the average excess returns in the past months are positive (negative), the excess returns in the following months are also likely to be positive (negative). Unlike cross-sectional momentum, which focuses on the relative returns of multiple assets, time series momentum focuses purely on the asset's own past returns. (Moskowitz et al., 2012) constructs the time series momentum strategy on any risky asset in the following way: for each month, the strategy calculates the average excess returns in the past K months, K being the look-back period, which is the same as that in the news momentum strategy. The strategy shorts the one month T-bill to invest in the market if the average return is positive and shorts the market to invest in the one month T-bill if negative. The position is held for H months. (Moskowitz et al., 2012) find that time series momentum outperforms the passive buy-and-hold strategy and generates significant abnormal returns after controlling for existing risk factors.

In the following sections, I look at momentums in the U.S. stock market and the international stock markets separately. First, I examine how news momentum is related to the cross-sectional and time series momentum within the U.S. stock market. Then I examine the globally diversified news momentum and how it is related to the globally diversified cross-sectional and time series momentum in the international stock market.

1.4.1 Momentum in the U.S. Market

Table VII reports the performance and correlations of news momentum versus cross-sectional and time series momentum. News momentum (News MoM) is constructed monthly on the SPX index with a look-back period of one month and a holding period of six months ($K = 6, H = 1$). The UMD factor is a cross-sectional momentum that buys the stocks that have good returns during the previous two to twelve months and shorts the stocks that have bad prior returns during the same period after controlling for the size factor. The data on the UMD is from Kenneth Data Library. Time series momentum (TSMoM) is constructed on the SPX index following the methodology in the study by (Moskowitz et al., 2012), with the same look-back period and holding period as in News MoM ($K = 6, H = 1$).

Panel A shows the excess returns of the three momentum strategies. The annualized excess return is 5.89% for news momentum, 9.49% for time series momentum, and 4.33% for cross-sectional momentum. Panel B shows the pairwise correlation between the three strategies. The correlation between any two of the three momentum strategies is positive and statistically significant. The correlation between News MoM and TSMoM is 0.57, while the correlation between News MoM and UMD is 0.27. Both correlation coefficients are statistically significant. It is not surprising that news momentum is more strongly correlated with time series momentum than cross-sectional momentum. Both news momentum and time series momentum are constructed on the same asset with the same look-back period, which are both different in cross-sectional momentum. Panel C reports the time series regressions of UMD and TSMoM returns on News MoM returns. The coefficients are positive and statistically significant in both regressions. The intercept in the regression that uses UMD as the dependent variable is not statistically different from zero, indicating that cross-sectional momentum does not provide extra returns above the news momentum strategy.

Figure 3 shows a plot of the cumulative excess returns for news momentum, time series momentum, and the passive buy-and-hold strategy on the SPX index from 1999 to 2014. As shown in the figure, both news momentum and time series momentum outperform the passive strategy. News momentum and time series momentum comove strongly. They both make profit during a big market drop by taking the short position. They also make profit when the market recovers, especially after the 2008 recession. However, news momentum loses money during the time period from 2003 to 2006 when the market experiences slow recovery, while time series momentum has a flat cumulative return during this period. In the later section, I will look further into the time varying feature of news momentum.

Because of the high correlation between news momentum and time series momentum, I look at whether the abnormal returns of the news momentum strategy will be suppressed by using time series momentum as an additional factor. Table VIII contains the time series regressions of news momentum on the five risk factors plus a time series momentum factor. As a comparison, I also report the regressions of time series momentum on the five risk factors plus a news momentum factor. Time series momentum generates a monthly abnormal return of 0.78% after controlling for the five risk factors, while news momentum generates a monthly abnormal return of 0.70%. However, after controlling for time series momentum, the news momentum stops generating significant abnormal returns. Similarly, after controlling for news momentum, the time series momentum stops generating significant abnormal returns. The R^2 after controlling for news momentum or time series momentum are significantly higher compared with that when just controlling for the five standard risk factors. The results again indicate that time series and news momentum are significantly related.

To test for the relationship in Table VIII for other (K, H) pairs, Table IX and Table X replicate the first and second models in Table 8, which regresses the excess returns of time series momentum on the five risk factors (MktRf, SMB, HML, UMD, and LIQ) , and then adding news momentum. As shown in Table IX, time series momentum generates significant abnormal returns for multiple (K, H) pairs, with t-statistics close to or above 2. In Table X, after controlling for additional news momentum, the abnormal returns all decrease. Most of the t-statistics drop below 2 and the abnormal returns are not statistically significant. The results suggest that news momentum subsumes time series momentum generally. Table XI and Table XII replicates the third and fourth models in Table VIII, which regresses excess returns of the news momentum on the five risk factors (MktRf, SMB, HML, UMD, and LIQ), and then adding time series momentum. Compared Table XI with Table IV, which only control for the Fama–French three factors, the news momentum strategy still generates significant abnormal returns after controlling for the five factors. Some of the (K, H) pairs generates abnormal returns which are close to 1% per month. However, after controlling for time series momentum in Table XII, the abnormal returns decrease and t-statistics drop as well. The exceptions are when $K = 1$, the abnormal returns are still positive and significant. For example, when $K = 1, H = 4$, the monthly abnormal return after controlling for the five risk factors and time series momentum is still 0.97% with t-statistics of 3.69. This happens because when $K = 1$, news momentum and time series are less strongly correlated; thus, controlling for time series momentum will not subsume the returns generated in the news momentum.

1.4.2 Globally Diversified Momentum

After showing that both cross-sectional and time series momentums are strongly correlated with news momentum in the U.S. market, I look at whether news momentum constructed in the global market is correlated with the globally diversified cross-sectional and time series momentums.

Existing studies have shown that U.S. macro news announcements move the stock markets in other countries ((Nikkinen et al., 2006), (Hayo et al., 2010)). (Rapach et al., 2013) find that the U.S. stock market returns have significant predictive power in international stock market returns. In this section, I examine whether this predictability is related to the global underreaction to U.S. macro news.

First, I construct news momentum following *U.S. IJC news* on equity indices in eight other countries. The eight indices are chosen following the study by (Moskowitz et al., 2012), including: SPI 200 (Australia), CAC 40 (France), DAX (Germany), FTSE/MIB (Italy), TOPIX (Japan), AEX (Netherlands), IBEX35 (Spain) and FTSE 100 (UK). The data on equity indices returns are from Bloomberg.

Table XIII shows the news momentum strategy compared with the passive buy-and-hold strategy for each of the eight indices and the SPX index. The excess returns from the news momentum strategy are higher than their passive strategy benchmarks for all indices. News momentum constructed on equity indices in other countries even outperforms that using the SPX index. For example, the excess return of the news momentum strategy is 11.09% compared with -0.62% of the buy-and-hold strategy using the French CAC40 index. For the TOPIX index, the excess return of the news momentum strategy is 11.54% compared with -0.39% of the passive strategy. This indicates that *U.S. IJC news* can predict international stock market returns even more strongly than predicting U.S. stock market returns.

After constructing a news momentum strategy using each of the nine indices, I construct globally diversified news momentum (Global News MOM) from those nine strategies. I weight the returns of news momentum on each of the nine indices by the inverse of the ex-ante volatility for each index. I compare this Global News MOM with globally diversified cross-sectional momentum (Global CSMOM) and globally diversified time series momentum (Global TSMOM). The monthly return of the Global CSMOM is from the study by (Asness et al., 2013). It is the average of the returns from cross-sectional momentum constructed in four stock markets

(U.S., U.K., E.U. and Japan), weighted by the inverse of the ex-ante volatility for each market. Global TSMOM is constructed similarly to Global News MOM. First, I construct time series momentum on each of the nine indices. Then I construct Global TSMOM, which is the weighted average of the returns of time series momentum for each of the nine indices, where the weight is the inverse of the ex-ante volatility. $K = 6$ and $H = 1$ for both news momentum and time series momentum.

Table XIV presents results on the three globally diversified momentum strategies. Global News MoM generates an annualized excess return of 7.38% compared with 5.99% for the Global CSMoM and 8.27% for Global TSMoM. The correlation between any two of the three diversified momentum strategies is positive and statistically significant. As in the U.S. market, Global News MoM is more strongly correlated with Global TSMoM than Global CSMoM. The correlation between Global News MoM and Global TSMoM is 0.66, compared with 0.32 between Global News MoM and Global CSMoM. Again, this could be due to the same look-back period being used in news momentum and time series momentum, which is different from that used in Global CSMoM. Additionally, both Global News MoM and Global TSMoM use the same set of assets, which is again different from that used in Global CSMoM.

Panel C of Table XIV shows the regression results of returns of Global CSMoM and Global TSMoM on returns of Global News MoM. As in the U..S market, the coefficients are positive and statistically significant in both regressions. The intercepts are not statistically significant from zero in both regressions, indicating that time series momentum and cross-sectional momentum do not provide extra returns over news momentum in the international market.

Table XV presents the risk-adjusted performance of Global New MoM and Global TSMoM on a different set of risk factors, including the MSCI world equity index, globally diversified value factor (Global Value), and Global CSMoM from the study of (Asness et al., 2013), as well as Global TSMoM constructed above. As shown in the table, Global News MoM and Global TSMoM generate significant abnormal returns after controlling for the MSCI index, Global value and Global CSMoM. The abnormal return is 0.65% per month (7.80% annualized) for Global News MoM and 0.43% (5.16% annualized) for Global TSMoM. However, Global TSMoM stops generating significant abnormal returns after controlling for Global New MoM. Similarly, Global New MoM stops generating significant abnormal returns after controlling for Global TSMoM.

Figure 4 shows the plot of the cumulative excess returns of Global News MoM, Global TSMoM, and the globally diversified pass buy-and-hold strategy (Global Passive). The globally diversified passive strategy is the weighted average of the excess returns for the nine equity indices, where the weights equal the ex-ante volatility of each index. Similarly to that in the U.S. market, both Global News MoM and Global TSMoM are above Global Passive throughout the entire time period. We also observe a strong comovement between Global News MoM and Global TSMoM, both of which gain higher excess returns during large market swings.

1.5 Time Varying Returns of News Momentum

The previous section shows that the stock market underreacts to IJC news. The market continues to rise following good news and fall following bad news. News momentum has a statistically significant correlation with time series momentum as documented by (Moskowitz et al., 2012). Figures 3 and 4 show the strong comovement between news momentum and time series momentum, both within U.S. and in the international stock market. Figures 3 and 4 also show that the news momentum strategy generates higher returns during large upward and downward market movements.

To test how the returns of news momentum vary during different market conditions, I run a time series regression of news momentum returns on a set of market volatility indicators, including the squared returns of the market index, VIX, and the monthly change of VIX. Table XIV Panel A shows the results for the news momentum strategy constructed on the SPX index. In the regression, which regresses the excess returns of news momentum on the SPX index returns and the SPX index squared returns, the coefficients are negative on the returns and positive on the squared returns, indicating that the returns of news momentum are higher when the market is experiencing large downward movements. The coefficients on VIX and the change of VIX are also significantly positive, suggesting the news momentum returns are higher during higher volatile markets.

Panel B shows the results for Global News MoM. Similarly as in Panel A, the beta on the MSCI index is negative, but the beta on the squared returns of the MSCI index, VIX and the change of VIX are all significantly positive. The results suggest that the globally diversified news momentum strategy also generates higher returns during large market downturn and when the market is volatile. (Moskowitz et al., 2012) also find that the diversified time series momentum returns are higher when the squared returns of the MSCI index are higher. However, they do not find such a relationship when they use VIX.

The results suggest that the returns from news momentum may be compensations for crash risk. When the market is going from normal to bad, the negative IJC news released will lead news momentum to take a short position in the market. When the market continues to go from bad to worse, news momentum will generate profits.

1.6 Conclusion

This paper shows that both the U.S. stock market and international stock markets under-react to U.S. macroeconomic news announcements, in particular the IJC news released by the U.S. Department of Labor. The stock market continues to drift in the direction of IJC news for several months following this news. A news momentum strategy that buys the stock market following good IJC news and shorts the stock market following bad IJC news outperform the passive buy-and-hold strategy significantly. This is found using SPX index or any of the equity indices in eight other developed countries.

Standard risk factors fail to fully explain the returns from the news momentum strategy. News momentum constructed on the SPX index generates a significant abnormal return of 8.4% per annum after controlling for standard five risk factors (MktRf, HML, SMB, UMD, and LIQ). A globally diversified news momentum strategy constructed on the nine major equity indices generates a significant abnormal return of 7.80% per annum after controlling for the MSCI index, and global value and momentum factors.

I find that news momentum is strongly related to time series momentum documented by (Moskowitz et al., 2012). The correlation between news momentum returns and time series momentum returns is around 0.6 and statistically significant at the 1% level, for both the

U.S. equity market and international equity markets. Although both time series and news momentum provide significant abnormal returns after controlling for the standard risk factors (MktRf, SMB, HML, UMD, and LIQ), the abnormal returns are not significantly different from zero after controlling for news momentum and time series momentum, respectively.

The findings in this paper provide evidence of investor underreaction to news, which is relevant to the aggregate market. This is different from existing literature which tests underreaction using firm-specific news. It raises further challenges to existing rational expectations models or behavioral models that try to explain underreaction to news. Any rational expectations model or behavioral model also needs to systematically explain why underreaction occurs following certain macro news announcements and not others. These questions are left for future research.

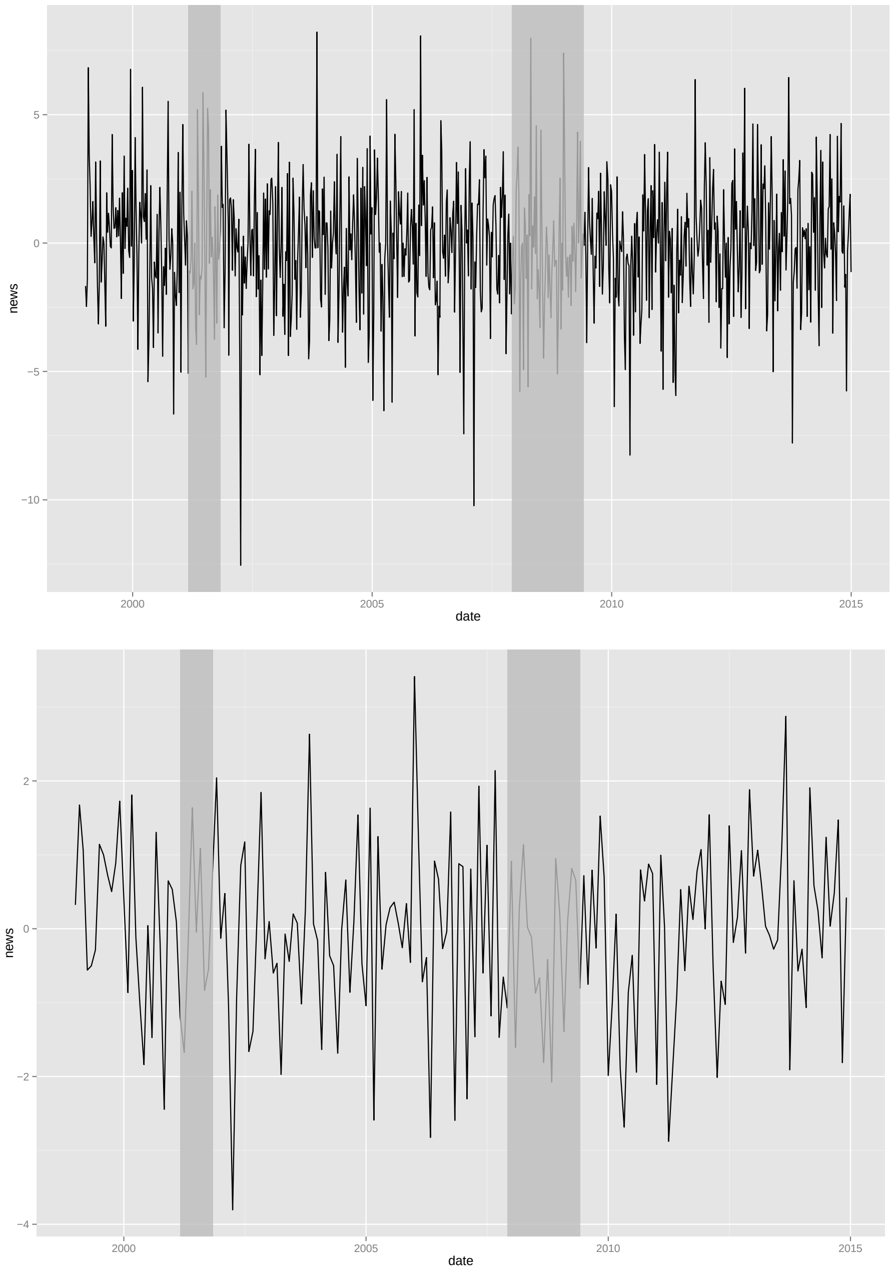
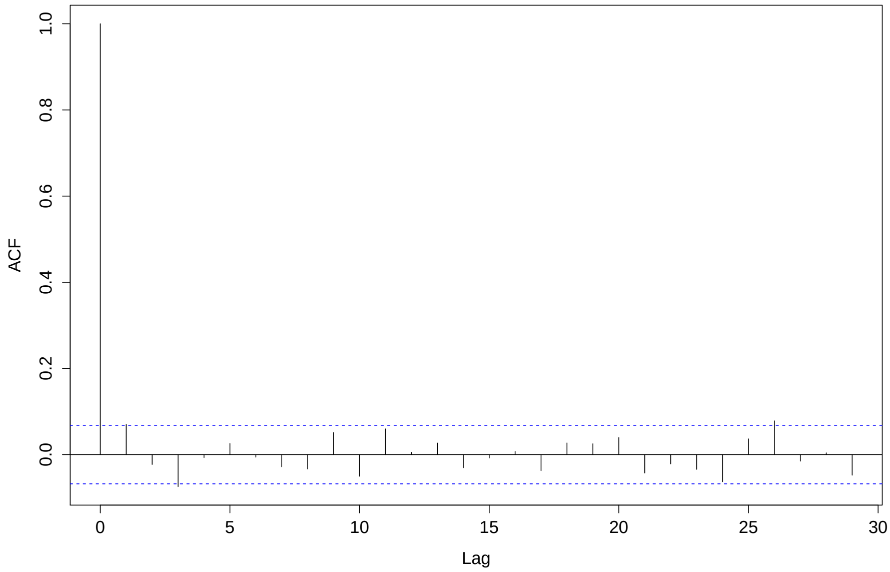


Figure 1. Time series plots of Initial Jobless Claims (IJC) news



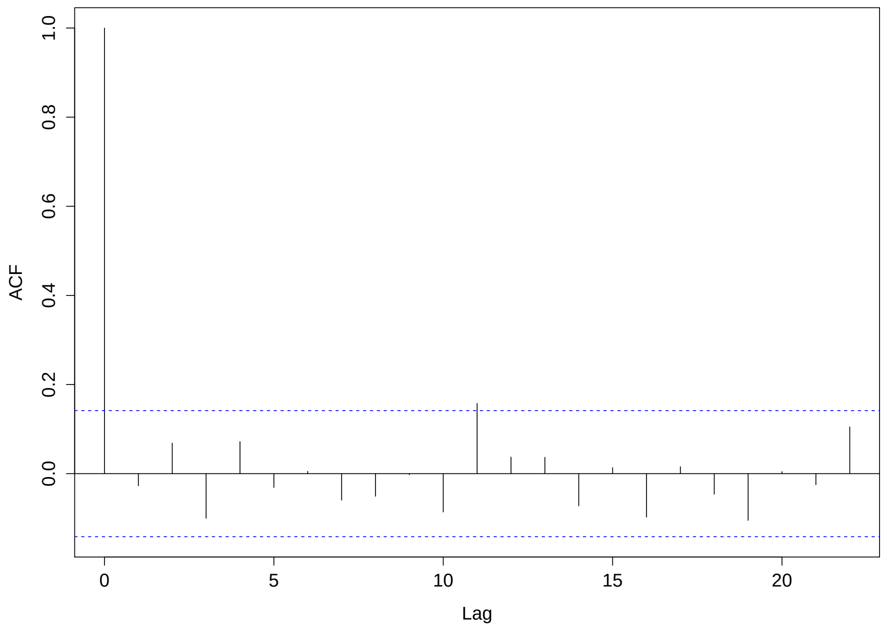


Figure 2. Autocorrelation of daily and monthly IJC news from Bloomberg.

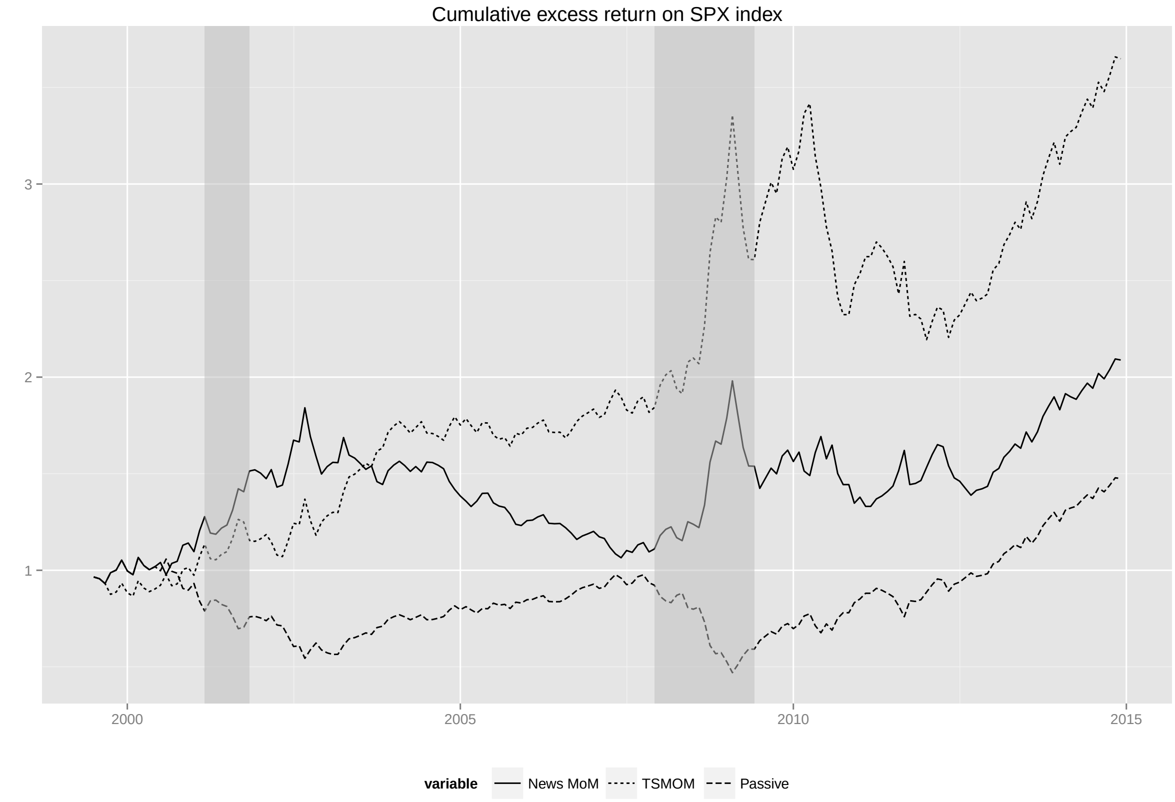


Figure 3. Cumulative excess returns of news momentum, time series momentum, and passive buy-and-hold strategy on the SPX index.

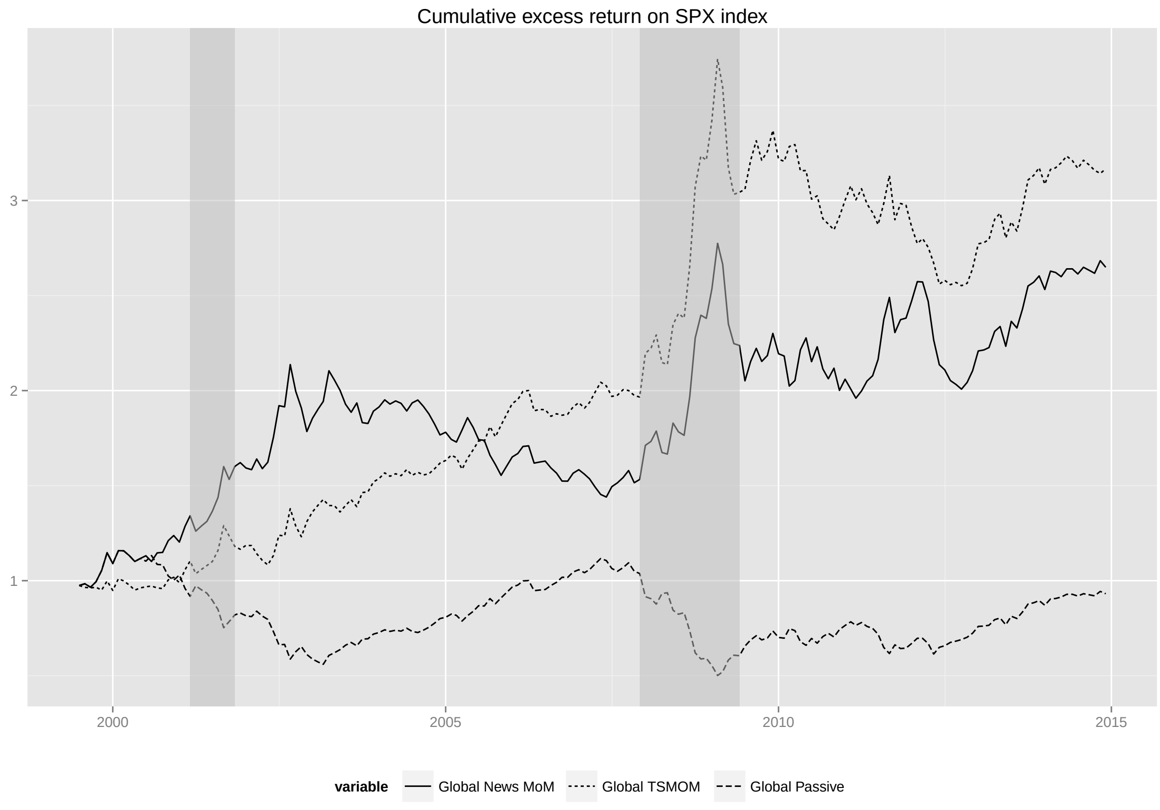


Figure 4. Cumulative excess returns of globally diversified news momentum, time series momentum and passive strategies.

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	0.0051	0.0063**	0.0051	0.0035	0.0045
	(0.0035)	(0.0029)	(0.0034)	(0.0034)	(0.0039)
Change in Nonfarm Payrolls$_t$	−0.0002				−0.0013
	(0.0012)				(0.0011)
Change in Nonfarm Payrolls$_{t-1}$	−0.0004				−0.0001
	(0.0013)				(0.0015)
Change in Nonfarm Payrolls$_{t-2}$	0.0003				−0.0002
	(0.0012)				(0.0015)
Change in Nonfarm Payrolls$_{t-3}$	0.0005				−0.0001
	(0.0011)				(0.0013)
Initial Jobless Claims$_t$		−0.0088***			−0.0078***
		(0.0024)			(0.0029)
Initial Jobless Claims$_{t-1}$		−0.0038			−0.0042
		(0.0025)			(0.0028)
Initial Jobless Claims$_{t-2}$		0.0015			0.0026
		(0.0026)			(0.0031)
Initial Jobless Claims$_{t-3}$		−0.0097***			−0.0083**
		(0.0026)			(0.0033)
GDP Annualized QoQ$_t$			0.0004		0.0001
			(0.0017)		(0.0018)
GDP Annualized QoQ$_{t-1}$			0.0012		0.0013
			(0.0023)		(0.0024)
GDP Annualized QoQ$_{t-2}$			0.0024		0.0015
			(0.0018)		(0.0019)
GDP Annualized QoQ$_{t-3}$			−0.0030*		−0.0026
			(0.0017)		(0.0018)
ISM Manufacturing$_t$				0.0016	0.0013
				(0.0021)	(0.0022)
ISM Manufacturing$_{t-1}$				0.0030**	0.0020
				(0.0014)	(0.0013)
ISM Manufacturing$_{t-2}$				0.0002	−0.0005
				(0.0014)	(0.0014)
ISM Manufacturing$_{t-3}$				0.0003	0.0002
				(0.0015)	(0.0018)
R^2	0.0019	0.1343	0.0302	0.0308	0.1538
Num. obs.	189	189	181	185	177

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE I

TIME SERIES REGRESSION OF THE MONTHLY SPX INDEX RETURNS ON FOUR MACRO NEWS ANNOUNCEMENTS.

Panel A: Summary Statistics of IJC news

	Good News		Bad News	
	N	Mean(Std)	*N*	Mean(Std)
weekly IJC news	409	1.8208	405	-1.9493
		(1.4969)		(1.6733)
monthly IJC news	98	0.8679	94	-1.0109
		(0.6699)		(0.8111)

Panel B: Regressions of the SPX index returns on IJC news

	Daily return	Monthly return
(Intercept)	0.0004	0.0055*
	(0.0004)	(0.0031)
weekly IJC news	0.0004*	
	(0.0002)	
monthly IJC news		0.0080***
		(0.0025)
R^2	0.0046	0.0484
Num. obs.	833	192

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE II

MARKET RESPONSE TO IJC NEWS.

Panel A: Excess return

	H	1	3	4	5	6	9	12
K	1	0.0033	0.0068	0.0082	0.0070	0.0046	0.0045	0.0019
	3	0.0032	0.0051	0.0050	0.0066	0.0046	0.0047	0.0005
	4	0.0059	0.0054	0.0034	0.0030	0.0011	-0.0002	-0.0016
	5	0.0041	0.0076	0.0059	0.0060	0.0037	0.0004	-0.0005
	6	0.0049	0.0038	0.0034	0.0031	0.0013	-0.0003	0.0009
	9	0.0039	0.0023	0.0020	0.0013	-0.0002	0.0005	0.0018
	12	0.0025	0.0005	-0.0002	-0.0003	-0.0007	-0.0033	0.0003

Panel B: Sharpe ratio

	H	1	3	4	5	6	9	12
K	1	0.0753	0.1577	0.2376	0.1612	0.1256	0.1028	0.0471
	3	0.0725	0.1171	0.1314	0.1530	0.1151	0.1085	0.0125
	4	0.1345	0.1249	0.0890	0.0691	0.0289	-0.0044	-0.0384
	5	0.0938	0.1759	0.1432	0.1375	0.0894	0.0101	-0.0124
	6	0.1123	0.0874	0.0799	0.0707	0.0314	-0.0067	0.0232
	9	0.0876	0.0518	0.0472	0.0286	-0.0049	0.0116	0.0411
	12	0.0556	0.0124	-0.0044	-0.0071	-0.0162	-0.0746	0.0066

TABLE III

PERFORMANCE OF THE NEWS MOMENTUM STRATEGY ON THE SPX INDEX WITH DIFFERENT LOOK-BACK PERIODS (K) AND HOLDING PERIODS (H). K AND H ARE IN MONTHS.

Panel A: Abnormal return

	H	1	3	4	5	6	9	12
K	1	0.0032	0.0078	0.0097	0.0093	0.0065	0.0064	0.0038
	3	0.0053	0.0075	0.0074	0.0092	0.0072	0.0079	0.0035
	4	0.0085	0.0079	0.0053	0.0056	0.0034	0.0027	0.0014
	5	0.0063	0.0096	0.0081	0.0085	0.0061	0.0030	0.0025
	6	0.0076	0.0064	0.0062	0.0061	0.0040	0.0019	0.0037
	9	0.0070	0.0056	0.0055	0.0048	0.0033	0.0045	0.0063
	12	0.0059	0.0039	0.0031	0.0029	0.0026	0.0004	0.0050

Panel B: t-statistics

	H	1	3	4	5	6	9	12
K	1	0.8947	2.2371	3.7015	3.0571	2.3962	1.9813	1.2939
	3	1.6220	2.3427	2.7779	3.0447	2.5206	2.6716	1.1865
	4	2.7698	2.6092	1.9166	1.8098	1.2021	0.8655	0.4683
	5	1.9256	3.1517	2.7562	2.7807	2.0651	0.9485	0.7885
	6	2.5604	2.2258	2.2204	2.0594	1.3718	0.5759	1.2714
	9	2.3623	1.9758	2.0369	1.7272	1.1864	1.6322	2.5165
	12	2.2418	1.4060	1.1156	0.9915	0.8876	0.1177	1.8709

TABLE IV

RISK-ADJUSTED PERFORMANCE OF THE NEWS MOMENTUM STRATEGY, CONTROLLED FOR FAMA-FRENCH THREE FACTORS.

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.0066^{**}	0.0076^{**}	0.0070^{**}	0.0070^{**}
	(0.0029)	(0.0030)	(0.0030)	(0.0030)
MktRf	-0.4547^{***}	-0.4304^{***}	-0.3659^{***}	-0.3656^{***}
	(0.0904)	(0.0996)	(0.1027)	(0.1035)
HML		-0.1266	-0.0984	-0.0988
		(0.1072)	(0.1024)	(0.1045)
SMB		-0.1706	-0.2118^{*}	-0.2116^{*}
		(0.1208)	(0.1148)	(0.1158)
UMD			0.1248^{**}	0.1250^{**}
			(0.0517)	(0.0525)
LIQ				-0.0043
				(0.0793)
R^2	0.2260	0.2446	0.2669	0.2669
Num. obs.	186	186	186	186

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE V

TIME SERIES REGRESSION OF THE NEWS MOMENTUM STRATEGY ON RISK FACTORS.

Holding Days	Excess return	Sharpe ratio	Abnormal return	t_stat
5	0.00038	0.0301	0.00041	2.0962
10	0.00037	0.0371	0.00042	2.6694
15	0.00031	0.0251	0.00037	1.9121
20	0.00033	0.0295	0.00038	2.1973
30	0.00020	0.0168	0.00026	1.4592
40	0.00022	0.0182	0.00028	1.5250
50	0.00041	0.0334	0.00049	2.6658
60	0.00022	0.0179	0.00030	1.6444
70	0.00042	0.0354	0.00052	3.0087
80	0.00034	0.0277	0.00044	2.4462
90	0.00028	0.0224	0.00037	2.0466
100	0.00035	0.0282	0.00045	2.4711
110	0.00028	0.0220	0.00037	2.0586
120	0.00028	0.0224	0.00039	2.1544

TABLE VI

PERFORMANCE OF THE WEEKLY NEWS MOMENTUM STRATEGY.

Panel A: Annualized returns

	News MoM	UMD	TSMoM
Return	0.0589	0.0433	0.0949
	(0.1513)	(0.2004)	(0.1498)

Panel B: Correlation

	News MoM	UMD	TSMoM
News MoM	1	0.2793***	0.5678***
UMD		1	0.3255***
TSMoM			1

Panel C: Regression results

	UMD	TSMoM
(Intercept)	0.0018	0.0051*
	(0.0044)	(0.0027)
News MoM	0.3698***	0.5621***
	(0.1417)	(0.0922)
R^2	0.0780	0.3224
Num. obs.	186	186

TABLE VII

NEWS MOMENTUM, CROSS-SECTIONAL AND TIME SERIES MOMENTUMS IN U.S. MARKET.

	TSMoM	TSMoM	News MoM	News MoM
(Intercept)	0.0078^{**}	0.0038	0.0070^{**}	0.0031
	(0.0035)	(0.0027)	(0.0030)	(0.0026)
MktRf	-0.0876	0.1179	-0.3656^{***}	-0.3216^{***}
	(0.1367)	(0.1033)	(0.1035)	(0.0812)
HML	0.1745	0.2301^{**}	-0.0988	-0.1865^{**}
	(0.1404)	(0.1119)	(0.1045)	(0.0818)
SMB	-0.0544	0.0645	-0.2116^{*}	-0.1842^{**}
	(0.1277)	(0.0960)	(0.1158)	(0.0899)
UMD	0.2444^{***}	0.1741^{***}	0.1250^{**}	0.0021
	(0.0659)	(0.0653)	(0.0525)	(0.0504)
LIQ	-0.1089	-0.1065	-0.0043	0.0505
	(0.1322)	(0.1078)	(0.0793)	(0.0595)
News MoM		0.5620^{***}		
		(0.0988)		
TSMoM				0.5026^{***}
				(0.0876)
R^2	0.1632	0.3996	0.2669	0.4740
Num. obs.	186	186	186	186

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE VIII

TIME SERIES REGRESSIONS OF MOMENTUM STRATEGIES ON RISK FACTORS.

Panel A: Abnormal return

	H	1	3	4	5	6	9	12
K	1	0.0036	0.0060	0.0048	0.0049	0.0037	0.0054	0.0054
	3	0.0047	0.0025	0.0033	0.0050	0.0046	0.0067	0.0062
	4	0.0045	0.0056	0.0048	0.0038	0.0016	0.0050	0.0057
	5	0.0097	0.0068	0.0056	0.0054	0.0052	0.0053	0.0056
	6	0.0078	0.0059	0.0042	0.0054	0.0053	0.0054	0.0064
	9	0.0067	0.0058	0.0054	0.0053	0.0060	0.0066	0.0060
	12	0.0078	0.0063	0.0062	0.0062	0.0067	0.0069	0.0047

Panel B: t-statistics

	H	1	3	4	5	6	9	12
K	1	1.0290	1.7532	1.6172	1.4039	1.3593	1.6559	1.7274
	3	1.3632	0.7080	1.0015	1.4678	1.3840	1.8694	1.7697
	4	1.3229	1.6806	1.4980	1.0950	0.5160	1.4389	1.6659
	5	3.0595	2.0517	1.7505	1.5712	1.5571	1.5349	1.6418
	6	2.2423	1.6718	1.2710	1.5419	1.5766	1.5653	1.7721
	9	1.9150	1.6502	1.5386	1.4816	1.7120	1.8156	1.5792
	12	2.1988	1.7450	1.7267	1.7069	1.8331	1.8338	1.2383

TABLE IX

ABNORMAL RETURN OF TIME SERIES MOMENTUM CONTROLLED FOR FIVE FACTORS.

Panel A: Abnormal return

	H	1	3	4	5	6	9	12
K	1	0.0030	0.0049	0.0008	0.0011	0.0006	0.0045	0.0045
	3	0.0033	-0.0005	-0.0006	0.0010	0.0007	0.0046	0.0051
	4	0.0005	0.0029	0.0028	0.0018	0.0008	0.0043	0.0056
	5	0.0074	0.0017	0.0018	0.0020	0.0029	0.0047	0.0053
	6	0.0038	0.0027	0.0010	0.0029	0.0038	0.0051	0.0051
	9	0.0037	0.0030	0.0028	0.0037	0.0050	0.0045	0.0029
	12	0.0058	0.0044	0.0048	0.0050	0.0056	0.0066	0.0016

Panel B: t-statistics

	H	1	3	4	5	6	9	12
K	1	0.8403	1.4102	0.3254	0.3648	0.2285	1.4148	1.6598
	3	0.9958	-0.1555	-0.2514	0.3712	0.2880	1.3416	1.6665
	4	0.1655	0.9427	0.8863	0.5667	0.2621	1.3293	1.7403
	5	2.5780	0.6908	0.7181	0.7059	1.0302	1.4280	1.6050
	6	1.4028	0.9153	0.4078	0.9883	1.3066	1.5966	1.6589
	9	1.0790	1.0278	0.9417	1.1367	1.5393	1.4505	0.8496
	12	1.7201	1.4225	1.5552	1.5563	1.7138	1.9037	0.4701

TABLE X

ABNORMAL RETURNS OF TIME SERIES MOMENTUM CONTROLLED FOR FIVE FACTORS AND NEWS MOMENTUM.

Panel A: Abnormal return

	H	1	3	4	5	6	9	12
K	1	0.0050	0.0096	0.0112	0.0110	0.0073	0.0059	0.0025
	3	0.0049	0.0067	0.0066	0.0086	0.0063	0.0071	0.0024
	4	0.0079	0.0069	0.0043	0.0047	0.0019	0.0015	0.0001
	5	0.0060	0.0092	0.0075	0.0079	0.0051	0.0019	0.0011
	6	0.0070	0.0061	0.0056	0.0053	0.0031	0.0007	0.0025
	9	0.0061	0.0051	0.0049	0.0041	0.0025	0.0040	0.0059
	12	0.0057	0.0038	0.0029	0.0028	0.0025	0.0006	0.0055

Panel B: t-statistics

	H	1	3	4	5	6	9	12
K	1	1.3942	2.7107	4.0261	3.4853	2.6070	1.7302	0.8460
	3	1.4337	1.9528	2.3560	2.8098	2.2264	2.4239	0.8151
	4	2.4055	2.2180	1.5466	1.4719	0.7150	0.4678	0.0449
	5	1.7426	2.9744	2.5065	2.5633	1.7601	0.5847	0.3465
	6	2.3288	2.1294	2.0626	1.8451	1.0928	0.2202	0.8436
	9	1.9615	1.8660	1.9035	1.5090	0.9321	1.4849	2.3940
	12	2.2201	1.3846	1.0508	0.9456	0.8301	0.1845	2.0964

TABLE XI

ABNORMAL RETURNS OF NEWS MOMENTUM CONTROLLED FOR FIVE FACTORS.

Panel A: Abnormal return

	H	1	3	4	5	6	9	12
K	1	0.0045	0.0089	0.0097	0.0094	0.0057	0.0049	0.0006
	3	0.0036	0.0056	0.0050	0.0063	0.0037	0.0053	0.0000
	4	0.0060	0.0048	0.0023	0.0031	0.0013	-0.0004	-0.0015
	5	0.0017	0.0054	0.0044	0.0056	0.0028	0.0003	-0.0005
	6	0.0031	0.0036	0.0034	0.0032	0.0008	-0.0011	0.0000
	9	0.0033	0.0026	0.0027	0.0024	0.0006	0.0016	0.0042
	12	0.0037	0.0014	0.0005	0.0006	0.0002	-0.0020	0.0038

Panel B: t-statistics

	H	1	3	4	5	6	9	12
K	1	1.2683	2.5625	3.6870	3.0809	2.2140	1.4547	0.2205
	3	1.0983	1.7975	2.1430	2.2707	1.6468	1.9758	0.0080
	4	1.9056	1.6308	0.8457	1.0689	0.4648	-0.1389	-0.5596
	5	0.5201	1.9699	1.6551	1.9824	1.1154	0.0881	-0.1742
	6	1.1849	1.4174	1.4756	1.2888	0.3417	-0.3663	0.0067
	9	1.1497	1.0941	1.2352	1.0008	0.2609	0.6589	1.8805
	12	1.6189	0.5637	0.2082	0.2217	0.0691	-0.6614	1.6201

TABLE XII

ABNORMAL RETURN OF NEWS MOMENTUM CONTROLLED FOR FIVE FACTORS AND TIME SERIES MOMENTUM.

	Excess return		Sharpe ratio	
	News MoM	buy-and-hold	News MoM	buy-and-hold
SPX (US)	0.0589	0.0368	0.3891	0.2419
AEX (Netherlands)	0.0935	-0.0168	0.4741	-0.0844
SPI 200 (Australia)	0.0481	0.0292	0.3798	0.2298
CAC 40 (France)	0.1109	-0.0062	0.6172	-0.0339
DAX (Germany)	0.0957	0.0441	0.4394	0.2012
FTSE/MIB (Italy)	0.0815	-0.0386	0.3832	-0.1806
TOPIX (Japan)	0.1154	-0.0039	0.6644	-0.0222
IBEX35 (Spain)	0.0411	0.0028	0.1985	0.0134
FTSE 100 (UK)	0.0412	-0.0066	0.2910	-0.0464

TABLE XIII

NEWS MOMENTUM IN THE INTERNATIONAL EQUITY MARKETS.

Panel A: Annualized returns

	Global News MoM	Global CSMoM	Global TSMoM
Return	0.0738	0.0599	0.0827
	(0.1485)	(0.1651)	(0.1288)

Panel B: Correlation

	Global News MoM	Global CSMoM	Global TSMoM
Global News MoM	1	0.3245***	0.6615***
Global CSMoM		1	0.4757***
Global TSMoM			1

Panel C: Regression results

	Global CSMoM	Global TSMoM
(Intercept)	0.0028	0.0034
	(0.0035)	(0.0021)
Global News MoM	0.3608***	0.5736***
	(0.1168)	(0.0748)
R^2	0.1053	0.4375
Num. obs.	186	186

TABLE XIV

GLOBALLY DIVERSIFIED NEWS MOMENTUM, CROSS-SECTIONAL MOMENTUM AND TIME SERIES MOMENTUMS.

	Global News MoM	Global News MoM	Global TSMoM	Global TSMoM
Intercept	0.0065^{**}	0.0035	0.0043^{*}	0.0013
	(0.0029)	(0.0025)	(0.0025)	(0.0021)
MSCI index	-0.4190^{***}	-0.2563^{***}	-0.2365^{**}	-0.0416
	(0.0922)	(0.0794)	(0.0961)	(0.0650)
Global Value	-0.1008	-0.2308^{**}	0.1889^{**}	0.2358^{***}
	(0.0993)	(0.0942)	(0.0773)	(0.0747)
Global CSMoM	0.1033	-0.1840^{*}	0.4176^{***}	0.3695^{***}
	(0.1050)	(0.0981)	(0.0731)	(0.0767)
Global TSMoM		0.6881^{***}		
		(0.0872)		
Global News MoM				0.4652^{***}
				(0.0677)
R^2	0.2743	0.5066	0.3476	0.5564
Num. obs.	186	186	186	186

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE XV

TIME SERIES REGRESSIONS OF THE GLOBALLY DIVERSIFIED NEWS MOMENTUM AND TIME SERIES MOMENTUM ON RISK FACTORS.

Panel A: News MoM on the SPX index

	SPX	SPX squared	VIX	VIX change
coefficient	-0.4235	3.1699		
(t-stat)	(-3.9351)	(2.2836)		
coefficient			0.0011	
(t-stat)			(2.0321)	
coefficient				0.0040
(t-stat)				(4.7135)

Panel B: Global News MoM

	MSCI	MSCI squared	VIX	VIX change
coefficient	-0.4049	2.1541		
(t-stat)	(-4.1355)	(2.1781)		
coefficient			0.0013	
(t-stat)			(2.4322)	
coefficient				0.0044
(t-stat)				(5.8281)

TABLE XVI

LINEAR RELATIONSHIP BETWEEN THE NEWS MOMENTUM STRATEGY AND THE STOCK MARKET VOLATILITY.

CHAPTER 2

CONCORDANT NEWS OR DISCORDANT NOISE: DOES CONCURRENT MACRO NEWS AFFECT REACTION TO EARNINGS NEWS?

This paper documents that investors react to firm-specific news differently in the presence of concurrent macroeconomic news. We construct an aggregated daily macro news index from Bloomberg between 1999 and 2014 and find that investors react strongly to firm-specific news when the macro news index and firm-specific news are concordant, i.e., when the macro news index and earnings news are both positive or both negative. We also find that the drift following positive earnings announcements is only seen when the concurrent macro news is negative. Those results suggest that investors underreact to discordant positive earnings news.

2.1 Introduction

Information diffusion is one the the key topics in finance literature. A large portion of asset pricing literature is to try to understand how information is traded into asset prices. Information, here, includes anything which may affect the asset prices, spanning from firm-specific information to macroeconomic information. Studies on the firm-specific information generally focus to understand how a firm's stock reacts to the news announcements using an event study approach. Studies on the macroeconomic information usually are seeking the priced risk factors among macroeconomic news candidates by looking at how the stock market moves as a whole. This paper, on the other hand, examines the situation of when those two types of information arrive at the stock market together and how a firm's stock price may react.

This paper falls into the earnings announcement literature. Earnings announcement, as the most frequent and standard information release by public firms, is one of the most studied events in the finance and accounting literature. Researchers have heavily relied on this information to understand investors' trading behaviors to new information release. A firm's stock reaction to its earnings announcement, known as the earnings response coefficients (ERC), indicates how strongly the stock's return responds to that new earnings information after controlling for the systemic market movement. Meanwhile, researchers have also found that the new earnings information is not necessarily traded into stock prices instantaneously, and the slow response of the stock return to the earnings announcements is normally known as the Post Earnings Announcements Drift (PEAD).

Part of the PEAD could be attributed to the investors' limited attention theory. Studies have found that investor are constrained by their limited attention and could not process all the information that comes to the market at a timely manner. If so, the information may be traded into prices with a delay and thus we could observe PEAD phenomena. Some of the empirical studies supporting this hypothesis have found that earnings announcements that are made on Friday tend to have lower ERC and higher PEAD, because investors are more likely to be distracted on Friday. Similar observations are made for earnings announcements which happen on sports days. Also, on days which multiple earnings announcements happen together, ERC is found lower because investors need to allocate the limited attention to many announcements.

To model the optimal attention allocation, (Lin and Xiong, 2006) theoretically argued that a rational investor should allocate more attention to process market wide information, and then firm-specific information, leading to the categorical learning behavior.

In this paper, we start by testing the categorical learnings hypothesis, looking at whether ERC are significantly different on days with and without a macroeconomic news announcement. Following the categorical learnings hypothesis, we will expect a concurrent macroeconomic news announcement released together with an earnings announcements will distract investors from processing the earnings news, and thus the ERC will be lower. We collect data for all the earnings announcements made from 1999 to 2014, for all the firms within the S&P 500 index. The panel regression includes a dummy variable, which takes the value of 1, if any important macroeconomic news announcement is released on that day. In our study, we did not find evidence that a concurrent macroeconomic news announcement decreases ERC.

In using macroeconomic news announcement as a distraction event, what was implicitly assumed is that investors view the macroeconomic news announcements as a pure distraction from earnings announcements, and do not take any information within the macro announcements when they processing the earnings news. Although this assumption may be true for viewing a sport event as a distraction event which contains irrelevant information for the financial market, this assumption may not be true for a macro event. Researchers have found that the price responses to the earnings news may vary when the market condition changes. (Mian and Sankaraguruswamy, 2012a) looked at how investors respond to earnings news during different investor sentiment periods and found that investors respond stronger to good earnings news during high sentiment periods than during low sentiment periods, whereas investors respond stronger to bad earnings news during low sentiment periods than during high sentiment periods. (Williams, 2015) studied how investors respond to earnings news after an increase or decrease of macro-uncertainty, using VIX as a proxy. He found that after an increase of VIX, investors respond stronger to bad earnings news than to good earnings news. By contrast, after a decrease of VIX, the response is symmetric to good and bad earnings news. (Conrad et al., 2002) found that the price response to bad and good earnings shocks changes as the relative level of the market changes, defined by P/E ratio. Those literature tend to focus on one aspect of the market condition: sentiment, uncertainty of price level. Considering that the stock market condition is largely shaped by macroeconomic environment, which is mostly communicated to investors through macro news announcements, we then look at directly how the information contained in the macro news announcements affect the price response to earnings news.

Our results show that when macroeconomic news and firm specific news are in the same sign, ERC are higher than when they are in the opposite sign. More specifically, when the earnings surprise is positive, more positive macroeconomic news will increase ERC; when the earning surprise is negative, more negative macroeconomic news will increase the ERC. We also look at the PEAD, and find that the drift following positive earnings announcements is only seen when the concurrent macro news is negative, suggesting that investors underreact to discordant positive earnings news.

2.2 Data

2.2.1 Earnings Announcements

The earnings announcements sample includes all the earnings announcements during the periods from January,1999 to December, 2014, for firms which are within or were ever within the S&P 500 index. To avoid survival bias, we include firms which were in the S&P 500 index on the days of the earnings announcements, even if they may not be in the S&P 500 index as of today. Following all the earnings literature, earnings news in this paper actually refer to the standardized surprise component, which are defined as:

$$News_{i,t} = \frac{Actual_{i,t} - Median(Forecast)_{i,t}}{\sigma(Forecast)_{i,t}}, \tag{2.1}$$

where i indexes a stock and t indexes one announcement of the news.

The earnings announcements dataset is from IBES, which collects the analyst forecasts for any earnings announcements. If an analyst revises the forecast, only the most recent forecast is included to calculate the median. The sample only includes the announcements when more than three analyst forecasts are available, so than a meaningful median and standard deviation can be calculated.

2.2.2 Macroeconomic News

The macroeconomic news index is constructed as a daily index, which sums up the surprise component of the most followed 20 macroeconomic announcements. The surprise component for each of the 20 news announcements is defined similarly as SUE, as:

$$News_{i,t} = \frac{Actual_{i,t} - Median(Forecast)_{i,t}}{\sigma(Forecast)_{i,t}}, \tag{2.2}$$

where i indexes a type of macro news and t indexes one announcement of the news.

Macroeconomic news data is from Bloomberg. Bloomberg collected analyst forecasts for all macroeconomic announcements since late 1996. Data before 1999 was not complete and thus the sample selected is from the beginning of 1999. On the day of actual macroeconomic announcement, Bloomberg publish both the actual announcements, as well as the median and mean analyst forecasts to public. Based on efficient market hypothesis, the expected component should already be incorporated into prices, and thus only the surprise component moves security prices.

Within U.S. alone, there are hundreds of macroeconomic news announcements. Not all of them are widely followed or equally important. The top 20 news announcements are selected to represent the most followed macroeconomic news announcements, based on the Bloomberg relevance score. This relevance score is part of the Bloomberg dataset, which indicates the number of people who subscribes to the news alerts, in the scale of 100. This is a objective measure of how investors view the importance of any macroeconomic announcements. The daily macroeconomic news index sums up all the news announcements within the top 20 list made on that day. If no news within the top 20 list is made, the index takes a value of 0. There is also possibility to see the index equals 0, if several news announcements are made but cancel out.

Table XVII lists the top 20 news announcements in the order of the relevance score. Change in Nonfarm Payrolls is the most followed macro news announcements according to this score. Initial Jobless Claims is another news announcement about employment market, which come the second. GDP news announcement ranked as the third. The top 20 news announcements have covered most news announcements which researchers deem as important. The list requires more than 50 observations for the macro news to be included. Four news which have high relevance score but are not included because lack of observations are: FOMC Rate Decisions which have 50 observations; MBA Mortgage Applications which have 2 observations; Markit US Manufacturing PMI which have 30 observations and PPI Final Demand MoM which have 11 observations. FOMC Rate Decision is one which people may wonder the materiality impact, as it was deeded as a market mover. Since most of the analyst forecasts equal the actual announcements, and the surprise component equal 0, excluding this announcements do not materially affect the analysis results.

Before summing the news announcement, we first flip the sign for three news: Initial Jobless Claims, Unemployment Rate and CPI, assuming higher unemployment and high inflation are negative news to the equity market. However, some studies do show that the macroeconomic news could cause different impact to the market, depending on the business cycle. (Boyd et al., 2005) showed that higher unemployment is actually good news during expansion period. Thus, we tried another approach by running univariate and multivariate regressions to obtain the signs for each of the 20 news announcement. However, due to the statistical insignificance of the coefficients, this exercise could actually pose more noise to the study. Thus, in this paper, we keep the signs consistent during the period and assume the signs based on common intuition and past research. In the future, we could expand the study to make it state dependent. Therefor, the daily Macro News Index is thus a sum of the 20 macro news, defined as below:

$$\text{Macro News Index}_t = \sum_{i=1}^{17} News_{i,t} + \sum_{i=1}^{3} (-News_{j,t}) \tag{2.3}$$

where i indexes the 17 news announcements who are assumed to have a positive coefficient with the equity market return, j indexes Initial Jobless Claims, Unemployment Rate and CPI, t indexes day.

Figure 5 is a plot of the Macro News Index. The shaded area are NBER recession dates. The figure shows that the index oscillates around 0 during this period, and there is no cluster of news during any period. This reflects the efficiency of analyst forecast and there is no consistent under or over-estimation.

Table XVIII shows the summary statistics of the Macro News Index. Panel A shows that the macro news index are positive on 1303 days, and negative on 1242 days. For the other 1480 day, the macro news index equal 0, due to no news announcements or canceling out. The means for the positive and negative sample are very close to zero, indicating that there is not systemic over- or underestimate from analysts. Panel B reports two simple regressions results, which regressed the market return as well as S&P 500 returns on the macro news index. The regression results show that the coefficients are both significantly positive, indicating that the macro news index is priced by the market. This justifies the construction of the macro news index, because we want the macro news index to be able to capture the macro information environment.

2.2.3 Control Variables

The controls variables are from IBES and Compustat, including number of analyst forecast for any earnings announcements, market capitalization, market to book value, the number of earnings announcements per day, the dummy variables indicating whether the actual earnings announcements are positive or negative. Also, we include a Friday dummy.

2.3 Empirical Results

2.3.1 Categorical Learning Hypothesis

The categorical learning behavior is first documented in (Lin and Xiong, 2006), which models the attention allocation for a attention-constrained investor when confronted with different kinds of news announcements. Under this hypothesis, a rational investor will allocate more attention to market wide information first, then to firm specific information. If a macro news is announced on the day of an earning announcement, the hypothesis indicates that investors will pay less attention to the earnings announcements and thus we will expect the earnings response coefficient to be lower under the presence of a macro announcement. we test this hypothesis by using the following specification:

$$CAR_{i,t-1,t+1} = \alpha + \beta_1 * SUE_{i,t} + \beta_2 * SUE_{i,t} * \text{Macro Dummy}_t + Controls_{i,t} + \epsilon_{i,t} \qquad (2.4)$$

where i indicates the stock, and t indicates time.

Macro dummy in the regression is a dummy variable which takes the value of either 1 or 0. It takes the value of 1 if on that day any of the 20 macro news is announced. The controls include: number of analyst forecasts (numest), market capitalization (MV), market to book value(MB), the number of earnings announcements on that day (eventperday), the negative earnings indicator (nearings) and a Friday dummy (fridaydummy). All the continuous variables in the regression are winsorized at the 1% level.

This is a panel regression, which pulled all the earnings announcements for companies within S&P 500 index during the 1999 to 2014 period. In total there are 32701 earnings announcements during this period. CAR is the cumulative abnormal returns from the day before to the day after the earnings announcement, after benchmarked to the Fama-French three factors. Essentially, it is the intercept α from the following regression:

$$Ret_{i,t-1,t+1} = \alpha_{i,t} + MKRF_t + SMB_t + HML_t + \epsilon \qquad (2.5)$$

The model 1 in Table XIX testes the earnings response coefficients without considering macroeconomic news announcements. The positive coefficient of SUE indicates that the stock prices respond positively to the earnings news announcements. Some other observations worth noting is that: the coefficient for Friday dummy is negative, which confirms the findings in (DELLAVIGNA and POLLET, 2009) that investors are more likely to be distracted on Friday, and thus earnings announcements released on Friday have a lower immediate response.

The model 2 in Table XXII testes whether a concurrent macro news announcement will change the ERC in some way. The coefficient of interest is the interaction variable SUE*MacroDummy. If the presence of a macro news announcement decrease investors attention, then this variable will be negative. The results show that this coefficient is not statistically significant from zero, indicating that investors do not react to earnings announcement any differently when a macro news announcement is also released on that day.

The model 3 considers the scale of macro news. Model 2 does not consider how much of a shock the macro news announcement is on any day. A macro news index with a value of 0.01 is treated the same as a value of 2, assuming that they pose the same level of distraction to earnings releases. Considering that investors may only be distracted by large shocks of macro news announcements, we replace the Macro dummy by the absolute value of the macro news index. The variable of interest is SUE*Abs(Macro News Index). Similarly, the coefficient is also not statistically significant from zero, again indicating that the presence of macro news does not affect the ERC.

2.3.2 Concordant News

Following the rejection of categorical learnings, we then think how a macro news announcement could affect an investors' response to an earnings announcement. Rather than being a distraction, macro news announcements may help investors to confirm the information content within the earnings announcements. A positive earnings announcement released on a positive macro news day may be traded differently from an earnings announcement released on a negative macro news day, similarly for the negative earnings announcements.

In Table XX, Model 1 has the same specification as that in equation 4, but only replacing the Macro Dummy variable by Macro News Index as constructed from equation 3. The interaction term is not statistically different from 0, as this specification does not separate positive and negative sample, assuming positive news are treated the same for positive and negative earnings announcements. In actual, our hypothesis is that the ERC is higher when the macro news and earnings news are in the same sign. Positive macro news increase the ERC for positive earnings news, while negative macro news increase ERC for negative earnings news. To separate this negative and negative sample, we test this hypothesis using the following specification:

$$CAR_{i,t-1,t+1} = \alpha + \beta_1 * SUE_{i,t} + \beta_2 * SUE_{i,t} * \text{Macro News Index}_t * NSUE + Controls_{i,t} + \epsilon_{i,t} \tag{2.6}$$

where NSUE is a dummy variable, which take the value of 1 when SUE is negative.

Two variables are of interests from this regression. One is the SUE*Macro News Index, and the other one is SUE*Macro News Index*NSUE. The coefficient for SUE*Macro News Index is 0.143, indicating that when SUE is positive, increasing macro news index increase the ERC. When SUE is negative, higher macro news decrease the ERC, as shown in the negative coefficient for SUE*Macro News Index*NSUE.

To get a further insight into this effect, we further separate the whole sample into six sub samples based on the signs of the earnings news and macro news. Table XXI shows the summary statistics of the six sub samples. There are more positive SUE compared to negative SUE. Within the positive and negative SUE samples, the positive macro sample are very much balanced compared to the negative macro sample.

Then we run a separate regression as the Model 1 in Table XIX for each of the sub sample. Table XXII reports the regression results. This tables shows more clearly how the ERC differ across the sub samples, when macro news and earnings interact. As shown, only two ERC are statistically significant among the six sub samples. One is the Positive SUE - Positive Macro sample, and the other is the Negative SUE - Negative Macro sample. So when the SUE are positive, the earnings news only move stock prices if the macro news index is positive. Vice versa, when SUE are negative, the earnings news only move stock prices if the macro news index is negative. Those two coefficients suggest that investors are not necessarily distracted by macro news announcements when they trade the earnings news, rather, they pay attention to the macro environment on that day.

This results are consistent with (Mian and Sankaraguruswamy, 2012a) who found the same pattern using sentiment measure. Our results suggest that this might be why investors respond differently during high versus low sentiment times.

2.3.3 Drift

The previous sections shows that macroeconomic news announcements announced on the days of earnings announcement affect how investors trade the earnings news. The earnings response coefficients are higher when macro news are in the same sign as the earnings news. In this section, we look at the drift following the the earnings announcements.

Post Earnings Announcements Drift was first documented by (Ball and Brown, 1968b) and was extensively studied by (Bernard and Thomas, 1989). They find that the stock returns tend to drift in the same direction of the earning surprise for several weeks after the earnings announcements. Researcher find that risk premium alone does not fully explain this phenomena.

Table XIII shows the post earnings announcement drift for the six subsamples. The dependent variables for this regression are the cumulative abnormal returns, which are the intercept in the following regressions:

$$Ret_{i,t+2,t+60} = \alpha_{i,t} + MKRF_t + SMB_t + HML_t + \epsilon \tag{2.7}$$

The regression results shown that the drift coefficients are significant for one earnings sample, which is the Positive SUE - Negative Macro sample. The coefficient is statistically significant at 1% level, and the coefficient is 18.66, which is much higher compared to other coefficients in the positive SUE sample. For this subsample, the initial response is muted as shown in Table XII. In contrast, for the Positive SUE - Positive Macro sample, the initial response is statistically significant, but the drift coefficient is not significant, indicating that the earnings news are incorporated into the stock prices on the days of earnings announcements. For the negative SUE samples, the results are somehow surprising. The coefficients for all three subsamples are not significant, indicating that the drift is not observed for negative earnings announcements during this period. Even more, the coefficients although not significant, all shown negative signs, indicating not drift but reversals. One possibility might be due to the sample selected. The stocks included are all big stocks within S&P index. Studies have shown that the PEAD is not as significant for big and widely followed stocks.

2.4 Conclusion

This paper documents the a firm's price response to earnings announcements when a concurrent macroeconomic news announcement is released together. We do not find evidence for investors' categorical learning behavior, which suggests that investors will be distracted by a concurrent macroeconomic news announcement and thus the ERC will be lower. Rather, we find that the information contained in the macroeconomic announcement affects a stock's price response to its earnings news, even after controlling for the price's systematic component.

We find that a macroeconomic news which has the same sign as a earnings announcement increase the ERC. More specifically, when the earnings surprise is positive, more positive macroeconomic news will increase ERC; when the earning surprise is negative, more negative macroeconomic news will increase the ERC. We also look at the drift following the earnings announcement, the drift following positive earnings announcements is only seen when the concurrent macro news is negative, which suggests that a positive concurrent macro news helps investors to fully incorporate the earnings news around the announcement window. This find may help to explain the findings in the (Mian and Sankaraguruswamy, 2012a), who found that investors respond stronger to good earnings news during high sentiment periods than during low sentiment periods, whereas investors respond stronger to bad earnings news during low sentiment periods than during high sentiment periods.

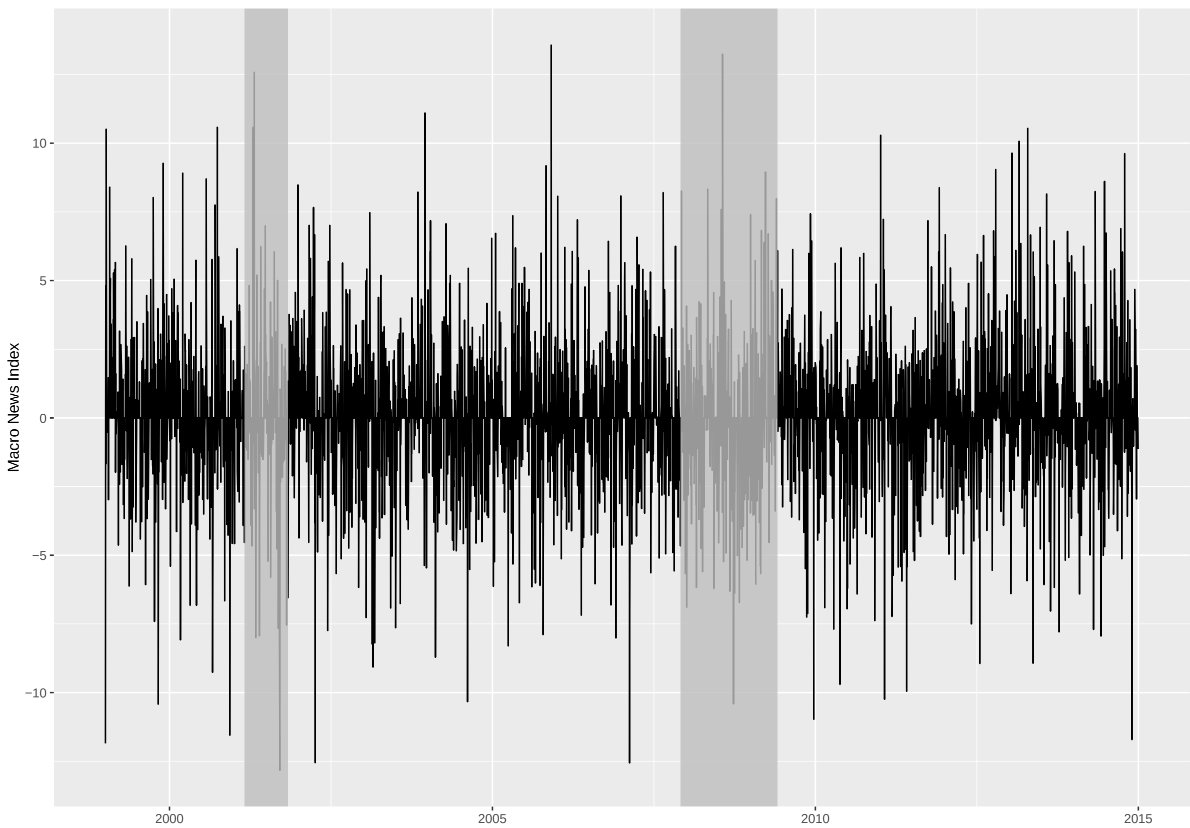


Figure 5. Time series plot of the daily macroeconomic news index.

Event	Num.Obs.	Mean	Std.
Change in Nonfarm Payrolls	192	-0.5247	2.5180
Initial Jobless Claims	833	-0.0537	2.4362
GDP Annualized QoQ	191	-0.0330	1.9703
ISM Manufacturing	192	0.1535	2.4640
Consumer Confidence Index	192	0.0600	3.0021
CPI MoM	192	-0.0767	1.4395
U. of Mich. Sentiment	370	-0.0463	2.5626
Durable Goods Orders	191	-0.1076	2.3319
New Home Sales	190	0.2186	3.2039
Retail Sales Advance MoM	163	0.0079	1.9769
Housing Starts	190	0.2443	2.8185
Unemployment Rate	192	0.5625	2.5505
Industrial Production MoM	190	-0.1743	1.7369
Existing Home Sales	118	0.1794	1.9947
Factory Orders	190	0.1717	1.3810
Personal Income	192	0.1399	1.7190
Personal Spending	191	-0.0214	1.2962
Trade Balance	191	-0.1185	2.7861
Leading Index	190	0.0749	1.1418
ADP Employment Change	100	0.2650	2.4808

TABLE XVII

SUMMARY STATISTICS OF TOP 20 MACROECONOMIC NEWS ANNOUNCEMENTS.

Panel A: Summary statistics of daily macronews index

	Pos Macronews	Neg Macronews	No Macronews
No.Obs	1303	1242	1480
Mean	2.3125	-2.3254	0
Std	2.0102	2.0198	NA

Panel B: Time Series regression of market on daily macronews index

	Market return	S&P 500 index return
(Intercept)	0.0002	0.0002
	(0.0002)	(0.0002)
macronews	0.0003^{***}	0.0003^{***}
	(0.0001)	(0.0001)
Adj. R^2	0.0027	0.0027
Num. obs.	4025	4025

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE XVIII

SUMMARY STATISTICS OF THE DAILY MACRO NEWS INDEX.

	Model 1	Model 2	Model 3
(Intercept)	0.020***	0.021***	0.020***
	(0.003)	(0.003)	(0.003)
sue3	5.112***	5.075***	5.131***
	(0.421)	(0.429)	(0.422)
MacroDummy		−0.000	
		(0.001)	
SUE:MacroDummy		0.062	
		(0.297)	
Abs(Macronews)			0.000
			(0.000)
SUE:Abs(Macronews)			−0.033
			(0.070)
log(MV)	−0.002***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.000)
MB	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
fridaydummy	−0.005***	−0.005***	−0.005***
	(0.002)	(0.002)	(0.002)
numest	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
eventperday	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
nearnings	−0.005***	−0.005***	−0.005***
	(0.002)	(0.002)	(0.002)
sue3:log(MV)	−0.100	−0.100	−0.096
	(0.112)	(0.113)	(0.113)
sue3:MB	0.051	0.051	0.051
	(0.035)	(0.035)	(0.035)
sue3:fridaydummy	−0.538	−0.548	−0.526
	(0.527)	(0.539)	(0.530)
sue3:numest	0.009	0.009	0.008
	(0.019)	(0.019)	(0.019)
sue3:eventperday	−0.002	−0.003	−0.002
	(0.007)	(0.007)	(0.007)
sue3:nearnings	−2.676***	−2.677***	−2.670***
	(0.275)	(0.275)	(0.276)
R^2	0.060	0.060	0.060
Num. obs.	32701	32701	32701

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE XIX

REGRESSION OF STOCK RETURNS ON THE SUE AND MACROECONOMIC NEWS VARIABLES.

	Model 1	Model 2
(intercept)	0.021^{***}	0.028^{***}
	(0.003)	(0.003)
SUE	5.105^{***}	5.086^{***}
	(0.927)	(0.909)
Macronews	-0.000	-0.000
	(0.000)	(0.000)
SUE:Macronews	0.011	0.143^{*}
	(0.054)	(0.085)
Nsue		-0.028^{***}
		(0.001)
SUE:Nsue		-1.214^{***}
		(0.383)
Macronews:Nsue		0.000
		(0.000)
SUE:Macronews:Nsue		-0.211^{*}
		(0.115)
R^2	0.060	0.080
Num. obs.	32701	32701

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE XX

REGRESSION OF STOCK RETURNS ON THE INTERACTION BETWEEN SUE AND MACRO NEWS INDEX.

	Positive SUE			Negative SUE		
	Pos Macro	Neg Macro	No Macro	Pos Macro	Neg Macro	No Macro
No. Obs	7773	7544	6239	2594	2357	1975
Mean SUE	0.0022	0.0023	0.0022	-0.0039	-0.0043	-0.0044
Median SUE	0.0010	0.0010	0.0009	-0.0011	-0.0010	-0.0011
Mean Macro	2.2624	-2.2098	0.0000	2.2805	-2.1870	0.0000
Median Macro	1.6600	-1.7100	0.0000	1.7100	-1.6900	0.0000

TABLE XXI

SUMMARY STATISTICS OF SUE AND MACRO NEWS IN THE SIX SUB SAMPLES.

	Positive SUE			Negative SUE		
	Pos Macro	Neg Macro	No Macro	Pos Macro	Neg Macro	No Macro
(Intercept)	0.042***	0.046***	0.046***	−0.058***	−0.005	−0.022
	(0.009)	(0.008)	(0.008)	(0.013)	(0.015)	(0.015)
SUE	8.145**	2.905	3.273	−1.059	6.743***	3.300
	(3.796)	(2.260)	(2.749)	(2.371)	(2.404)	(2.539)
log(MV)	−0.003***	−0.003***	−0.003***	0.004***	−0.002	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
MB	0.000	0.000*	0.000	−0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
fridaydummy	−0.001	−0.002	−0.001	0.005	0.011**	0.001
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)
numest	−0.000	−0.000	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
eventperday	−0.000	−0.000**	−0.000	0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
nearnings	−0.002	−0.009**	−0.003	−0.003	−0.002	−0.005
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
sue3:log(MV)	−0.598	−0.127	−0.230	0.330	−0.291	−0.167
	(0.445)	(0.286)	(0.333)	(0.271)	(0.247)	(0.313)
sue3:MB	0.122	−0.040	0.072	0.007	−0.004	−0.026
	(0.086)	(0.075)	(0.071)	(0.101)	(0.082)	(0.102)
sue3:fridaydummy	−2.357**	−2.276*	−3.555**	0.754	0.561	1.734
	(1.175)	(1.326)	(1.671)	(1.172)	(1.215)	(2.180)
sue3:numest	0.062	0.012	0.069	0.029	−0.035	0.003
	(0.059)	(0.044)	(0.061)	(0.046)	(0.041)	(0.070)
sue3:eventperday	−0.021	0.032*	0.011	−0.005	−0.028*	−0.006
	(0.023)	(0.019)	(0.027)	(0.016)	(0.017)	(0.023)
sue3:nearnings	−2.090**	−0.403	−1.230	−1.279	−2.573**	−1.132
	(1.059)	(0.787)	(0.998)	(0.860)	(1.150)	(0.949)
R^2	0.045	0.041	0.027	0.017	0.033	0.028
Obs.	7760	7535	6220	2589	2350	1970

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE XXII

INITIAL PRICE REACTION TO EARNINGS NEWS FOR THE SUB SAMPLES.

	Positive SUE			Negative SUE		
	Pos Macro	Neg Macro	No Macro	Pos Macro	Neg Macro	No Macro
(Intercept)	0.071^{***}	0.018	0.090^{***}	0.058^{*}	0.085^{**}	0.066^{*}
	(0.018)	(0.018)	(0.019)	(0.032)	(0.035)	(0.040)
SUE	0.151	18.664^{***}	1.493	−6.251	−2.760	−11.699
	(5.877)	(5.130)	(5.944)	(5.686)	(5.813)	(8.067)
log(MV)	-0.006^{***}	−0.002	-0.009^{***}	-0.007^{*}	-0.007^{*}	−0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
MB	0.001^{*}	0.001^{**}	0.001^{**}	0.001	0.001	−0.002
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
fridaydummy	−0.004	−0.002	−0.018	0.001	0.017	-0.032^{*}
	(0.007)	(0.009)	(0.014)	(0.012)	(0.018)	(0.017)
numest	-0.001^{*}	0.000	0.000	0.000	−0.001	−0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
eventperday	0.000	0.000^{*}	−0.000	0.000^{*}	-0.000^{**}	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
nearnings	0.002	−0.004	−0.012	−0.007	0.007	−0.003
	(0.011)	(0.011)	(0.012)	(0.012)	(0.014)	(0.015)
sue3:log(MV)	0.094	-2.204^{***}	0.099	0.385	0.414	1.461
	(0.725)	(0.727)	(0.759)	(0.617)	(0.655)	(1.003)
sue3:MB	-0.278^{*}	−0.066	−0.164	0.054	0.307^{***}	0.388^{***}
	(0.157)	(0.132)	(0.196)	(0.169)	(0.063)	(0.141)
sue3:fridaydummy	−1.478	1.877	3.432	3.538	−2.766	−3.945
	(1.929)	(2.905)	(8.040)	(2.413)	(3.388)	(4.428)
sue3:numest	0.016	0.128	−0.087	0.112	−0.075	−0.227
	(0.124)	(0.136)	(0.137)	(0.097)	(0.088)	(0.205)
sue3:eventperday	−0.016	−0.022	−0.004	0.115^{***}	−0.014	0.057
	(0.045)	(0.037)	(0.054)	(0.043)	(0.039)	(0.066)
sue3:nearnings	−0.047	0.768	1.096	−1.616	−0.905	−0.790
	(2.088)	(1.894)	(2.386)	(1.524)	(2.036)	(2.768)
R^2	0.007	0.020	0.010	0.023	0.033	0.071
Obs.	7760	7535	6220	2589	2350	1970

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE XXIII

DRIFT FOLLOWING THE EARNINGS ANNOUNCEMENTS FOR THE SUB SAMPLES.

CHAPTER 3

WHAT WORKS IN STOCK MARKET DESIGN?

A key role of market design is to help allocate capital efficiently at the lowest possible cost. We collect data on 26 trading rules from 42 countries since the 1980s to study how stock market design affects financial markets. We categorize the rules into five categories: competition and pricing; financial disclosure; information access; market dynamics; and market stability. We find that stock market design affects financial market development and efficient capital allocation. For example, information access and market stability rules are most relevant in decreasing the cost of equity, while market dynamics rules are most relevant in increasing the financial market's allocative efficiency. The findings show that not all rules are equally important, and regulators can implement particular rules to accomplish specific policy goals.

3.1 Introduction

Recent advances in information technology have led to changes in market structure. Trading has become predominantly electronic; competition has arisen among trading venues; and, trading and intermediation have been automated. This has led to new features in markets: increased pre- and post-trade transparency; algorithmic trading; high-frequency trading; and, fragmentation of liquidity. Many studies have shown that these changes improved market efficiency; however, some researchers and policy makers have wondered if this market efficiency yields macroeconomic benefits or is just rent-extracting.

Our goal is to assess the macroeconomic effects of changes in how markets function. In particular, we look at changes in laws, rules, and practice which have been associated with market efficiency across 42 countries; changes are grouped based on how they affect markets. Since markets exist to allocate capital, we then assess these groups of market changes with changes in measures associated with economic development and allocative efficiency. To yield interpretable and policy-relevant results, we also look at changes from prior decades since many of those earlier changes, e.g. financial reporting rules and restrictions on insider trading, have better-understood economic effects. We also attempt to discern which particular changes to market practice have the most benefit.

We find that many recent changes to markets are also associated with economic benefits. In particular, changes in market dynamics and competition for order flow yield benefits of a similar magnitude to changes requiring regular financial reporting and restricting insider trading. Improvement of information access such as disclosing higher depth of limited order book is associated with lower cost of capital. Lower trading costs and greater market making competition are also associated with lower costs of capital in recent years. New trading infrastructure made possible by the development of new technology, such as the introduction of colocation and direct market access, are associated with higher allocative efficiency. Changes of rules in all groups are shown to positively affect financial market capitalization.

Since our study period begins in the 1980s, we also include rules implemented earlier and shown to affect market quality or have macroeconomic benefits. Some of those rules have been changed frequently and used extensively as policy tools during, especially during the 2008 crisis.

For example, many countries banned short selling or naked short selling during the crisis. There is also a general trend of mandating more timely information disclosure in the past decade. We document the recent changes of those prior-implemented rules to investigate how their effect on the economy may change through time.

In total, we include 26 rules which we break into five categories: competition and pricing rules which aim to reduce trading costs and increase competition among market actors; financial disclosure rules which are related to mandatory financial reporting; information access rules which relate to market data availability and actionable price signals after market hours; market dynamics rules which seek to improve market completeness; and, market stability rules which aim to reduce market volatility or ameliorate financial crises. Some of the rules may be implemented with several goals in mind. Since this complicates categorization, we have chosen what we believe to be the best-fitting group.

The 26 rules are picked from existing studies which have shown them to affect market efficiency or some dimension of market quality. Although it is better to include more rules in the study, we think these rules are sufficient to characterize the different aspects of market rules and practice. We also have focused on rules with sufficient variation across time or countries to yield valid inferences. Since these rules have more variation and collecting the data was lengthy and labor-intensive, we believe that adding more rules would result in more difficult data collection for little marginal benefit. Given these 26 rules, we average the rules (which are dummy variables) within a category to get a category index. There are several advantages to looking at studying rules by category: First, averaging rules can take care of the strong collinearity between rules; and second, averaging decreases the noise in the rules dataset.

We pick three dependent variables to measure the economic benefits: the cost of equity capital, the ratio of market capitalization to GDP, and a measure of allocative efficiency. A well-designed financial market should have a lower cost of equity capital because that makes it easier for funds to flow throughout an economy; and, we believe that means funds will tend to go where they are most needed. Corporations with flexibility to choose where to list their shares will choose to list in a market with a lower cost of capital. This leads to higher investment and equity market capitalization. Many researchers, such as (Charoenrook and Daouk, 2009) and (Porta et al., 2006) have used the cost of equity capital and ratio of market capitalization to GDP to examine the economic benefit of certain rule changes.

Since financial markets allocate capital in an economy and promote economic growth, we also look at a measure of allocative efficiency developed in (Wurgler, 2000). Although a lower cost of equity capital makes it cheaper for funds to flow through an economy, funds might not flow to the sector where they would be most beneficial.(Wurgler, 2000) estimates a country-level allocative efficiency coefficient by regressing the industry level investment growth on the industry level value-added growth. The argument is that a market with greater allocative efficiency will increase investment more in industries with increasing value added by shifting funds away from industries with declining value added.

Compared to similar studies, we look at a more complete list of rules; we look at all of the rules simultaneously; and, we have updated the rules for changes made in recent years. These differences let us discern and compare economic effects and enable us to look at how effects vary across time. Our goal is to provide a more robust and complete look at how the financial market design affects the real economy. The paper proceeds as following: Section 2 discusses prior studies on how some rules have affected financial market efficiency. Section 3 shows how we construct the rules dataset and how we estimate the economic measures. Section 4 presents empirical analysis results. Finally, Section 5 concludes.

3.2 Literature Reviews

A number of studies have shown that changes in market practice are associated with increased market quality. Most of those studies have used financial measures such as liquidity, volatility, volume, or autocorrelation in prices to represent some dimensions of financial market quality. For consistency, we address these prior studies by how we have categorized rules.

In the area we call competition and pricing, studies have shown that competition and lower transaction costs are beneficial to financial market quality. Reductions in minimum price increments ("tick size") have been shown by (Chordia et al., 2008) to lead to higher liquidity and thus higher market efficiency. A number of studies, including (Umlauf, 1993) and most recently (Pomeranets and Weaver, 2011) have shown that securities transactions taxes increase trading costs, decrease asset values, do not eliminate some common forms of destabilizing trading, and decrease market efficiency. Finally, (Venkataramana and Waisburda, 2007) and (Anand et al., 2009) show that the allowing for market makers and market maker competition increases market efficiency.

Regarding financial disclosure rules, (Porta et al., 2006) and (Jere R. Francis and Pereira, 2005) show that greater information disclosure is associated with a lower cost of equity capital and higher financial market development.(Bhattacharya and Daouk, 2002) and (Beny, 2005) show that the existence and enforcement of anti-insider trading laws has led to a lower cost of equity capital and higher financial market development.

Market practices affecting information access have also been shown to be important.(Boehmer et al., 2005) and (Madhavan, 1996) show that increasing information transparency (pre-trade transparency) has led to lower price volatility and higher market quality. (Barclay and Hendershott, 2003) show that trading after hours generates significant price discovery, although prices in after-hours sessions are less efficient compared to pre-open sessions.

Market practices that affect market dynamics have been shown to have a large effect on market efficiency. (Bris et al., 2007) and (Charoenrook and Daouk, 2009) show that allowing and facilitating short selling increases the speed of price discovery and lowers the cost of equity capital. Similarly, (Beber and Pagano, 2013) find that banning short-selling during the 2008 financial crisis decreased liquidity and failed to support prices. More recently, many studies have looked at the effects of practices associated with algorithmic and high-frequency trading. Allowing market participants to place their order processing systems in the same data center as the market ("colocation") has been shown by (Brogaard et al., 2015) and (Boehmer et al., 2015) to increase liquidity and information efficiency. Finally, (Chakravarty et al., 2004) and (Kumar et al., 1998) show that derivatives markets aid price discovery in the underlying stock market and improve market quality.

Finally, market stability rules include policies such as price control rules ("circuit breakers"). (Lauterbach and Ben-Zion, 1993) and (Kim and Rhee, 1997) have shown that these have mixed effects on market quality. These may be macro-prudential measures that sacrifice some efficiency in good times for increased efficiency in times of crisis.

3.3 Data

3.3.1 Independent Variables

Our independent variables are five indices constructed from 26 trading rules. We document changes to each rule for 42 countries since 1980s. The data on the changes of rules are largely hand-gathered. The definition for each rule and the five categories are listed in table XXIV.

The 42 countries are a balanced sample of developing and developed financial markets. The rules in our study are implemented either at the country level or exchange level. Country level rules are normally defined in the securities laws which govern all exchange or over-the-counter trading activities within the country. Exchange level rules are normally defined in the exchange's listing requirement and thus only concern stocks listed on the exchange. Some rules may be enforced at both country and exchange levels. For rules enforced both in securities laws and in exchange listing requirements, we take the "stricter" rule. For example: securities laws may require investors to disclose when they hold more than 5% of a single stock; however, exchange rules may require investors to disclosure when they hold more than 2% of the stock. In this case, the large shareholder disclosure rule would be recorded as 2% for the country.

For most of the countries, we only collect data on the rules from the dominant exchange. For a few countries (such as US, China, and India) where there are several main exchanges and where data is available, we collect rules data for all large exchanges. If two exchanges within a country have different rules, again we take the "strict" one as for the country.

Our rule dataset has observations at a monthly frequency. We take the value at the end of each month as the value for the month. For example, if a rule changes from 1 to 0 on 15 Jan 1990, the rule will take a value of 1 for December 1989 and take a value of 0 for January 1990. If we cannot find the exact month when a rule changes, we record the new value as of January for the year it changes. For differences between when a rule is proposed, approved, and implemented, we use the date when a rule change is implemented. Sometimes announcement of a rule change is made ahead of implementation date, so the effect of a rule change can happen on the announcement date. Therefore, using the implementation date should reduce our estimates of the effects and yield more conservative results.

The rules data are manually collected. We compile the rules dataset from published literature, securities law books, newspapers, regulators and exchange websites, and financial news reports. If data does not come from an official release, we cross check from at least two data sources if available. For a few cases when different sources show different dates, we try to cross check from a third source. It is nearly impossible to construct this dataset "directly". We instead construct our dataset "indirectly" by using some judgment and extrapolation, based on the fact that rules do not change frequently. Most similar studies use a cross-sectional dataset for one or more rules as of a certain date. Those studies serve as a good starting point for us to construct our rule dataset. If two cross-sectional studies done at different times show different values for a rule, we suspect the rule has changed sometime between those two dates. We then search to confirm the change and find the exact date of the rule change. If two cross-sectional studies show the same value for a rule, we also search to confirm that no change happened between the dates.

For a dataset like this, missing values are inevitable. If we cannot find any data source for a rule, then the data is missing for that rule. We deal with missing values in two ways. The first way is to use complete data: we only include country and month observations with no missing value for all the rules. However, this results in a large loss of information. The second way is to assume 0 for missing values. This is not as arbitrary as it sounds:. If we cannot find any documentation for a rule, it is highly possible that the rule was not implemented in the country. Coding missing data as a 0 for all months for the country will not create a big bias when we include a country fixed effect. In our analysis, we focus on the second way which assumes 0 for the missing values. We also report results for only complete observations. The general results hold.

After we have the rule dataset, we construct five indices by averaging the values for the rules within each category. The five categorical indices are the independent variables used in our analysis. Our dependent variables are in either quarterly or annual frequency, so we take the value at the end of quarter as the value for the quarter. We average the four quarters to get the annual values.

One rule which worth noting is the tick size rule. This rule depends on the availability of the finance data as well. Exchanges normally use different tick size for stocks which are traded at different price ranges. We define the relative tick size as the tick size divided by the trading price. We compute the relative tick size for each stock within each country at each quarter. The tick size rule for the country at each quarter is the average of the relative tick size for all the stocks.

Table XXV presents the summary statistics of the rules and indices. Panel A and B report the average of the rules and indices across countries at the end of 1980, 1985, 1990, 1995, 2000, 2005 and 2010. Panel A and B differ in how they handle missing values. Panel A treats missing values for any rule as a 0. Panel B use only complete observations. Panels C and D are the correlation matrices for the five indices constructed from Panels A and B. Although the correlations across indices differ a lot depending on how we handle missing values, the general results shown in the following do not change much.

3.3.2 Dependent Variables

Our dependent variables consist of three measures related to economic development: the cost of equity capital, the log-ratio of market capitalization to GDP, and (Wurgler, 2000) allocative efficiency measure.

3.3.2.1 Cost of Equity Capital

We use the realized return as a proxy for the cost of equity capital. The finance data for international stocks are from Datastream. We collect price data for all the stocks at the end of each quarter since they were included in Datastream. To avoid survival bias, we also include stocks from Datastream's "dead" list - the stocks delisted from the exchanges. The cost of equity capital for each country and each quarter is the market-cap weighted average of the realized return for all the stocks. We also Winsorize our sample based on returns, market values and prices: for each country and each quarter, we exclude any stock if its return, market value or price is above the 99th percentile or below the 1st percentile. We also exclude stocks whose prices are traded below 1 in the market's quoted currency.

3.3.2.2 Log(Market Capitalization/GDP)

The market capitalization/GDP ratio is downloaded from the World Bank website. The data are for the period. Since the ratio is skewed, we take the log of this ratio so that outliers do not skew our results. The data are at an annual frequency, so we annualized our quarterly independent variable indices by averaging them across the four quarters within a year.

3.3.2.3 Allocative Efficiency

We construct our allocative efficiency measure following (Wurgler, 2000). This country-level measure comes from regressing an industry's investment growth on the industry's value-added growth:

$$\ln\left(\frac{I_{i,c,t}}{I_{i,c,t-1}}\right) = \alpha_c + \beta_c * \ln\left(\frac{V_{i,c,t}}{V_{i,c,t-1}}\right) + \epsilon_{i,c,t} \tag{3.1}$$

where I is investment, V is value added, and i, c, and t index industry, country, and time in years.

The theory behind this measure is that a highly efficient economy increases investment in their growing industries and decreases investment in their relatively declining industries. The β_c in the above equation is the allocative efficiency measure and estimates the rate of substitution from declining value-added industries to increasing value-added industries for each country.

Industry data including gross capital formation and value added are from INDSTAT2. INDSTAT2 is a dataset published by United Nations Industrial Development Organization (UNIDO). It contains time series data for industries at the 2-digit ISIC level since 1963. In terms of data transformation and filtering, we follow the procedures in (Wurgler, 2000). First we change the industry data in INDSTAT2 from local currencies to US dollars using the year's average exchange rate (from the World Bank website). We then covert the data into real dollars by deflating the capital fixed formation using the US Purchaser Price Index (PPI) for capital equipment and deflating the value added using the US PPI for finished goods. As argued in (Wurgler, 2000), this transformation implicitly assumes purchasing power parity for capital goods and finished goods. Finally, we apply two data filters: First, we exclude small industries whose value added for a year is smaller than 1% of the country's total value added for that year. Second, we exclude observations for which the log value added growth or log investment growth exceeds +/-1.

We section the data into five periods: 1986-1990, 1991-1995, 1996-2000, 2001-2005 and 2006-2012. We estimate one allocative efficiency coefficient for each country and for each of those sub-periods. We require that a country have more than 30 industry observations within each sub-period to run the regression. The sub-period regression coefficients are pulled together to form our dependent variables. The rule indices are aggregated from annual level into five sub-periods by averaging across years within each sub period.

3.3.3 Control Variables

For most of analysis we do, we include country fixed effects. For the analysis which is done in a cross-sectional setting at the end of each year, we include the law origin from (Porta et al., 2006) as a control variable.

Table XXVI presents the summary statistics of the dependent and control variables. The summary statistics are for observations included in our analysis. For example, at the end of 1980, there are only 18 countries included in our studies. This is mainly due to the required data availability of the three dependent variables.

3.4 Results & Policy Implications

3.4.1 Cost of Equity Capital

Table XXVII presents results for a pooled regression of the cost of equity capital on five rule indices. Panels A and B differ in how to handle missing values. Panel A assumes 0 for all missing values. Panel B deletes the observations if any rule within each category is missing. All regressions include a country fixed effect. The univariate regressions in both Panels A and B return negative and significant coefficients for all except the infoindex in Panel B. This suggests that implementation of those rules are associated with a lower of cost of equity capital. If we look at the multivariate regression reported in Model 7 of Panel A, the information access, market dynamics and market stability indices remain negative and statistically significant.

To make a comparable and intuitive interpretation of those coefficients, we can divide the coefficients by the number of rules within each category to compare how passing one rule within each category decreases the cost of capital. In the multivariate regression, one more rule passed in the information access category will decrease the cost of equity capital by $0.1156/3 = 0.038 = 3.8\%$. Similarly, one more rule passed in the market dynamics category decreases the cost of equity capital by $0.0389/6 = 0.0064 = 0.64\%$ and one more rule passed in the market stability category decreases the cost of equity capital by $0.0483/3 = 0.016 = 1.6\%$.

Compared to Panel A, the coefficients in Panel B are smaller due to the decreased number of observations. Since the missing values for each index happen for different country-quarter observations, we are able to perform a multivariate analysis. However despite the limited data, we still observe significant coefficients for most of the rules indices. Thus in the following sections, we focus on the analysis using rule indices from Panel A, which assumed 0 for missing values.

Table XXVIII is a sensitivity test which takes one index out each time from the multivariate regression in model 7 of Panel A from Table XXVII. This tests whether the regression results observed might be driven by one index; this is important to check since there may be collinearity between the indices. We find that the statistical power for the information access, market dynamics, and market stability indices are consistent across all models. The coefficients for the information access index are similar across all models. The market dynamics index coefficient gets stronger in model 6 when the market stability index is left out. Similarly the market stability index coefficient gets stronger when the competition index or the market dynamics index is left out. The results suggest that rules implemented in those three groups are more strongly related to a lower cost of equity capital. However, this does not mean that rules that are in the competition and financial reporting groups do not effectively decrease cost of equity capital: Averaging the rules within groups may obscure the effect of a single rule.

To test how each rule separately affects the cost of equity capital, we run the univariate regressions of the cost of equity capital on each of the 26 rules separately. Table XXIX reports those regression results. All regressions use only country-quarter observations for which the rule data is available and include a country fixed effect. A quick glance shows that all the regression coefficients are negative. Some new trading technology-induced rules such as direct market access (DMA) and colocation are shown to strongly decrease the cost of equity capital.

Our evidence also confirms results from existing studies on rules such as insider trading laws, the presence of competing market makers, negotiable brokerage commission, and brokerage insurance: we confirm that these all decrease the cost of equity capital. However, some results fail to confirm or even contradict prior findings. For example, a securities transaction tax has been shown to harm price discovery and reduce market efficiency; however, our analysis suggests that it does not strongly affect the cost of equity capital. Similarly, allowing short selling has been shown to improve price discovery; but, we do not find that it decreases the cost of equity capital. However, care should be taken in interpreting these univariate results since these models are more likely to be affected by an omitted variable problem.

Similar rule changes across countries tend to be clustered in time. Rules of the same type tend to be implemented around the same time as policy tools or because of changes enabled by new technology. For example, equity derivatives were mostly introduced across countries in the 1990s. In the 1990s and early 2000s, financial markets began promoting increased information access; thus regulators made many changes to these rules. Short selling rules, although implemented quite early, were reduced in the early 2000s but then increased during the recent financial crisis as policy makers attempted to support prices. High frequency trading-related rules, such as colocation and DMA, are trading practices recently invented and enabled by internet technology.

To study how the economic effect of those rules may change across time, Table XXX presents the cross-sectional regressions for each year from 1991 to 2012. We aggregate the cost of equity capital and rule indices across four quarters to get country-year observations. For each year, we require more than 30 country observations to conduct the analysis. All regressions include the legal origin and log-market capitalization as control variables. Panel A presents univariate regressions of the cost of equity capital on each rule index. Panel B presents the multivariate regression of the cost of equity capital on the five indices together each year.

In general, we see a lot of dynamics in the rule effects around the recent crisis. The competition index shows the strongest effect around the crisis. This may be because competition rules have been shown to help improve liquidity and liquidity carries higher risk premia during crises. Another variable worth noting is the market stability index. Although the coefficients are not statistically significant, we observe consistent positive coefficients for this index during good times before 2008. Market dynamics rules, such as short selling rules, experienced a lot of changes during the recent crisis and are associated with a lower cost of equity capital in the univariate analysis in Panel A. The financial reporting rules are associated with a lower cost of equity capital in the late 1990s when rules were made to improve timely financial reporting.

3.4.2 Log(Market Capitalization/GDP)

The previous section has shown that higher rule indices are associated with a lower cost of equity capital. A lower cost of equity capital attracts corporations to list shares on the equity market because of the lower cost of financing. We would expect this to lead to a higher market capitalization relative to the economy's development. To investigate this, we examine the log-ratio of the stock market capitalization (i.e., market value, MV) to GDP, aka log(MV/GDP).

Since our data on MV/GDP is at an annual frequency, we calculate rule indices using 0 for missing values: while this creates a downward bias on the inferred effects, it ensures we have sufficient data to make some inferences. We average rules across the four quarters to get country-year observations. We include country fixed effects in all regressions to take care of omitted country characteristics that may drive stock market development.

First, we replicate the univariate and multivariate regressions on rule indices (as in Table XXVII Panel A), except now using log(MV/GDP) as the dependent variable; Table XXXI presents these results and shows that the regression coefficients are all positive and statistically significant. In the multivariate regression, the coefficients decrease versus those in the univariate regression; however, all coefficients remain positive and statistically significant. To compare the coefficients for different indices, we scale them by the number of rules within each category and interpret the effect like that of a log-return. For example, one rule implemented in the competition and pricing category will increase log(MV/GDP) by about 0.2443/5. Thus we see an increase in market capitalization versus GDP of exp(0.2443/5) = about 5% per additional rule in the competition and pricing category; exp(0.9405/9) = 11% per financial reporting rule; exp(0.4175/3) = 15% per information access rule; exp(0.4075/6) = about 6% per market dynamics rule; and, exp(0.8929/3) = 35% per market stability rule.

Thus it seems that rules affecting market stability and information access have the greatest effect on the market value as a fraction of GDP. This suggests these rules may increase the value of listed stocks or encourage more firms to seek a public listing of their shares. While these rules have the strongest effect, none of these effects is economically insignificant.

Table XXXII shows how sensitive these estimated log(MV/GDP) effects are to any one index by removing one index at a time and re-estimating the model. The results show the coefficients for all indices in all regressions are positive and statistically significant. The coefficients increase slightly in Models 2-6, compared to Model 1, which includes all five indices. This could be due to the correlation between the five indices. The adjusted R^2 are all above 70%, suggesting omitting one category of rules can still describe up to 70% of the cross-country and time variation in financial market development.

We do not replicate the prior regressions by looking at log(MV/GDP) versus individual rules or versus all rules over the five sub-periods. The reason for these omissions is due to a lack of data: Since the market capitalizations and GDP data are at an annual frequency, any inferences made on individual rules would be likely to include spurious results; and, inferences over the sub-periods would add little information versus the already-annual data.

3.4.3 Allocative Efficiency

In this section, we replicate the preceding analyses using the (Wurgler, 2000) allocative efficiency measure as the dependent variable. While this measure makes use of time as well as industry variation, we want to get some time-related information instead of smothering that dimension of the data. Therefore, we estimate an allocative efficiency coefficient from the model in equation (1) for each country and each of five sub-periods: 1986-1990, 1991-1995, 1996-2000, 2001-2005 and 2006-2012. Since we only have five sub-periods, we do not include country fixed effects in those regressions. We create the dependent variables (rule indices) by averaging rule variables over each year in the sub-period.

We first replicate the univariate and multivariate regressions on rule indices (as in Table XXVII Panel A) using these allocative efficiency coefficients as the dependent variable. Table XXXIII presents these results in two panels: Panel A has no fixed effects for each sub-period while Panel B includes a sub-period fixed effect. For the univariate regressions in Models 1-6 of Panel A, the coefficients in front of all five indices are positive. Three rule category indices are also statistically significant: competition and pricing, information access and market dynamics. Similarly in panel B, all the coefficients in Models 1-6 are positive. The financial reporting index becomes marginally significant compared to not being statistically significant in Panel A. Aside from this difference, the coefficients are similar to what we observe in Panel A. In both Panel A and Panel B, the coefficients for the multivariate regressions do not have much statistical power, except for the market dynamics index in Panel B. This may be due to the higher correlations when we average the rules indices over the five years period, or the use of sub-periods might eliminate the time variation which would allow us to discern significant effects.

Table XXXIV assesses the sensitivity of these results by showing how the multivariate regression changes if we leave out one rule index at a time. As in Table XXXIII, Panel B includes a fixed effect for the sub periods while Panel A does not. In both Panels A and B, the market dynamics index is the one which is most consistent in terms of the estimated coefficients and is most often statistically significant. If we remove this index from the regression, the information access index becomes significant in both Panels A and B; and, the competition and pricing index becomes marginally significant in Panel B. As we mentioned earlier, rules surrounding market making and pre-trade transparency might be changed in similar time periods as rules in the market dynamics category. If so, the correlation may be stronger between those indices when we average them across the five sub-periods. This would lead to what we observe in Table XXXIV.

3.5 Conclusion

In this paper, we document the economic effects of changes of trading rules. In particular, we look at many changes that have historically been seen as increasing market efficiency or reducing rent-seeking. Our goal is to show that these changes might also have larger economic benefits. By extending and building on existing studies, we show how changes to these rules are associated with three different measures of economic benefits: the cost of equity capital, the ratio of market capitalization to GDP, and (Wurgler, 2000) measure of allocative efficiency. In general, we find that the rules which have been shown to improve financial market quality and to increase market efficiency also lead to economic benefits: a lower cost of equity capital;

more developed financial markets as proxied for by a higher market capitalization versus GDP; and, higher allocative efficiency.

By using a more complete set of countries and rules across a few decades, we are able to discern the effect and compare the relative importance of those rules. We find that, on average, rules which increase information access to investors and which stabilize the market are associated with a lower cost of equity capital over our sample period. However, the rules which promote competition and lower trading costs reduce the cost of equity capital more strongly in recent years. Market dynamics rules, which are targeted to improve the completeness of the market, are associated with higher allocative efficiency. All five categories of rules are strongly associated with later increases in the development of financial markets as proxied for by higher market capitalization to GDP ratios.

We do not go further in explaining why different rules seem to be important for these different economic measures. It may be because these analyses are done on different frequencies, an unfortunate artifact of some of the data; information may get lost when we average rules; and, averaging across time or sub-periods might also cause some information loss. These differences in results could also be due to the time clustering of rule changes. Finally, there may be subtle differences between these economic measures: perhaps certain rules affect one measure to the detriment of another. In future work, we hope to examine these issues to learn which rules have stronger effects as well as the subtle differences between these measures of economic benefits.

Rule	Variable name	Definition
Competition and Pricing		
Negotiated Brokerage Commission	negcom	1 if brokerage commission is negotiated; 0 otherwise.
Security Transaction Tax	stt	1 if no tax is charged in transfer of stocks; 0 otherwise.
Tick Size	decimal	1 if mean of tick size/price is less than 0.01; 0 otherwise.
Market Making Allowed	mmallow	1 if exchanges allow market making for stocks; 0 otherwise
Market Making Competition	mmcompete	1 if exchanges allow multiple market makers for each stock; 0 if exchanges allow only one market maker for each stock.
Competition and Pricing Index	compindex	Average of the rules in Competition and Pricing category
Financial Reporting		
Insider Trading Law Existence	itext	1 if insider trading law exists; 0 otherwise.
Insider Trading Law Enforcement	itenf	1 if presecutions against inside trading have taken place; 0 otherwise.

Large Shareholder Disclosure	lgdis	1 if large shareholders are required to disclose their holding; 0 otherwise. We include requirement defined by securities laws and exchange rules.
Large Shareholder Disclosure_threshold	lgamt	1 if the large shareholder threshold is defined as equal or less 5%; 0 otherwise.
Large Shareholder Disclosure_delay	lgtm	1 if maximum delay of large shareholder reporting is equal or less than 5 days; 0 otherwise.
Company Annual Report_dummy	comprpt	1 if listed companies are required to publish audited annual financial report; 0 otherwise. We include requirement defined by securities laws and exchange rules.
Company Annual Report_delay	comprpttm	1 if maximum delay of publishing audited annual reporting is equal or less than 3 months; 0 otherwise.
Company Periodic Report	periodrpt	1 if companies are required to publish quarterly report, 0.5 if companies are required to publish semi-annual report; 0 otherwise. We include requirement defined by securities laws and exchange rules.
Company Periodic Report_delay	periodrpttm	1 if maximum delay of interim reporting is equal or less than 2 month; 0 otherwise.

Financial Reporting Index	frindex	Average of rules in Financial Reporting category
Information Access		
Pre-trade transparency_broker	preinfo_broker	1 if more than 5 BBO of the limit order book is displayed to brokers; 0 otherwise.
Pre-trade transparency_investors	preinfo_investor	1 if more than 5 BBO of the limit order book is displayed to public investors; 0 otherwise.
After Hour Trading	afterhour	1 if after hour trading is allowed; 0 otherwise.
Information Access Index	infoindex	Average of rules in Information Access category
Market Dynamics		
Short Selling_legal	sslegal	1 if short selling is allowed for all stocks; 0.5 if partially banned(mostly for finance stocks); 0 if not allowed.
Short Selling_feasible	ssfeas	1 if short selling is allowed and feasible; 0 otherwise.
Short Selling_naked	ssnaked	1 if naked short selling is allwed for all stocks; 0.5 if partially banned(mostly for finance stocks); 0 if not allowed
Direct Market Access	dma	1 if direct market access is offered on the exchange; 0 otherwise.
Colocation	colocation	1 if colocation is offered on the exchange; 0 otherwise.

Derivative	deriv	1 if index or single stock future or option exists; 0 otherwise.
Market Dynamics Index	mdindex	Average of rules in Market Dynamics category
Market Stability		
Market Wide Circuit Breaker	mktcb	1 if market wide circuit breaker exists; 0 otherwise.
Brokerage Insurance Fund	insure	1 if brokerage insurance fund exists; 0 otherwise.
Independent Regulator	selfreg	1 if Independent regulator exists; 0 otherwise
Market Stability Index	msindex	Average of rules in Market Stability Index
Total index	**totalindex**	**Average of compindex, frindex, infoindex, mdindex and msindex.**

TABLE XXIV: DESCRIPTION OF RULES AND INDICES

Panel A: Assuming zero for missing values

	1980	1985	1990	1995	2000	2005	2010
compindex	0.2889	0.3500	0.3625	0.4410	0.5073	0.5571	0.5476
frindex	0.2253	0.2778	0.3750	0.4587	0.5745	0.6693	0.7235
infoindex	0.4815	0.4667	0.3750	0.3504	0.3577	0.3730	0.3730
mdindex	0.4444	0.4000	0.3594	0.3803	0.4553	0.4643	0.5734
msindex	0.1111	0.1167	0.1563	0.1709	0.2927	0.3492	0.3730
totalindex	0.3102	0.3222	0.3256	0.3603	0.4375	0.4826	0.5181
negcom	0.0556	0.2000	0.3438	0.3846	0.4146	0.4524	0.4524
stt	0.2778	0.2500	0.2500	0.3846	0.4878	0.5000	0.4762
mallow	0.3333	0.3500	0.3750	0.4359	0.5854	0.6667	0.6429
mmcompete	0.1667	0.2000	0.2500	0.2821	0.3902	0.4762	0.4762
decimal	0.6111	0.7500	0.5938	0.7179	0.6585	0.6905	0.6905
itext	0.2778	0.4000	0.6875	0.9744	1.0000	1.0000	1.0000
itenf	0.1667	0.2000	0.2813	0.5128	0.7317	0.8333	0.8810
lgdis	0.1667	0.2500	0.4688	0.5128	0.7073	0.9048	0.9762
lgamt	0.1111	0.2000	0.3125	0.4103	0.5610	0.7381	0.8333
lgtm	0.0556	0.1000	0.2500	0.3077	0.4634	0.6429	0.7857
comprpt	0.8889	0.9000	0.9063	0.8462	0.8780	0.8810	0.8810
comprpttm	0.1111	0.1500	0.0938	0.1795	0.1951	0.1905	0.2143
periodrpt	0.1944	0.2000	0.2188	0.2308	0.3659	0.4524	0.4881
periodrpttm	0.0556	0.1000	0.1563	0.1538	0.2683	0.3810	0.4524
preinfo_broker	0.6111	0.6000	0.5000	0.4615	0.4390	0.4524	0.4524

preinfo_investor	0.3333	0.3000	0.2500	0.2564	0.2927	0.3333	0.3333
afterhour	0.5000	0.5000	0.3750	0.3333	0.3415	0.3333	0.3333
sslegal	0.8333	0.7500	0.5938	0.6410	0.8049	0.8095	0.7976
ssfeas	0.8333	0.7500	0.5625	0.5128	0.5854	0.5952	0.6190
ssnaked	0.7778	0.7000	0.4688	0.4615	0.4634	0.4524	0.4048
dma	0.0000	0.0000	0.0000	0.0000	0.0976	0.1429	0.3095
colocation	0.0000	0.0000	0.0000	0.0000	0.0000	0.0238	0.5238
deriv	0.2222	0.2000	0.5313	0.6667	0.7805	0.7619	0.7857
mktcbd	0.0000	0.0000	0.0625	0.1538	0.1951	0.2381	0.2619
insure	0.1667	0.1500	0.2500	0.2308	0.5366	0.6905	0.7143
selfreg	0.1667	0.2000	0.1563	0.1282	0.1463	0.1190	0.1429

Panel B: Using only non-missing values

	1980	1985	1990	1995	2000	2005	2010
compindex	0.3143	0.4000	0.4526	0.5300	0.5810	0.6381	0.6476
frindex	0.6389	0.7407	0.7315	0.7361	0.7444	0.7854	0.8244
infoindex	0.6364	0.6111	0.6667	0.6667	0.6875	0.7292	0.7292
mdindex	0.5000	0.5000	0.4697	0.4861	0.5444	0.5778	0.7833
msindex	0.1111	0.1176	0.1733	0.1905	0.3563	0.4111	0.4333
totalindex	0.3844	0.5311	0.5711	0.5711	0.6378	0.6037	0.6444
negcom	0.0714	0.2667	0.5789	0.7500	0.8095	0.9048	0.9048
stt	0.2778	0.2500	0.2857	0.4688	0.5882	0.6000	0.5714

mallow	0.3333	0.3500	0.3871	0.4474	0.6000	0.6829	0.6585
mmcompete	0.1667	0.2000	0.2581	0.2895	0.4000	0.4878	0.4878
decimal	0.6111	0.7500	0.6786	0.8235	0.7714	0.8056	0.8056
itext	0.2778	0.4000	0.6875	0.9744	1.0000	1.0000	1.0000
itenf	0.1667	0.2000	0.2813	0.5128	0.7317	0.8333	0.8810
lgdis	0.1765	0.2632	0.4839	0.5405	0.7250	0.9268	1.0000
lgamt	0.6667	0.8000	0.6667	0.8000	0.7931	0.8158	0.8537
lgtm	0.3333	0.4000	0.5333	0.6000	0.6552	0.7105	0.8049
comprpt	0.8889	0.9000	0.9667	0.9429	1.0000	1.0000	1.0000
comprpttm	0.1250	0.1667	0.1034	0.2121	0.2222	0.2162	0.2432
periodrpt	0.2917	0.3077	0.3684	0.3913	0.6250	0.7600	0.8200
periodrpttm	0.2000	0.3333	0.5000	0.4615	0.5000	0.6667	0.7600
preinfo_broker	0.7857	0.8000	0.9412	0.9474	0.9474	1.0000	1.0000
preinfo_investor	0.4615	0.4000	0.4444	0.5000	0.6000	0.7000	0.7000
afterhour	0.5294	0.5263	0.4800	0.4483	0.4828	0.4828	0.4828
sslegal	0.8333	0.7500	0.5938	0.6410	0.8049	0.8095	0.7976
ssfeas	0.8333	0.7500	0.5625	0.5128	0.5854	0.5952	0.6190
ssnaked	0.7778	0.7000	0.4688	0.4615	0.4634	0.4524	0.4048
dma	0.0000	0.0000	0.0000	0.0000	0.2222	0.3333	0.7222
colocation	0.0000	0.0000	0.0000	0.0000	0.0000	0.0323	0.7097
deriv	0.6667	0.6667	0.8947	0.8667	0.8889	0.8889	0.9167
mktcbd	0.0000	0.0000	0.0667	0.1714	0.2162	0.2632	0.2895
insure	0.2000	0.1765	0.3200	0.3103	0.7333	0.9355	0.9677

selfreg	0.1667	0.2000	0.1563	0.1282	0.1463	0.1190	0.1429

Panel C: Correlation for Panel A

	compindex	frindex	infoindex	mdindex
compindex				
frindex	0.2758			
infoindex	0.2682	0.0736		
mdindex	0.4275	0.3098	0.5309	
msindex	0.2119	0.4956	0.1479	0.2556

Panel D: Correlation for Panel B

	compindex	frindex	infoindex	mdindex
compindex				
frindex	0.1747			
infoindex	-0.3498	-0.0216		
mdindex	0.5214	0.3694	0.0228	
msindex	0.0146	0.0943	0.3060	0.0470

TABLE XXV: SUMMARY STATISTICS OF RULES AND INDICES

	1980	1985	1990	1995	2000	2005	2010
Dependent varaible							
Stock Return	0.0429	0.0761	-0.0255	0.0096	0.0623	0.0832	0.0403
MV/GDP ratio	NA	NA	37.4019	54.2083	79.8702	81.5125	82.9502
Allocative efficiency elasticity	NA	NA	0.677809	0.67126	0.5112	0.52102	0.67445
Controls							
englishlaw	8	8	11	12	12	12	12
germanlaw	4	5	5	8	8	8	8
frenchlaw	4	4	12	15	17	18	18
Scandinavianlaw	2	3	4	4	4	4	4

TABLE XXVI

SUMMARY STATISTICS FOR DEPENDENT VARIABLES AND CONTROL VARIABLES

Panel A: Assume 0 for missing rule values

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	0.1074***	0.0528***	0.0602***	0.1874***	0.0900***	0.0582***	0.1916***
	(0.0188)	(0.0094)	(0.0103)	(0.0554)	(0.0151)	(0.0096)	(0.0513)
Total index	-0.1282***						
	(0.0309)						
comindex		-0.0530***					0.0087
		(0.0179)					(0.0187)
frindex			-0.0482***				-0.0041
			(0.0133)				(0.0165)
infoindex				-0.1507***			-0.1156**
				(0.0549)			(0.0511)
mdindex					-0.0753***		-0.0389*
					(0.0183)		(0.0221)
msindex						-0.0835***	-0.0483**
						(0.0222)	(0.0217)
Country fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.0449	0.0413	0.0420	0.0441	0.0427	0.0440	0.0464
Num. obs.	4479	4479	4479	4479	4479	4479	4479

Panel B: Use only non-missing rule values

	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.0447***	0.1136***	0.051**	0.0927***	0.0463***
	(0.0088)	(0.0407)	(0.0221)	(0.0218)	(0.0085)
compindex	-0.0262*				
	(0.0148)				
frindex		-0.0837**			
		(0.0421)			
infoindex			-0.0143		
			(0.0208)		
mdindex				-0.0792***	
				(0.0289)	
msindex					-0.0372**
					(0.0147)
Country fixed	Yes	Yes	Yes	Yes	Yes
Adj.R2	0.0016	0.0358	-0.0021	0.0610	0.0078
Num.obs.	2499	1649	1932	1492	3353

TABLE XXVII

COST OF EQUITY CAPITAL ON INDICES

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.1916***	0.1905***	0.1919***	0.0830***	0.1720***	0.2068***
	(0.0513)	(0.0516)	(0.0511)	(0.0145)	(0.0529)	(0.0543)
compindex	0.0087		0.0071	0.0003	0.0046	-0.0039
	(0.0187)		(0.0174)	(0.0196)	(0.0184)	(0.0182)
frindex	-0.0041	-0.0018		-0.0072	-0.0142	-0.0132
	(0.0164)	(0.0153)		(0.0164)	(0.0155)	(0.0160)
infoindex	-0.1156**	-0.1142**	-0.1159**		-0.1152**	-0.1269**
	(0.0511)	(0.0516)	(0.0509)		(0.0511)	(0.0533)
mdindex	-0.0389*	-0.0380*	-0.0406*	-0.0383*		-0.0503**
	(0.0221)	(0.0218)	(0.0208)	(0.0222)		(0.0219)
msindex	-0.0483*	-0.0461**	-0.0495**	-0.0612**	-0.0571***	
	(0.0217)	(0.0211)	(0.0211)	(0.0245)	(0.0216)	
Country fixed	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.0464	0.0465	0.0466	0.0442	0.0460	0.0457
Num.obs.	4479	4479	4479	4479	4479	4479

TABLE XXVIII

COST OF EQUITY CAPITAL: LEAVE-ONE-OUT REGRESSION

	Estimate	SE	t	P value
negcom	-0.0145	0.0070	-2.0816	0.0375
stt	0.0042	0.0069	0.6071	0.5438
mmallow	-0.0508	0.0149	-3.4211	0.0006
mmcompete	-0.0197	0.0076	-2.5993	0.0094
decimal	-0.0187	0.0135	-1.3860	0.1658
itext	-0.0197	0.0072	-2.7440	0.0061
itenf	-0.0182	0.0063	-2.8915	0.0039
lgdis	-0.0168	0.0062	-2.7124	0.0067
lgamt	-0.0147	0.0153	-0.9588	0.3377
lgtm	-0.0245	0.0108	-2.2670	0.0235
comprpt	-0.0175	0.0180	-0.9697	0.3322
comprpttm	-0.1366	0.0853	-1.6021	0.1092
periodrpt	-0.0594	0.0335	-1.7727	0.0764
periodrpttm	-0.0089	0.0101	-0.8844	0.3766
preinfo_broker	-0.0041	0.0105	-0.3957	0.6923
preinfo_investor	-0.0075	0.0112	-0.6676	0.5045
afterhour	-0.7792	0.2784	-2.7994	0.0051
sslegal	-0.0074	0.0100	-0.7387	0.4601
ssfeas	-0.0115	0.0120	-0.9626	0.3358
ssnaked	-0.0061	0.0118	-0.5203	0.6029
dma	-0.0442	0.0105	-4.1933	0.0000
colocation	-0.0341	0.0076	-4.4782	0.0000
deriv	-0.0223	0.0210	-1.0621	0.2883
mktcb	-0.0915	0.0339	-2.7011	0.0069
insure	-0.0185	0.0061	-3.0169	0.0026
selfreg	-0.0069	0.0146	-0.4730	0.6362

TABLE XXIX

UNIVARIATE REGRESSION OF COST OF EQUITY CAPITAL ON RULES

Panel A: Univariate regressions of cost of equity on indices

	totalindex	compindex	frindex	infoindex	mdindex	msindex
1991	-0.4429	-0.1618	0.1482	-0.2287*	-0.0808	-0.0469
1992	-0.9049	-0.5598	0.2138	-0.3716	-0.0764	-0.1179
1993	-0.3189	-0.1549	0.2693	-0.1498	-0.1785	-0.0887
1994	-0.5212	-0.3060	0.2352	-0.1774	-0.2767**	-0.1752
1995	0.0232	0.0231	-0.0487	0.0112	0.0202	-0.0049
1996	-0.0670	-0.0009	-0.1878**	0.0077	-0.0289	-0.0325
1997	-0.0014	0.0834	-0.1897**	-0.0004	0.1197	-0.0490
1998	0.0758	0.0189	0.0100	0.0904**	-0.0747	-0.0204
1999	-0.0754	-0.127**	0.1491	-0.0667**	-0.0782	0.1316
2000	-0.0004	0.0458	-0.1391**	0.0102	0.1024	-0.0817
2001	-0.0696*	-0.0634***	0.0187	-0.0272	-0.0695**	0.0056
2002	-0.0276	-0.0311	0.0504	-0.0301	-0.0389	0.0490
2003	-0.0270	0.0113	0.0177	-0.0329	-0.0182	0.0156
2004	-0.0579	-0.051*	0.0425	-0.0272*	-0.0489	0.0084
2005	-0.0029	-0.0204	0.0944	-0.0226	-0.0603	0.0741*
2006	-0.0607	-0.0474**	0.0296	-0.0328**	-0.0549*	0.0272
2007	-0.254*	-0.1893***	0.0535	-0.0987**	-0.1997*	0.0265
2008	-0.0230	0.0008	-0.0667	-0.0113	0.0184	-0.0244
2009	-0.1274**	-0.1062***	-0.0123	-0.0529**	-0.0843**	0.0156
2010	-0.0881**	-0.088***	-0.0325	-0.0396***	-0.0471	0.0326
2011	-0.049**	-0.0200	-0.0343	-0.0151	-0.0300	-0.0050

2012	-0.0334	0.0038	-0.0750	-0.0087	-0.0108	-0.0099

Panel B: Multivariate regression of cost of equity on indices

	compindex	frindex	infoindex	mdindex	msindex
1991	-0.114	0.218	-0.312	0.322	-0.096
1992	-0.627	0.497	-0.542	0.839	-0.215
1993	-0.111	0.307	-0.112	0.029	-0.155
1994	-0.229	0.271	-0.073	-0.110	-0.183
1995	0.019	-0.054	0.012	0.004	0.000
1996	-0.003	-0.1999**	0.045	-0.033	-0.004
1997	0.087	-0.2302**	-0.055	0.220	-0.016
1998	0.010	0.003	0.1642*	-0.230	-0.025
1999	-0.1284**	0.141	-0.092	0.021	0.1564*
2000	0.012	-0.1136*	-0.016	0.134	-0.064
2001	-0.0467*	0.023	-0.008	-0.042	0.015
2002	-0.007	0.043	-0.050	0.003	0.067
2003	0.046	0.052	-0.062	0.018	0.040
2004	-0.031	0.026	-0.023	-0.009	0.024
2005	0.021	0.072	-0.044	-0.024	0.083
2006	-0.024	0.006	-0.032	-0.003	0.0433*
2007	-0.1101***	-0.005	-0.030	-0.104	0.039
2008	-0.002	-0.044	-0.018	0.033	-0.012
2009	-0.0777**	-0.029	-0.018	-0.033	0.030
2010	-0.0846**	-0.059	-0.018	0.007	0.0563*

2011	-0.010	-0.049	0.002	-0.035	-0.002
2012	0.005	-0.085	0.003	-0.028	-0.001

TABLE XXX: ANNUAL REGRESSION OF COST OF EQUITY ON INDICES,CONTROLLING FOR LOG-MARKET CAP AND LAW ORIGIN

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	2.4578***	3.9279***	3.4666***	3.274***	3.2979***	3.817***	2.7533***
	(0.1227)	(0.0880)	(0.0854)	(0.2184)	(0.1355)	(0.0931)	(0.1935)
totalindex	3.2548***						
	(0.1860)						
compindex		1.4059***					0.2443*
		(0.1188)					(0.1394)
frindex			1.5603***				0.9405***
			(0.1014)				(0.1120)
infoindex				1.1375***			0.4175**
				(0.2022)			(0.1819)
mdindex					1.5503***		0.4029**
					(0.1497)		(0.1567)
msindex						1.7837***	0.8929***
						(0.1303)	(0.1388)
country fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R2	0.7359	0.6649	0.714	0.6341	0.6783	0.7027	0.74
Num.Obs	967	967	967	967	967	967	967

TABLE XXXI

REGRESSION OF LOG(MV/GDP) ON RULE INDICES,ASSUMING 0 FOR MISSING VALUES

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	2.7533***	2.7316***	2.8212***	3.1423***	2.9039***	2.656***
	(0.1935)	(0.1944)	(0.2117)	(0.1095)	(0.1869)	(0.2003)
compindex	0.2443*		0.5346***	0.2762**	0.284**	0.4314***
	(0.1394)		(0.1405)	(0.1394)	(0.1374)	(0.1333)
frindex	0.9405***	0.9882***		0.9507***	1.0202***	1.1445***
	(0.1120)	(0.1078)		(0.1112)	(0.1115)	(0.1157)
infoindex	0.4175**	0.4609**	0.5021***		0.4529***	0.4214**
	(0.1819)	(0.1836)	(0.1888)		(0.1752)	(0.1918)
mdindex	0.4029**	0.4266***	0.6927***	0.4184***		0.6858***
	(0.1567)	(0.1536)	(0.1647)	(0.1560)		(0.1546)
msindex	0.8929***	0.9422***	1.2201***	0.8937***	1.0177***	
	(0.1388)	(0.1310)	(0.1484)	(0.1386)	(0.1367)	
country fixed	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R2	0.74	0.7394	0.7197	0.7392	0.7379	0.7281
Num.Obs	967	967	967	967	967	967

TABLE XXXII

REGRESSION OF LOG(MV/GDP) ON RULE INDICES, LEAVING OUT ONE

Panel A :With no period fixed effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	0.362***	0.4554***	0.5317***	0.4973***	0.4126***	0.5966***	0.3832***
	(0.0885)	(0.0767)	(0.0940)	(0.0553)	(0.0734)	(0.0522)	(0.1060)
totalindex	0.5583***						
	(0.1684)						
compindex		0.3072**					0.1741
		(0.1239)					(0.1458)
frindex			0.1373				-0.0584
			(0.1535)				(0.2002)
infoindex				0.2681***			0.1337
				(0.0868)			(0.1137)
mdindex					0.4253***		0.308
					(0.1365)		(0.2098)
msindex						0.0415	-0.0937
						(0.1383)	(0.1737)
period fixed	No	No	No	No	No	No	No
Adj.R2	0.0554	0.0343	-0.0011	0.0474	0.0615	-0.0069	0.0615
Num.Obs	136	136	136	136	136	136	136

Panel B: With period fixed effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Intercept)	0.4162***	0.5459***	0.5684***	0.5684***	0.4855***	0.6601***	0.3869***
	(0.1047)	(0.0916)	(0.1091)	(0.0864)	(0.0952)	(0.0795)	(0.1203)
totalindex	0.8279***						
	(0.2018)						
compindex		0.3689***					0.2252
		(0.1358)					(0.1521)
frindex			0.3481*				0.1755
			(0.1969)				(0.2197)
infoindex				0.2681***			0.0884
				(0.0941)			(0.1129)
mdindex					0.5599***		0.3727*
					(0.1435)		(0.1930)
msindex						0.1134	-0.0562
						(0.1558)	(0.1714)
Period fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R2	0.1039	0.0529	0.0231	0.053	0.0965	0.0013	0.0989
Num.Obs	136	136	136	136	136	136	136

TABLE XXXIII

REGRESSION OF ALLOCATIVE EFFICIENCY ELASTICITY ON RULE INDICES

Panel A: With no period fixed effect

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.3832***	0.4258***	0.3669***	0.3967***	0.3972***	0.3865***
	(0.1060)	(0.0955)	(0.0852)	(0.1043)	(0.1087)	(0.1044)
compindex	0.1741		0.1701	0.1922	0.2266	0.1717
	(0.1458)		(0.1453)	(0.1376)	(0.1460)	(0.1434)
frindex	-0.0584	-0.0372		-0.0813	0.0499	-0.103
	(0.2002)	(0.1987)		(0.1971)	(0.1842)	(0.1840)
infoindex	0.1337	0.1492	0.1375		0.2205**	0.1338
	(0.1137)	(0.1136)	(0.1108)		(0.0923)	(0.1122)
mdindex	0.308	0.3598*	0.2877	0.4075**		0.3009
	(0.2098)	(0.2062)	(0.1900)	(0.1750)		(0.2071)
msindex	-0.0937	-0.0869	-0.1168	-0.0941	-0.0743	
	(0.1737)	(0.1710)	(0.1604)	(0.1758)	(0.1687)	
period fixed	No	No	No	No	No	No
Adj.R2	0.0615	0.0574	0.068	0.0586	0.0485	0.0665
Num.Obs	136	136	136	136	136	136

Panel B: With period fixed effect

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.3869***	0.4366***	0.4221***	0.3953***	0.4189***	0.3878***
	(0.1203)	(0.1158)	(0.1007)	(0.1182)	(0.1219)	(0.1187)
compindex	0.2252		0.2251	0.2389	0.28*	0.2241
	(0.1521)		(0.1511)	(0.1447)	(0.1510)	(0.1504)
frindex	0.1755	0.1751		0.1724	0.2697	0.1501
	(0.2197)	(0.2163)		(0.2196)	(0.2124)	(0.2080)
infoindex	0.0884	0.1114	0.0866		0.1952**	0.0884
	(0.1129)	(0.1124)	(0.1121)		(0.0949)	(0.1117)
mdindex	0.3727*	0.4323**	0.4093**	0.4418***		0.3688*
	(0.1930)	(0.1885)	(0.1877)	(0.1618)		(0.1900)
msindex	-0.0562	-0.0494	-0.0041	-0.0562	-0.036	
	(0.1714)	(0.1679)	(0.1673)	(0.1721)	(0.1660)	
period fixed	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R2	0.0989	0.0872	0.1007	0.1016	0.0774	0.1051
Num.Obs	136	136	136	136	136	136

TABLE XXXIV

REGRESSION OF ALLOCATIVE EFFICIENCY ELASTICITY ON RULE INDICES, LEAVING OUT ONE AT A TIME

CITED LITERATURE

Anand, A., Tanggaard, C., and Weaver, D. G.: Paying for market quality. Journal of Financial and Quantitative Analysis, 44(6):1427–1457, December 2009.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C.: Real-time price discovery in global stock, bond and foreign exchange markets. Journal of International Economics, 73:251–277, 2007.

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H.: Value and Momentum Everywhere. Journal of Finance, 68(3):929–985, 2013.

At-Sahalia, Y. and Saglam, M.: High frequency traders: Taking advantage of speed. Working paper, 2014.

Baker, M. and Wurgler, J.: Investor sentiment in the stock market. The Journal of Economic Perspectives, 21(2):129–151, 2007.

Ball, R. and Brown, P.: An empirical evaluation of accounting income numbers. Journal of Accounting Research, 6(2):159–178, 1968.

Ball, R. J. and Brown, P.: An empirical evaluation of accounting income numbers. Journal of Accounting Research, pages 159–178, 1968.

Barclay, M. J. and Hendershott, T.: Price Discovery and Trading After Hours. Review of Financial Studies, 16(4):1041–1073, 2003.

Beber, A. and Pagano, M.: Short-selling bans around the world: Evidence from the 200709 crisis. Journal of Finance, 68(1):343381, 2013.

Beny, L. N.: Do Insider Trading Laws Matter? Some Preliminary Comparative Evidence. William Davidson Institute Working Papers Series wp741, William Davidson Institute at the University of Michigan, January 2005.

Bernanke, B. S. and Kuttner, K. N.: What explains the stock marketś reaction to federal reserve policy? Journal of Finance, 60(3):1221 –1257, 2005.

Bernard, V. L. and Thomas, J. K.: Post-earnings-announcement drift: Delayed price response or risk premium? Journal of Accounting Research, 27(1):1–36, 1989.

Bernard, V. L. and Thomas, J. K.: Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. Journal of Accounting Economics, 13(1):305–340, 1990.

Bhattacharya, U. and Daouk, H.: The world price of insider trading. Journal of Finance, 57(1):75–108, 2002.

Boehmer, E., Fong, K., and Wu, J.: INTERNATIONAL EVIDENCE ON ALGORITHMIC TRADING. Working papers, 2015.

Boehmer, E., Saar, G., and Yu, L.: Lifting the Veil: An Analysis of Pre-trade Transparency at the NYSE. Journal of Finance, 60(2):783–815, 04 2005.

Boyd, J. H., Hu, J., and Jagannathan, R.: The stock market's reaction to unemployment news: Why bad news is usually good for stocks. Journal of Finance, 60(2):649–672, 2005.

Bris, A., Goetzmann, W. N., and Zhu, N.: Efficiency and the Bear: Short Sales and Markets Around the World. Journal of Finance, 62(3):10291079, 2007.

Brogaard, J., Hagstrmer, B., Nordn, L., and Riordan, R.: Trading fast and slow: Colocation and liquidity. Review of Financial Studies, 2015.

Chakravarty, S., Gulen, H., and Mayhew, S.: Informed trading in stock and option markets. Journal of Finance, 59(3):12351257, 2004.

Charoenrook, A. and Daouk, H.: A Study of Market-Wide Short-Selling Restrictions. Working Papers 51180, Cornell University, Department of Applied Economics and Management, June 2009.

Chordia, T., Goyal, A., Sadka, G., Sadka, R., and Shivakumar, L.: Liquidity and the post-earnings-announcement drift. Financial Analyst's Journal, 65(4):18–32, 2009.

Chordia, T., Roll, R., and Subrahmanyam, A.: Liquidity and market efficiency. Journal of Financial Economics, 87(2):249–268, 2008.

Chordia, T. and Shivakumar, L.: Earnings and price momentum. Journal of Financial Economics, 80(3):627–656, 2006.

Conrad, J., Cornell, B., and Landsman, W. R.: When is bad news really bad news? Journal of Finance, 57(6):25072532, 2002.

DELLAVIGNA, S. and POLLET, J. M.: Investor inattention and friday earnings announcements. Journal of Finance, 64:709–749, 2009.

Flannery, M. J. and Protopapadakis, A. A.: Macroeconomic factors do influence aggregate stock returns. Review of Financial Studies, 15(3):751 –782, 2002.

Gilbert, T., Scotti, C., Strasser, G. H., and Vega, C.: Is the Intrinsic Value of Macroeconomic News Announcements Related to Their Asset Price Impact? Boston College Working Papers in Economics 874, 2015.

Green, T.: Economic news and the impact of trading on bond prices. Journal of Finance, 59(3):12011234, 2004.

Grkaynak, R. S., Sack, B., and Swanson, E.: Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. International Journal of Central Banking, 1(1), 2005.

Hayo, B., Kutan, A. M., and Neuenkirch, M.: The impact of u.s. central bank communication on european and pacific equity markets. Economics Letters, 108(2):172–174, 2010.

Hong, H., Lim, T., and Stein, J. C.: Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. Journal of Finance, 55(1):265–295, 2000.

Hong, H. and Stein, J. C.: A unified theory of underreaction, momentum trading, and overreaction in asset markets. Journal of International Economics, 54:2143–2184, 1999.

Ikenberry, D. L., Rankine, G., and Stice, E. K.: What do stock splits really signal? Journal of Financial and Quantitative Analysis, 31(3):357–375, 1996.

Jan Hanousek and Evzen Kocenda: Foreign News and Spillovers in Emerging European Stock Markets. Review of International Economics, 19(1):170–188, 2011.

Jegadeesh, N. and Titman, S.: Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. Journal of Finance, 48(1):65–91, 1993.

Jere R. Francis, I. K. K. and Pereira, R.: Disclosure incentives and effects on cost of capital around the world. The Accounting Review, 80(4):1125–1162, 2005.

Kim, K. A. and Rhee, S. G.: Price limit performance: Evidence from the tokyo stock exchange. Journal of Finance, 52(2):885–901, 1997.

Kumar, R., Sarin, A., and Shastri, K.: The impact of options trading on the market quality of the underlying security: An empirical analysis. Journal of Finance, 53(2):717732, 1998.

Lander, J., Orphanides, A., and Douvogiannis, M.: Earnings Forecasts and the Predictability of Stock Returns: Evidence from Trading the S&P. Technical Report 1997-6, Board of Governors of the Federal Reserve System (U.S.), 1997.

Lauterbach, B. and Ben-Zion, U.: Stock market crashes and the performance of circuit breakers: Empirical evidence. Journal of Finance, 48(5):19091925, 1993.

Lin, P. and Xiong, W.: Investor attention, overconfidence and category learning. Journal of Financial Economics, 80:563–602, 2006.

Liu, S.: Securities Transaction Tax and Market Efficiency: Evidence from the Japanese Experience. Journal of Financial Services Research, 32(3):161–176, December 2007.

Liu, Y., Szewczyk, S. H., and Zantout, Z.: Underreaction to Dividend Reductions and Omissions? Journal of Finance, 63(2):987–1020, 2008.

Livnat, J. and Mendenhall, R. R.: Comparing the postearnings announcement drift for surprises calculated from analyst and time series forecasts. Journal of Accounting Research, 44(1):177–205, 2006.

Livnat, J. and Petrovits, C.: Investor sentiment, post-earnings announcement drift, and accruals. Working paper, 2009.

Loh, R. K.: Investor inattention and the underreaction to stock recommendations. Financial Management, 39(3):1223–1252, 2010.

Madhavan, A.: Security Prices and Market Transparency. Journal of Financial Intermediation, 5(3):255 – 283, 1996.

Mian, G. M. and Sankaraguruswamy, S.: Investor sentiment and stock market response to earnings news. The Accounting Review, 87, 2012.

Mian, M. and Sankaraguruswamy, S.: Investor sentiment and stock market response to earnings news. The Accounting Review, 87(4):1357–1384, 2012.

Michaely, R., H.Thaler, R., and L.Womack, K.: Price reactions to dividend initiations and omissions: Overreaction or drift? Journal of Finance, 50(2):573–608, 1995.

Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H.: Time series momentum. Journal of Financial Economics, 104(2):228–250, 2012.

Nikkinen, J., Omran, M., Sahlstrom, P., and Aijo, J.: Global Stock Market Reactions to Scheduled U.S. Macroeconomic News Announcements. Global Finance Journal, 17(1):92–104, 2006.

Pastor, L. and Stambaugh, R. F.: Liquidity Risk and Expected Stock Returns. Journal of Political Economy, 111(3):642–685, 2003.

Pomeranets, A. and Weaver, D. G.: Securities transaction taxes and market quality. Bank of canada working paper, 2011.

Porta, R. L., LOPEZ-DE-SILANES, F., and SHLEIFER, A.: What works in securities laws? Journal of Finance, 61(1):132, 2006.

Rapach, D. E., Strauss, J. K., and Zhou, G.: International stock return predictability: What is the role of the united states? Journal of Finance, 68(4):1633 – 1662, 2013.

Rui Albuquerque and Clara Vega: Economic news and international stock market co-movement. Review of Finance, 13(1):401–465, 2009.

Savor, P. and Wilson, M.: How much do investors care about macroeconomic risk? evidence from scheduled economic announcements. Journal of Financial and Quantitative Analysis, 48(2):343 – 375, 2013.

Shen, P.: Market timing strategies that worked. Research Working Paper RWP 02-01, Federal Reserve Bank of Kansas City, 2002.

Umlauf, S. R.: Transaction taxes and the behavior of the swedish stock market. Journal of Finance, 33(2):227–240, 1993.

Venkataramana, K. and Waisburda, A. C.: The Value of the Designated Market Maker. Journal of Financial and Quantitative Analysis, 42(3):735–758, September 2007.

Veronesi, P.: Stock market overreaction to bad news in good times: A rational expectations equilibrium model. Review of Financial Studies, 12(5):975 – 1007, 1999.

Williams, C. D.: Asymmetric responses to earnings news: A case for ambiguity. The Accounting Review, 90(2):785–817, 2015.

Womack, K. L.: Do brokerage analysts' recommendations have investment value? Journal of Finance, 51(1):137–167, 1996.

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