The Impact of Market News on the Dispersion of Market Risks

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Abstract

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Keywords: News, Public Information, CAPM Beta, High Frequency
JEL Codes: G12, G14, G41

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1 Introduction

News can have significant impact on stock price, volume and volatility. In this project, I assess the effect that the public information release has on the stock risk over the market hours. As pointed out by Andersen, Thyrsgaard, and Todorov (2021), the distribution of the stock's risk (captured by the CAPM β) is more dispersed in the beginning of the trading day and tend to be more concentrated in the late hours. They argue that this higher risk dispersion in the early hours of the day is explained by the bigger effect that stock-specific shocks have overnight and in the first hours of the trading day, as company news usually tend to be published early. As the market reaches its closing hours, news topics tend to be concentrated around macroeconomic subjects (such as inflation, GDP, interest rates, etc.) which affect the stock market more uniformly and reduce the dispersion of the β.

This work will study this stylized fact by matching stock market data with real-time news data to study how do shocks caused by news release affect the cross-section of betas.

2 Objectives

This work intends to analyze how do news release affect the cross-section of betas over the trading day. As argued by Andersen et al. (2021), the initial dispersion of the stock's risk is due to the fact that the market is mostly affected by stock-specific shocks in the beginning of the trading day. By the end of the trading day, shocks related to general macroeconomic variables become more important and the cross-section of CAPM β converges towards 1. The main objective of this work is to understand how much of this trend in the dispersion of betas can be explained by shocks caused by news releases. This would be done by matching stock market returns with a comprehensive sample of news articles released in top business newsletters.

3 Literature Review

Despite the large literature studying the effect of public information release in the stock market, mosts of the results focus on the effect it has on volatility and volume. French and Roll (1986) show that the volatility in the market hours is significantly bigger than in the overnight period. They argue that this is due to the fact that news shocks arrive mostly during business hours. Likely, Mitchell and Mulherin (1994) use the number of announcements made by Dow Jones & Co. to market activity and show that a higher degree of information release leads to higher absolute market returns, while trading volume does not significantly differ in these events. More recently, Engle, Hansen, Karagozoglu, and Lunde (2021) use a large unstructured news database from Dow Jones to identify for company-specific news and conclude that they strongly correlate with increases in stock volatility.

This feature has also had a large attention in the literature of Behavioral Finance. For example, Barber and Odean (2008) show that ompanies that show up in the media tend to gather the attention of the investor. Andersen et al. (2021) show that the dispersion of the CAPM β is also bigger in the beginning of the trading day and converges towards 1 by the end of the day. They argue that this is due to the fact that the market is more affected by stock-specific shocks in the beginning of the trading day and by macroeconomic shocks by the end of the day.

4 Model

Consider an economy with infinitely many asset $i \in [0,1]$ with returns R^i. The market is efficient in the sense that returns are only generated by shocks to the companies or the macroeconomy. Each security i then is defined as a combination of these two shocks

$$R_i = \varepsilon_i + \beta_i \eta$$

Where ε_i is a mean zero shock related to company-specific innovations and η is a macro shock that affects all companies in the economy. β_i represents the sensitivity of the asset i to the market asset η and $\sum_i \beta_i = 1$. The market portfolio takes the average across the whole set of returns, therefore its return R^M can be described by

$$R^M = \eta$$

and is not affected by any ε_i.

The estimated CAPM β in this model then contains noise from the company-specific innovations:

$$\beta_i^{CAPM} := \frac{\mathbb{C}\left(R^i, R^M\right)}{\mathbb{V}\left(R^M\right)} = \beta_i + \frac{\mathbb{C}\left(\varepsilon_i, \eta\right)}{\mathbb{V}\left(\eta\right)}$$

Therefore, the stylized facts presented in FIGURE can be explained by the fact that the covariance between the company-specific innovations and the market returns shrink towards zero over the trading day. That can happen either because the frequency in which ε_i appears converges towards zero or because the correlation between ε_i and η disappears:

$$\mathbb{C}\left(\varepsilon_i, \eta\right) = \operatorname{corr}\left(\varepsilon_i, \eta\right) \sqrt{\frac{\mathbb{V}\left(\varepsilon_i\right)}{\mathbb{V}\left(\eta\right)}}$$

$$\mathbb{C}\left(\varepsilon_i, \eta\right) \to 0 \iff \operatorname{corr}\left(\varepsilon_i, \eta\right) \to 0 \text{ or } \mathbb{V}\left(\varepsilon_i\right) \to 0$$

5 Data

I will proxy the innovations ε_i using data on public news releases from RavenPack Analytics (RPA). RavenPack collects unstructured data from news sources and social media and translate into an informative database using text analysis techniques. Their sources include Alliance News, Benzinga Pro, Dow Jones Newswires, The Fly and others. All news items are classified and quantified according to their sentiment, relevance, topic, novelty, and market impact. I exploit two different datasets: RPA Equities which gathers information about firm-specific news and RPA Global Macro which contains information about macroeconomic news.

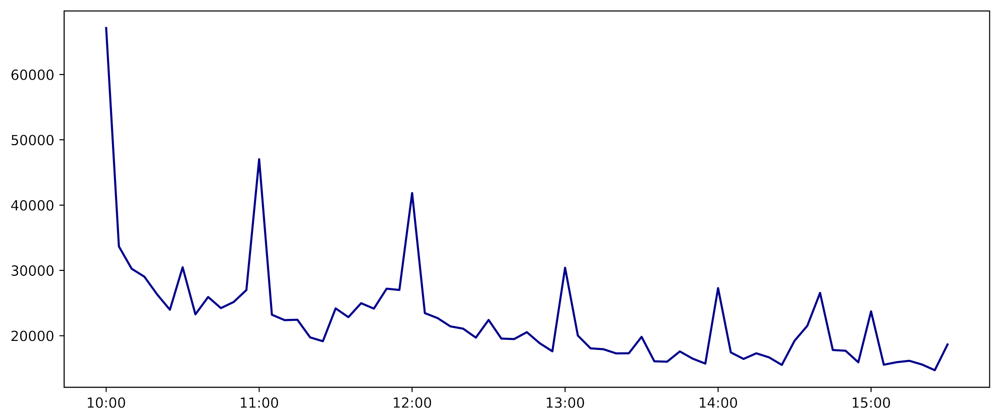
The most important variable in the RPA database is *Relevance*. This corresponds to a score of 0 to 100 which translate how strongly related the mention of an entity (e.g. companies, countries, organizations, etc.) is to the underlying news story. The score is based on the paragraph in which the entity was refered to, the number of times it was mentioned in the text and the overall number of entities mentioned in the text. Scores above 90 mean that the entity was mentioned in the headline of the news and scores from 0 to 89 mean they were only mentioned in the body of the text. According to RPA, a score higher than 75 means that an entity is *significantly relevant* to the topic. For this reason, I will only use news with a relevance score higher than 75 in my analysis. That leaves me with 11.088.195 observations in the RPA Equities dataset and 4.413.420 observations in the RPA Global Macro dataset.

The universe of stocks will initially be the constituents of the S&P 500 index, for which trading and news data are available and trading volume is sufficiently high.

6 News Releases over the Trading Day

I start by investigating the pattern of news releases over the trading day. I calculate the amount of news that appear in every portion of the trading day. I use the frequency of 1 second to aggregate the releases. The results are presented in Figure 1 on a 5 minute moving average. We can see that the amount of news released is not constant over the trading day. There is a spike in the amount of news released in the first 30 minutes of the trading day. Moreover, the proportion of releases varies significantly from the beginning to the end of the trading day. As we can see in Figure 1, in the beginning of the trading day, company-specific news tend to be more predominant. As the trading day closes to an end, we see more global macro articles being published. This is consistent with the findings of Andersen et al. (2021) and suggest that the initial dispersion of betas is indeed explained by the timing of the news release.

Figure 1: Frequency of news

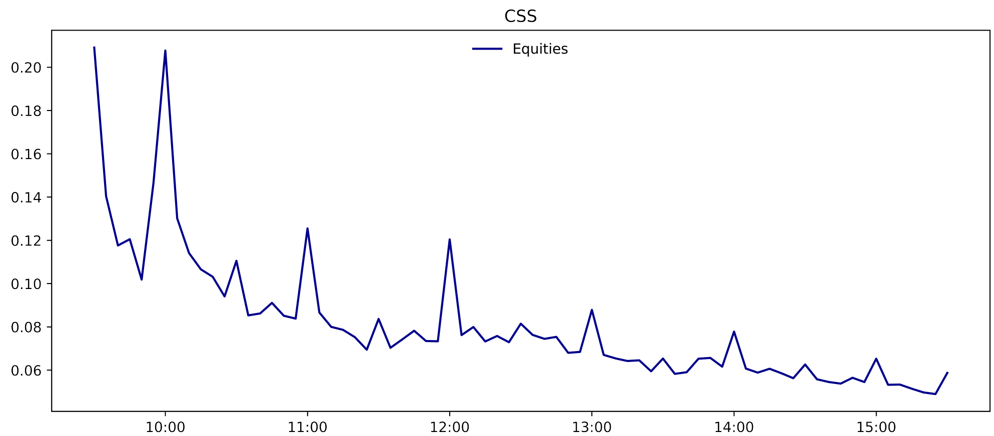


Some of these news, however, can be weakly related to the stock market or have insignificant impact on the stock price. I then use the *Event Sentiment Score* (ESS) to control for that. This variable is present in the RavenPack dataset and uses text analysis techniques to capture the overall sentiment caused by the news articles. This variable ranges from -1 to 1. A score of -1 means that the news has a very negative tone and a score of 1 means that the news has a very positive one. To measure the total impact of the news on the stock market, I calculate the total absolute sentiment that news stories have over the trading day. I do this by summing the absolute ESS for every news article and aggregate at every second of the trading day. The results are shown in Figure 2.

7 Methodology

By using high-frequency data on the stock market, I can estimate the β of each stock for arbitrarily small windows along the trading day. I will then use the news data to identify the type of news that were released during each window and assess its effect on the distribution of the stock's

Figure 2: Total News Sentiment over the Trading Day



β. An initial regression could be

$$R_{i,\Delta} = \alpha_i + \beta_i R^M_\Delta + \beta^N_i \left(N_{i,\Delta} \times R^M_\Delta\right) + \beta^M_i \left(N^M_\Delta \times R^M_\Delta\right) + \epsilon \tag{1}$$

where R_i is the return of the asset; Δ is the time interval of the trading hours I am analyzing (e.g. 10:00-10:05); R^M is the market return; N_i is news variable that can indicate either the amount of news released over Δ related to the stock i or the average sentiment of the articles over that period; and N^M is the news variable for the market.

By then comparing the evolution of β and β^N along the day we can infer if the stylized facts observed by Andersen et al. (2021) are due to the effect of news release. More explicitly we can infer if the initial dispersion of the cross-section of β is explained by the information released in the beginning of the trading day. If that is indeed the case, then after controlling for our news variable (N), the dispersion of the new β should be constant along the trading day.

Equation 1 can be extended to include other regressors as in **?**, which add the usual financial factors such as size, book-to-market, momentum, and others to the analysis. Their findings suggest that the inclusion of these factors can reduce the dispersion of betas, but it doesn't eliminate the time trend observed initially.

I consider every news released in traditional news sources (*provider_id* $\neq$ MRVR) published from 2000 to 2023. I only consider articles that are labeled as being facts (*fact_level* = fact). Finally, I filter for articles that are related to the constituents of the S&P500 on May 5$^{\text{th}}$, 2023. For the Global Macro database, I only use news about the 10 biggest economies in the world (by GDP).[1]

8 Expected Results

The main result of this work would be to show that the initial dispersion of betas goes away as we control for the information shocks. This would imply that the timing of the news release is indeed the main factor that explains the different betas on the market. If that happens not to be the case, then we can conclude that there are other factors that are also relevant in explaining the initial dispersion of the cross-section of betas.

[1] *country_code* $\in$ (US, CN, JP, DE, GB, IN, FR, BR, IT, CA)

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