出國報告（出國類別：國際會議）

參加「西方經濟協會」國際研討會

服務機關：國立臺北大學企業管理學系
姓名職稱：林美珍教授
派赴國家：美國
出國期間：102 年 6 月 28 日至 7 月 7 日
報告日期：102 年 8 月 31 日

摘要

本次「西方經濟協會」舉辦的第88次年會暨國際研討會在美國西雅圖海悅大飯店舉行，會期自2013 年6 月28 至7 月2 日，為期5天。本次會議的二場主題演講分別為波士頓大學財務教授Edward J. Kanez發表之「美國的金融安全網的全球化」，和哈佛法學院法律、經濟與財務教授Lucian A. Bebchuk發表之「公司治理」。研討會分為300個場次，本人所發表的場次為第53場次，論文題目是「分析師推薦與股價反應之資訊性質」，該場次有3篇論文被宣讀，同一場次的其他議題包含中原大學胡為善教授所發表之「能源價格對歐元現貨價格之影響」和加州州立大學Pomona校區LiBo Sun教授所發表之「不動產投資信託基金投資組合多角化效率性」之實證研究。除了進行論文發表，本人同時擔任論文評論人，評論的文章為「機構投資人於監督公司多角化投資時所扮演的角色」。

目次

壹、 目的

每年夏天「西北經濟協會(Western Economic Association International)」舉辦的年會暨國際研討會都會吸引超過 1000 位來自世界各地的學者參與，此研討會討論之議題涵蓋經濟、財務、數量方法、銀行與金融市場等議題。鑑於許多參與此國際研討會之人員乃相關領域之佼佼者，其發表之文章具有啟發思考後續相關研究議題之潛力，故本人於 2012 年年底投稿該研討會，投稿之論文題目為「分析師推薦與股價反應之資訊性質」，希望可以透過出席研討會，聆聽傑出學者之演講，提升研究能量。本人於收到接受函後，即著手準備發表論文之工作，此時，除了期望藉由口頭報告的論文發表，訓練獨立與國外研究人員互動之能力，並獲得參與學者提供之寶貴修改意見之外，亦希望透過與參與人員之交流，尋求未來合作之可能。

貳、 過程

6 月28 日

搭乘長榮 BR26班機於晚上11點由台北直飛西雅圖，於當地時間6月28日晚上6點50分抵達，接著搭乘巴士前往研討會所在地之飯店「海悅(Grand Hyatt)」大飯店進住。

6 月29 日:

先完成註冊報到手續後，撥空再次複習即將報告之論文。本人所發表的論文時間為6 月29 日上午10:15至12:00之第53場次，場次名稱為「財務經濟I (Financial Economics I)」，我參加之場次有3篇論文被宣讀，每篇論文由作者於30分鐘內宣讀並與聽眾討論完畢。同一場次的其他議題包含中原大學胡為善教授發表之「能源價格對歐元現貨價格之影響」和加州州立大學Pomona校區LiBo Sun教授所發表之「不動產投資信託基金投資組合多角化效率性」之實證研究。本人報告之論文主旨在於因為人的注意力是有限的，故分析師推薦對於股價之影響效果會受到投資人關注程度所影響。分析師關注度越低的公司越依賴投資人之注意以傳遞價格資訊，而且高度分析師關注度公司與低度分析師關注度公司股價之間的領先落後關係亦主要起因於投資人對高度分析師關注度公司有較高的注意力。評論人認為本文十分有趣，研究方法嚴謹，研究結論亦具實務參考價值，但提醒我宜加入分析摘要統計量，文字敘述部分則建議宜與過去相關文獻進行比較，才能更突顯本論文之潛在貢獻。對於評輪人提醒之寫作技巧與建議，本人受益良多。

除了進行論文發表，本人同時擔任論文評論人，評論的文章為「機構投資人於監督公司多角化投資時所扮演的角色」。該文發現多角化投資會降低不動產投資信託基金之價值，而降低幅度受到管理品質與管理者忽視程度高低之影響。本人提供作者幾點意見以供參考，包含:為何地理多角化程度較高之不動產投資信託基金而非財產多角化之不動產投資信託基金其價值折現幅度較低，此現象似乎缺乏合理之解釋；機構投資人之持股規模與持股穩定度是否影響折現幅度?以及建議作者應納入更廣泛之代理問題替代指標等。LiBo Sun 對本人之建議皆相當認同，亦表示會將之納入後續修正之範圍。

6 月30 日:

參加10:15至12:00之第139場次，該場為波士頓大學財務教授Edward J. Kanez發表之「美國的金融安全網的全球化」專題演講。1997年的亞洲金融危機，2007年的美國次貸危機以及2008年底席捲華爾街與美國银行體系的金融風暴，都突顯

了金融風險管理的重要性。他認為將政府貸款或保險視為安全網是錯誤的，安全網必須要能在私人公司不願提供資金給虧損公司時，提供吸收虧損的權益資金。吸收損失能力來自於政府財政部門或中央銀行通過納稅人的"支持"提供之顯性和隱性的短期股權"資金"給陷入困境之企業。例如立法保護破產企業的交易對手及透過存款保險、貼現窗口貸款、會計救濟（即資本寬容）協助該企業應付竄起之緊急資金需求。救援方案雖可以幫助收入較高的金融部門債權人和利益相關者，但卻會造成一般百姓未來租稅負擔加重，但不紓困又會造成危機加劇，全民皆受影響。故Edward J. Kanez認為監管過程必須重新設計，以重新平衡政府和產業的激勵機制，立法機關可以重新檢視故意剝削安全網不是不可避免的"道德風險"，而是盜竊檢控的形式，使納稅人在預期的危機管理政策下成為少數股權投資者。而此立法會導致金融機構反彈，為舒緩可能的反彈，金融法規應透過談判協商而來，而不是強加的。然而Edward J. Kanez認為可惜的是目前美國和G-20國家卻是朝向錯誤的方向改革金融安全網。，在此全球化加速發展的今天，金融安全日益重要，Edward J. Kanez的演講內容精闢，對於如何發展一個納稅人與金融機構皆蒙其利之金融安全網的設計，相當具有參考價值。

7 月 1 日:

參加14:30至16:15之第158場次，場次名稱為「金融危機 (Financial Crisis)」，該場次包含由布朗大學Ross Levine教授發表之「危機後的全球新監管環境，促進或阻礙資本市場」、德雷克塞爾大學Ramys Ghosh教授發表之「後危機時代的挑戰、金融聯繫和亞洲新興經濟體的宏觀經濟政策管理」以及克萊蒙特研究大學Puspa Amri發表之「資本激增和信用貸款繁榮」等論文。Ross Levine認為危機後的全球新監管環境過於嚴苛，會阻礙公司籌募資金。Ramys Ghosh認為金融自由化和全球金融整合，特別是金融動盪的蔓延，使得管理總體經濟政策更具挑戰性。在不斷變化的金融環境當中，貨幣政策和總體經濟政策的成功與否取決於決策者設計政策的能力，即決策者是否能明確的考慮總體金融通路，並更謹慎地分析金融體系中斷運作可能迅速破壞總體經濟的穩定所產生的潛在風險。Puspa Amri發現金融危機發生之前往往信用貸款十分繁榮，伴隨著大規模的資本淨流入到新興市場經濟體，廉價外國資本的大量湧入造成匯率升值、資產價格增值、物價上漲，最後造成國內銀行信用擴張與金融危機。Puspa Amri雖然說明金融危機、資本流入與信用貸款的關係，卻未分析什麼因素會使資本流入激增會轉移到促進信用貸款的繁榮，也許這是我後續可以思考的方向。

7 月 2 日

參加 10:15 至 12:00 之第 294 場次，場次名稱為「金融危機的影響和蔓延(Financial Crisis and Contagions)」，該場次有 3 篇論文被宣讀，每篇論文由作者於 30 分鐘內宣讀並與聽眾討論完畢。分別由 Alberta 大學 Ning Cao 教授發表之「金融危機

對飛機航班和蔓延的影響」、Alberta 大學 Yasser Fahmy 教授發表之「對 2008 年金融危機的反應和未來期許」以及芝加哥大學 Yue Yuan 教授發表之「經濟嚴重衰退，快速復甦和金融危機：來自美國的證據」。Yasser Fahmy 彙整分析 2008 年金融危機期間美國政府的因應措施，包含：美國聯邦儲備委員會和世界各地的央行聯合採取措施，擴大貨幣供應，以避免通貨緊縮風險和低工資與高失業率導致的全球消費下降。此外，美國政府亦採行大規模的財政刺激措施，試圖通過借貸和消費，以抵消私人部門需求減少所造成的危機。這些措施有助於提供金融機構流動性，降低通貨緊縮所造成的經濟進一步衰退的風險。Yue Yuan 檢視美國的歷史經驗，試圖回答是否嚴重衰退會伴隨著快速的復甦？如果信貸緊縮或銀行恐慌伴隨著經濟衰退是否對經濟無重大影響？如果經濟衰退與房地產是否無關？他認為答案取決於金融危機的定義和復甦的程度，一般而言金融危機衍生的衰退常伴隨著快速地復甦，但是有三次例外情形：1930 年代經濟大蕭條時期的復甦、1990 年代初期經濟衰退後的復甦以及目前的復甦。目前的復甦相較於 1990 年代是相當緩慢，他認為住宅投資的復甦緩慢是原因之一。

配合航班之規劃，於7月 6 日日搭乘長榮 BR25班機於凌晨1點30分由西雅圖直飛台北，於台灣時間7月7日早上5點30分返抵桃園。

參、 心得及建議

此次研討會我主要選擇與「金融危機」有關的場次參與、聆聽。聆聽眾多發表人之論文後，我對金融危機有如下之看法:

1. 金融危機是金融業長期過度發展的結果，金融自由化與金融監管寬鬆，造成金融業規模快速擴張、財務槓桿不斷累積，信用風險因此急遽增長。
2. 雖然金融危機後，美國政府已制定相關法規試圖降低金融體系的風險、阻止另一次危機之發生，但是除非銀行被迫在貸款和投資時，更加依賴銀行所有者和股東的資金，否則金融體系很難處於安全的狀況。
3. 金融危機後，美國政府的監管措施主要為降低銀行的槓桿率，但是這種要求銀行減少對借款的依賴，會損害銀行向企業和個人發放貸款的能力，因此銀行業者對此監管措施十分抗拒。
4. 金融危機五年後，銀行仍存在龐大、複雜而不透明的金融資產，這些風險極高的金融資產可能對經濟產生威脅。
5. 總之，現今美國政府還沒有學會如何防止或處理金融危機，他們在監管鬆弛會造成金融體系不穩定、加強金融監理又會引起銀行業者反彈之間游移不定，卻又很自信的認為事情都在它們掌握之中。

肆、 附錄

一、 會議議程

請參見附檔 Prelim-Schedule-5-28-13.pdf

二、 發表論文全文

Analysts coverage and the nature of information into stock prices

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Abstract

This study examines the role of investor attention in the information diffusion by analyst coverage. Using trading turnover as a proxy for investor attention, it's found that attention is a crucial factor in investors' reaction to information provided by financial analysts. Firms with less analyst coverage rely more on investor attention to transmit information. The lead-lag effect among high and low analyst-following firms is caused by relative more attention to firms with high analyst-followings, and relative slower diffusion of information about firms with low analyst-following.

Key words: limited attention, analyst coverage, lead-lag, turnover

1. Introduction

A bunch of psychological research demonstrates that people can only process a limited amount of information during a given period. As a consequence, investors, when facing vast amounts of information, have to be selective in their information processing. A growing literature has linked investors' limited attention with securities' mispricing and investors' trading behaviors. Barber and Odean (2008) and Aboody, Lehavy, and Trueman (2010) show that salient events attract investors' attention and therefore influence stock buying and selling decisions. Similarly, Hirshleifer, Hou, Teoh, and Zhang (2004) find that investors with limited attention tend to overvalue firms whose net operating income over time outstrip free cash flow. Limited attention has also been conjectured as an explanation for the profitability of price and earnings momentum strategies (Hou, Peng, and Xiong, 2008). Hirshleifer, Lim, and Teoh (2011) post that limited investor attention to earnings contributes to post-earnings announcement drift and the profit anomaly, and investors' inattention to earnings components causes accrual and cash flow anomalies. Chan (2003) examines returns to a subset of stocks following prominent firm-related information released, and finds that investors underreact to information, which is strongest after bad news. Gilbert et al. (2007) show that investor inattention causes a significant mispricing of the S&P 500 Index and Treasury bonds.

There has also been analysis of how firms can exploit limited investor attention by disclosing bad news at times when other firms are making salient disclosures (Hirshleifer and Teoh, 2009), or on days of the week when investors are less attentive (Dellavigna and Pollet, 2009). Hirshleifer, Lim, and Teoh (2003) analyze firms' accounting disclosure policy and the resulting price dynamics when investors are inattentive. Klibanoff et al. (1998), studying closed-end country funds, show that country-specific news which appears on the front page of the *New York Times* is incorporated more quickly into the stock prices. In a case study, Huberman and Regev (2001) describe EntreMed's substantial and permanent stock price rise after the *New York Times* carried an article on a potential new cancer drug being researched by EntreMed. This information was not new, and had been reported no less than five months earlier in *Nature* and in numerous popular newspapers like the *New York Times*. Thus, important news or information is not reflected in prices until investors pay attention to it.

Owing to limited attention, investors may rely on highly visible and easy to processed information, like analyst earnings forecasts.[1] Despite the growing empirical evidence about limited attention, to my best knowledge, no research has yet investigated whether stock price reactions to the information flow from analyst coverage is affected by investor attention. This study intends to fill in this gap and examines the role of investor attention in the information transition by analyst coverage. My idea is that information regarding analyst earnings forecast would not be impounded in prices until investors keep an eye on it (Huberman and Regev, 2001). That is, reactions to analyst coverage depend on investors' attention: the greater the attention, the faster and more magnitude the information provided by financial analysts is processed by investors and reflected in the stock prices. Furthermore, stocks with lower analyst coverage should, all else equal, be ones where information moves more slowly across the investing public. Thus, these firms might depend more on investor attention to diffuse information than firms with higher analyst coverage.

My empirical work is related to Piotroski and Roulstone (2004) and Chan and Hameed (2006). They find that financial analysts generate valuable new information through their earnings forecasts, and reduce information asymmetry. analyst activity increases the relative amount of fundamental information reflected into prices. My results provide additional evidence that public attention can improve information diffusion from financial earnings forecasts. Additionally, as expected, investor attention has greater influence on firms with smaller analyst coverage.

This study contributes to the literature in three ways. First, this study is the first to shed light on the relationship between investor's attention and the extent to which analyst coverage incorporates fundamental information. My results first show that This is similar to the well-known idea is that financial analysts generate valuable new information through their earnings forecasts, and reduce information asymmetry. The more financial analysts' coverage, the more information asymmetry would be attenuated. This confirms the viewpoint that Also as expected, firms with low analyst following depend more on investor attention to process information. In this sense,.

[1] Financial analysts generate valuable firm-specific information through their earnings forecasts (e.g., Lys and Sohn, 1990). In addition to firm-specific information, financial analysts also make their efforts on obtaining and interpreting industry- and market-level information (Clement, 1999; Jacob, Lys and Neale, 1999; Ramnath, 2002).

Second, I empirically show the dual role of investor attention. Investor attention, on the one hand, adds to fundamental information impounded into stock prices. On the other hand, it can induce investors to overreact to fundamental information when attention interacts with investors' behavioral biases, such as extrapolative expectations and overconfidence (Peng and Xiong, 2006).

Third, I analyze the implications of investor attention for the lead-lag relationship among the returns of portfolios sorted by the number of analysts. It's found that the lead-lag effect among high and low analyst-following firms is caused by relative more attention to firms with high analyst coverage, and relative slower diffusion of information about firms with low analyst coverage. Above results are in line with the view that analyst forecasts that catch investor attention have greater influences on stock prices. In addition, they are consistent with the argument that slow diffusion of common information is a leading cause of the lead-lag effect in stock returns (Lo and MacKinlay,1990; Hou and Moskowitz, 2005), and that low volume firms adjust more slowly to market-wide information, which causes the lead-lag effect (Chordia and Swaminathan, 2000).

The paper is organized as follows. Section 2 reviews the related studies on attention and form the testable hypotheses. Section 3 describes the data used in this empirical analysis. In Sections 4, I test the relation between limited attention and information diffusion by analyst coverage by forming portfolios and running regression. I also adopt a semi-parametric model and examine the lead-lag relationship between firms with different analyst coverage. I conclude in Section 5.

2. Related literature and testable hypotheses

The stock price of an individual firm reflects market-wide, industry-level and firm-specific information, as well as noise. Following Morck, Yeung, and Yu (2000), a number of studies interpret a stock' return synchronicity can be used as a measure of the relative amount of firm-specific information reflected in returns.[2] A low synchronicity usually indicates that more firm-specific information is incorporated in stock prices. However, other studies question this interpretation and conclude the

[2] Some examples include Wurgler (2000), Durnev, Morck, Yeung, and Zarowin (2003, 2004), Piotroski and Roulstone (2004), Jin and Myers (2006), Chan and Hameed, (2006), and Bakke and Whited (2006).

opposite, namely that low synchronicity firms have high firm-specific uncertainty (or idiosyncratic noise) (Roll, 1988; Ashbaugh-Skaife, Gassen, and LaFond, 2006; Chan and Hameed, 2006; Griffin, Kelly, and Nadari, 2006; Kelly, 2007; Hou, Peng, and Xiong, 2013). Hou, Peng, and Xiong (2013) document that stock price fluctuations reflect both fundamental information flow and investor sentiment (Shiller, 1981; Hirshleifer, 2001; Barberis and Thaler, 2003). To this extent, lower return R^2 actually captures market inefficiency rather than efficiency. Similarly, Dasgupta, Gan, and Gao (2010) theoretically and empirically show that stock return synchronicity increases with information transparency. Their perspective is that stock prices respond only to announcements that are not already anticipated by the market. In a more transparent environment, in which more firm-specific information is available, there exists less "surprise" about future events. Consequently, there is less *new* firm-specific information impounded into the stock price, and the return synchronicity should be higher. Xing and Anderson (2011), using the number of voluntary disclosures, firm size and analyst following as proxies of public firm-specific information, show that stock price synchronicity increases with public firm-specific information at an decreasing rate.

Firm size is a useful measure of the rate of information diffusion (Hong and Stein, 1999; Hong, Lim, and Stein, 2000). The reason is that investors, in face of fixed information acquisition costs, prefer to make more effort to learning about those stocks in which they can take large positions. Aside from firm size, analyst coverage is an alternative proxy for the rate of information flow. Previous studies show that analyst coverage can reduce information asymmetry among investors (e.g., Bowen, Chen, and Cheng, 2008; Hong, Lim, and Stein, 2000). In particular, Hong, Lim, and Stein (2000) posit that stocks with higher analyst coverage are ones where firm-specific information moves more quickly across the investing public. Thus, if return synchronicity increases with information transparency as documented by Dasgupta, Gan, and Gao (2010), size and analyst coverage would be positively correlated with synchronicity. As a result, I form the first and second hypotheses as follows:

Hypothesis 1: Large stocks have higher price synchronicity.

Hypothesis 2: Stocks with more analyst coverage have higher price synchronicity.

Limited attention affects the perception and behavior of investors. If a stock raises investors' attention, it experiences higher trade activities. For example, Barber and Odean (2008) find that individual investors are net buyers of attention-grabbing stocks such as stocks in the news, experiencing high abnormal trading volume, or with extreme one-day returns. Peng and Xiong (2006) argue that limited attention leads to category learning, i.e., investors process more market- and sector-level information, instead of firm-specific information. Therefore, a relatively smaller portion of firm-related information is incorporated into the stock prices. However, when investors pay more attention to one stock, they may spend more time in gathering and analyzing firm-related information. Consequently, the stock prices are more informative about their future fundamentals, and their returns have relatively more firm-specific variation. As a result, I form the following testable hypothesis:

Hypothesis 3: Firms with higher investors' attention tend to display stronger synchronicity.

Hou, Peng, and Xiong (2008) posit that investor attention could have a dual role on stock prices. On the one hand, limited attention directly causes some useful information being ignored; on the other hand, when attention interacts with investors' behavioral biases, such as extrapolative expectations and overconfidence, it can generate price overreaction. Along this line of reasoning, when investors pay less attention to a company, they are more likely to ignore its fundamental information. Therefore, a relatively smaller portion of firm-related information is incorporated into the stock prices when investors are inattentive. On the contrary, when investors pay more attention to one stock, they may spend more time in gathering and analyzing firm-related information. This may in turn enhance the relative amount of firm-specific, but reduce the relative amount of industry-level and market-level, information being impounded into this stock's prices. However, when attention interacts with overconfidence, investors exaggerate their information-processing ability. As a result, the investors overestimate the precision of her information, which in turn causes them to overreact to information. In accordance with this view, Peng, and Xiong (2006) show that stock prices contained more firm-specific information tend to have more pronounced overreaction-driven return predictability. Accordingly, synchronicity might first increase with investor attention as more firm-specific information are gathered and processed, it then decreases with the degree of the marginal investor's overreaction to firm-specific information. The works of Andrade et al. (2005), Barberis et al. (2005), Kumar and Lee (2005), and Greenwood (2005) also suggest that non-fundamental factors affect firms' stock price synchronicity. Taken together, I form the fourth hypothesis as follows:

Hypothesis 4: Investor attention and synchronicity exists a nonlinear relationship.

From the case of EntreMed provided by Huberman and Regev (2001), stock prices response to news released only when it attracts investors' attention. Thus, public attention is an important condition for financial analysts' coverage to affect stock prices. However, due to limited attention, investors can merely take notice of a subset of all available information. Therefore, investor attention may affect the effects of analyst coverage in enhancing information diffusion and thus reducing information asymmetry. That is, the effects of analyst coverage on price synchronicity may be associated with investors' attention. For firms with lower analyst coverage, all else equal, their information moves more slowly across the investing public (Hong, Lim, and Stein, 2000). They might rely more on investors' attention to diffuse information. Thus, my prediction is that investors' attention has greater effects upon improving price synchronicity for firms with lower analyst coverage than those with higher ones. The fifth hypothesis is:

Hypothesis 5: The effect of investor attention on improving stock synchronicity is more pronounced for stocks with low analyst coverage.

The attention that investors allocate to stocks not only affects the effects of financial analyst on information diffusion, but also on the lead-lag relationship between firms with high and low analyst coverage. The lead-lag relationship is widely studied in the literature. Lo and MacKinlay (1990) first document that the weekly returns of large firms lead those of small firms. Another research has also discovered a large cross-serial correlation between small-firm portfolio returns and lagged large-firm portfolio returns (e.g., Lo and MacKinlay, 1990; Boudoukh, Richardson, and Whitelaw, 1994; Campbell, Lo, and MacKinlay, 1997). This is explained by a result of differential information diffusion. Due to market imperfections like transaction costs, information will be impounded first in large-firm stock prices, and then in small-firm stock prices. In addition to firm size, the lead-lag relationship is also found in terms of institutional ownership (Badrinath, Kale, and Noe, 1995), numbers of analyst coverage (Brennan, Jegadeesh, and Swaminathan, 1993), and trading volume (Chordia and Swaminathan, 2000).

Investors can have difficulty in acquiring and processing information in certain situations, this sometimes causes stock prices to adjust slowly to new information. Thus, investor attention can have influences on the speed and magnitude of information diffusion. Along this line, the stock prices of firms which catch more attention from investors may react more rapidly to aggregate shocks than do those catching less attention. In this sense, attention shocks might strengthen this lead-lag relationship. In particular, since stock prices with higher analyst following incorporate more information, attention on stocks with more analyst following, rather than on those with less analysts following, would strengthen the lead-lag relationship between high and low analyst following portfolios. Hypothesis 6 is as follows:

Hypothesis 6: More attention on higher analyst following stocks strengthens the lead-lag relationship between high and low analyst following portfolios.

3. Data and construction of variables

The sample covers NYSE, AMEX and NASDAQ firms with available data from the intersection of CRSP and COMPUSTAT data sets. I exclude firms with price less than $5 (Hong, Lim, and Stein, 2000). This ensures that the results are not driven by illiquid micro-capitalization securities or the bid-ask bounce. I also require the sample firms to be covered by the I/B/E/S analyst forecast data set. I begin the sample in 1984 because reliable estimates of analyst coverage from the I/B/E/S Detailed Earnings Forecasts file can be only obtained from 1984 onwards (Bowen, Chen, and Cheng, 2008; Chan and Chan, 2011). Thus, the data period covers January 1984 to December 2011.

The following subsection describes the methodology to measure the effects of limited attention on information nature based on the cross-sectional and cross-series lead-lag tests, respectively.

3.1 Measurement of stock price synchronicity

One general conclusion in the finance literature is that information reflected in the stock prices can be classified into market-wide, industry-level, and firm-specific information. To test whether limited attention influences the extent to which analyst forecasting activity in providing the relative flow of firm-specific, industry and market information into prices, I first calculate the stock price synchronicity using the following model:

$$ret_{i,t} = a_0 + a_1 rmt_t + a_2 rmt_{t-1} + e_{i,t}, \tag{1}$$

where $ret_{i,t}$ is the return at week *t* for firm *i*, and rmt_t is the market return variable, which is proxied by the return on value-weighted market index of the sample firms. The stock returns data are collected from the daily stock file in the CRSP dataset. Because daily returns introduce more confounding microstructure influences such as bid-ask bounce and nonsynchronous trading, they are more likely to generate estimation error (Hou and Moskowitz, 2005; Dasgupta, Gan, and Gao, 2010). Furthermore, Chordia and Swaminathan (2000) argue that due to the weekend effect, Friday-to-Friday weekly returns exhibit higher autocorrelations. Weekly returns are calculated as the compounded daily returns from Wednesday to the following Wednesday. The inclusion of lagged market returns variables into equation (1) allows us to incorporate the delayed response of stock price to market-level information and the effects of possible non-synchronous trading (Dimson, 1979). I define R_1^2 as the regression R-square from the single-factor market model. Synchronicity is measured for each firm based on the weekly return observations of the year. I estimate equation (1) over the 52 weeks. To ensure the estimated R_1^2 is reliable and not distorted by firms with fewer observations, I exclude R_1^2 with less than 26 available weekly observations in estimating equation (1). Similar to prior studies of stock price synchronicity (e.g., Morck, Yeung, and Yu, 2000; Piotroski and Roulstone, 2004), I define stock price synchronicity (*SYN*) for each firm-year estimation as:

$$SYN1 = \log\left(\frac{R_1^2}{1-R_1^2}\right). \tag{2}$$

Through this transformation, it creates a continuous variable that is more normally distributed than the distribution of R^2 values, which are bounded by zero and one (Morck et al., 2000; Piotroski and Roulstone, 2004). A higher SYN_1 indicates that more market-related information is impounded in the stock prices.

To differentiate the industry-level information impounded into the prices, I follow

Roll (1988) and Piotroski and Roulstone (2004) to include industry returns to explain stock returns in the regression model.

$$ret_{i,t} = a_0 + a_1 rmt_t + a_2 rmt_{t-1} + a_3 indret_{i,t} + a_4 indret_{i,t-1} + \varepsilon_{i,t}, \quad (3)$$

where $indret_t$ is the week t industry return to which firm i belongs. $indret$ is obtained from Fama and French 48 industry portfolios. I include lagged industry and market returns to alleviate concerns over delayed reaction of stock price to market- and industry-level information (Scholes and Williams, 1977; Piotroski and Roulstone, 2004). I define R_2^2 as the regression R-square from the two-factor model and define stock price synchronicity (SYN) based on this two-factor model as:

$$SYN2 = \log\left(\frac{R_2^2}{1-R_2^2}\right). \quad (4)$$

A higher SYN_2 indicates that more market- and industry-related information is in the stock prices.

3.2 Measurement of investor attention and analyst coverage

Prior research has documented that investors buy a stock that attracts their attention, even if there is no new information about the company (Huberman and Regev, 2001). These "attention-grabbing" stocks have higher turnover and volume (Barber and Odean, 2008). Therefore, this study adopts a widely-used attention proxy, turnover ratio, for analysis (e.g. Lo and Wang, 2000; Chordia and Swaminathan, 2000; Gervais et al., 2001; Hou, Peng, and Xiong, 2008). I define turnover ($TURN$) as shares traded divided by shares outstanding. Following Lo and Wang (2000), the weekly turnover is the sum of five daily turnovers starting at Wednesday and working backward.

Previous studies show that analyst coverage can reduce information asymmetry among investors (e.g., Bowen, Chen, and Cheng, 2008). Hong, Lim, and Stein (2000) show that stocks with higher analyst coverage should, all else equal, be ones where firm-specific information moves more quickly across the investing public. I use the number of analyst following to examine whether the effects of investors' attention on return synchronicity is more pronounced within firms with fewer analyst coverage. Analyst coverage ($ANALYST$) is defined as the number of unique analysts issuing fiscal year earnings forecasts for a firm during a given calendar year. Similar to Hong, Lim, and Stein (2000), Bowen, Chen, and Cheng (2008) and Chan and Chan (2011), if the I/B/E/S dataset does not report any earnings forecasts for a firm, the analyst coverage of this firm is set as zero. As Chan and Chan (2011) do, since the marginal effect of analyst coverage on stock return synchronicity is likely to diminish with analyst coverage, I use the log transformation of $ANALYST$ (i.e., $\log(1+ANALYST)$) in my regression model to capture the nonlinear relationship between stock return synchronicity and analyst coverage. There are 130,767 year-firm observations in total, including 76,443 observations of zero-analysts following.

3.3 Controls

Stock return synchronicity is principally affected by the underlying economics of the firm and its industry. To control for these cross-sectional differences, following previous related research (Piotroski and Roulston, 2004; Chan and Hameed, 2006; Wei and Zhang, 2006; Ferreira and Laux, 2007), I include the following control variables that are known to influence synchronicity: log of market capitalization of equity ($SIZE$), book-to-market ratio (BM), return volatility ($VOLATILITY$). The market capitalization of equity and the book to market value of equity are values in a year; return volatility is the standard deviation of the individual stock return estimated from weekly returns within a given year.

3.4 Empirical specifications

For stocks in each year, I first run regressions (1) and (3), respectively, to obtain $SYN1$ and $SYN2$. To control for variables that may affect synchronicity, I estimate the equation that explains the stock return synchronicity for company *i* in year *t*. To examine whether the increase in return synchronicity will be more pronounced within firms with more analyst coverage when investors are less attentive, the interactive term of $TURN$ and $\log(1+ANALYST)$ is included. The following regressions (5) and (6) are run.

$$SYN1_{i,t}=\beta_0+\beta_1 TURN_{i,t}+\beta_2\log\left(1+ANALYST_{i,t}\right)+\beta_3 TURN_{i,t}*\log\left(1+ANALYST_{i,t}\right)+\beta_4\,SIZE_{i,t-1}+\beta_5 BM_{i,t-1}+\beta_6 VOLATILITY_{i,t}+\varepsilon_{i,t} \tag{5}$$

$$SYN2_{i,t}=\beta_0+\beta_1 TURN_{i,t}+\beta_2\log\left(1+ANALYST_{i,t}\right)+\beta_3 TURN_{i,t}*\log\left(1+ANALYST_{i,t}\right)+\beta_4\,SIZE_{i,t-1}+\beta_5 BM_{i,t-1}+\beta_6 VOLATILITY_{i,t}+\varepsilon_{i,t} \tag{6}$$

Analysts have more incentives to follow firms with high trading volumes as there will be more brokerage commissions (Alford and Berger, 1999; Chan and Hameed, 2006). Thus, one concern with using analyst coverage in the test of stock synchronicity is that analyst coverage could be endogenous with respect to stock synchronicity and other variables in the regression model. Also, collinearity problems could arise when analyst coverage are positively correlated with other variables. In this setting, ordinary least squares estimation would likely yield biased and inconsistent coefficient estimates. To address this concern and avoid assumptions about the distribution of the model's error structure, I therefore estimate the model using the general method of moments (GMM) regression approach (Hansen, 1982). The advantage of the GMM estimation procedure is that it accounts for conditional heteroskedasticity of an unknown form and serial correlation in the error term.

3.5 Asymmetry lead-lag relationship and investor attention

To ascertain whether firms that are both followed by more analysts and attract more attention have more market-wide information incorporated into their stock prices, I examine the lead-lag relationship among the returns of high and low analyst coverage. Following Connolly and Stivers (2003; 2006), I compute a market-adjusted relative turnover ($MRTO$), which is denoted as the unexpected stock turnover after controlling for the trend in turnover and the variation associated with the absolute market return. $MRTO$ is defined as the residual from the following time series model.

$$\mathrm{Ln}(TVR_t) = \varphi_0 + \sum_{\tau=1}^{6} \varphi_\tau \ln(TVR_{t-\tau}) + \varphi_7 |R_{m,t}| + \varphi_8 D_t^- |R_{m,t}|$$

$$+\varphi_9 |R_{m,t-1}| + \varphi_{10} D_t^- |R_{m,t-1}| + v_t, \quad (7)$$

where TVR is the average turnover of the market portfolio, $|R_m|$ is the absolute value of the market return, $D^- = 1$ if the market return is negative, and the φ's are estimated coefficients.[3] By including the explanatory variables in the right part of equation (7), $MRTO$ can proxy for the abnormal investors' attention, beyond the normal variation associated with the sign and/or the magnitude of the market return (Conolly and Stivers, 2003).

Chan and Hameed (2006) examine the lead-lag relationship among portfolios sorted by the number of analyst coverage while controlling for the influence of firm

[3] Conolly and Stivers (2003) use the log transformation of the raw turnover because it exhibits little heteroskedasticity over time, nearly no skewness and only modest excess kurtosis.

size. They find that lagged returns of high analyst-following portfolio are able to predict the returns of low analyst-following portfolios. As a result, they posit that, for firms with more analyst coverage, their adjustment speed to market-wide information increases. Like Chan and Hameed (2006), to control for the influence of firm size, for each year, firms are first divided into three portfolios according to the firm size at the end of the year. Firms within each size-sorted portfolio are further ranked into four analyst-following sub-portfolios (zero, low, medium, high) on the basis of the number of analysts following. This method ensures that firms in different analyst-following portfolios but in the same size portfolio vary only in terms of the number of analyst coverage but not in terms of the firm size. I examine the lead-lag relationship between low and high analyst-following portfolios of a particular firm-size portfolio by running the following model:

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 MRTO_{k,t})R_{H,t-1} + \beta_3 R_{L,t-1} + \varepsilon_t, \tag{8}$$

where $R_{L,t}$ is the excess weekly return of low-analyst following portfolio at week *t*, $MRTO_{k,t}$ is the $MRTO$ of portfolio *k* at week *t*, *k* is either market portfolio, *M*, or low-analyst following portfolio, *L*, and high-analyst coverage portfolio, *H*.

In terms of *H*, if β_2 is positive, then attention shocks of the high analyst-following portfolio have predictive ability for future returns of the low analyst-following portfolio. If investors' attention does improve the speed and magnitude of market-wide information conveyed by analysts, then I expect that more systematic information will be inferred from the firms with more analysts following and investors' attention. Therefore, I predict that the high analyst-following portfolio with more investors' intention will lead the same analyst-following portfolio with lower investors' attention.

4. Empirical results

4.1 Descriptive statistics

Table 1 presents descriptive statistics for key variables used in the empirical tests. For each variable, I report the mean and median figures, as well as standard deviation, the first and third quartiles. In the table, R_1^2 and $SYN1$ are the R-squared statistic and the synchronicity measure, respectively, computed from Equation (1), while R_2^2 and

$SYN2$ are the same measures, computed from Equations (3). The mean and median R_1^2 are 0.171 and 0.123, respectively, while the mean and median R_2^2 are 0.217 and 0.153, respectively. The mean and median $SYN1$ are -2.119 and -1.968, respectively, while the mean and median $SYN2$ are -1.664 and -1.727, respectively. The low R^2 suggests that stock prices of US-listed firms tend to co-move, to a less (more) extent, with market-wide and/or industry-wide information (firm-specific information).

Both R-square and synchronicity display considerable cross-sectional variations. This is similar to those reflected in the relatively high standard deviations and inter-quartile ranges. For example, $SYN1$ is -2.463 at the lower quartile, while it is -0.916 at the upper quartile, with a standard deviation of 1.321. The significantly high variations in R^2 and synchronicity across firms suggest that the flow of firm-specific information to the market varies widely across firms. Table 1 also provides descriptive statistics for the main variables used in the later analyses. The dramatic difference between the mean and median of market value ($SIZE$) reveals that the sample contains some very large or small firms. Similarly, the firms also display considerable cross-sectional variation in turnover (average turnover of 0.615; median turnover of 0.008) and numbers of analyst following (mean and median Analyst of 23.806 and 13). The mean and median of book to market ratio (BM) are 0.722 and 0.532, which indicate that the shares generally sell at values substantially above book value.

4.2 Analyst coverage and synchronicity

In this section, I first examine the relation between size, analyst coverage, and synchronicity. For every calendar year, I first sort firms into three groups based on their market value at the end of the last December. “Small” are stocks in the smallest 30 percent, “medium” includes the middle 40 percent, and “large” includes the largest 30 percent. I then sort firms within each size groups into to four groups on the basis of analyst coverage, like Zero, Low, Medium, or High analyst following. Finally, the firms within each size-analyst following portfolio are further are divided into three portfolios on the basis of turnover ratio. The cut points for analyst coverage and turnover are the same as firm size. Thus, average synchronicity on these three-way sorted portfolios can be obtained. I then compare the difference in average synchronicity between high-turnover group and low-turnover group within the same level of analyst coverage to get a preliminary result about limited attention on synchronicity.

Table 2 reports average synchronicity of portfolios sorted by market value at the end of last year, numbers of analysts following, and share turnover. Panels A and B are the results of $SYN1$ and $SYN2$, respectively. As shown, the synchronicity spread between large and small firms is statistically and significantly positive. In addition, firms with more analyst coverage have greater synchronicity than those with less analyst coverage. These results provide preliminary evidence for Hypothesis 1 and 2, and consistent with Chan and Hameed (2006) and Brandt, et al. (2010), who show that stocks with lower return synchronicity tend to be smaller and have lower analyst coverage. Moreover, it confirms the viewpoint of Dasgupta, Gan, and Gao (2010) that synchronicity is higher in a more transparent environment where more firm-specific information is available. This is also in accordance with Hong, Lim, and Stein (2000) that firms with large size and more analyst coverage are accompanied with higher rate of firm-specific information diffusion. There is also a positive relationship between investor attention and synchronicity, which supports Hypothesis 3. This implies that, when investors pay more attention to one stock, they spend more time in gathering and analyzing firm-related information. This increases the relative amount of firm-specific information being impounded into this stock's prices.

However, the results in Table 2 do not consider the effect that analyst coverage is strongly correlated with firm size (Bhushan, 1989). To control for the influence of size on analyst coverage, I sort stocks into groups according to their size and analyst coverage. Table 3 reports average synchronicity of portfolios sorted by market value at the end of prior year and numbers of analysts following. It's found that large firms have higher $SYN1$ and $SYN2$ than small firms when controlling for analyst coverage. This is consistent with prior research that firm size is a useful measure of the rate of information diffusion and information about small firms spread more slowly (Hong, Lim, and Stein, 2000).

Moreover, small firms rely more on analyst coverage than large firms to diffuse information. In particular, only among small firms, firms with higher analyst coverage have significantly larger price synchronicity than those with lower/zero analyst coverage. It is reasonable since investors choose to devote more effort to learning about large firms, these stocks depend less on analyst earnings forecast to diffuse information. This confirms with the viewpoint of Hong, Lim, and Stein, (2000) that the importance of analyst coverage is decreasing in firm size.

Table 4 reports the results regarding whether the effect of investor attention on improving stock synchronicity is more pronounced for stocks with low analyst coverage. As shown, within small-size, high turnover stocks have stronger price synchronicity for low- and median-analyst groups. Within median-size, price synchronicity is stronger among high turnover stocks, with the exception of high-analyst groups. For large size portfolios, turnover has effects on the difference in synchronicity only when the number of analyst following is low or zero. Taken together, for all low analyst groups, high-turnover firms tend to have higher $SYN1$ and $SYN2$ than low-turnover firms, regardless of firm size. Above results indicate that investor attention will improve the diffusion of information by analyst coverage into prices. But this effect is not apparent when firms have high analyst following or large firms with moderate analyst coverage since a lot of related information is provided through their earnings forecasts or observed through firm size. Overall, Hypothesis 5 is supported. That is, the effect of investor attention on improving stock synchronicity is more pronounced for stocks with low analyst coverage.

4.3 Regression approach

To control for other cross-sectional differences like size, numbers of analyst following, book-to-market ratio (BM) and return volatility ($VOLATILITY$) and consider the interaction effects, Table 5 shows the GMM estimation results. The estimation includes firms with zero analysts following. The t-statistics, as shown in parenthesis, are corrected for heteroskedasticity and autocorrelation based on the Newey-West adjustment (1987). First of all, the significant and positive coefficient of $TURN$ confirms the results in Tables 2 and 3 and indicates that stock prices of firms that attract more investors' attention contain more information, which supports Hypothesis 3. Turning to the coefficients for the $TURN^2$ term, I find they are positive and significant. This indicates that synchronicity increases with investor attention at an increasing rate. However, the $TURN^3$ coefficient is significantly negative. This supports Hypothesis 4 and confirm the dual role of investor attention of Hou, Peng, and Xiong (2008), i.e., although investor attention is helpful in transmitting information, investors' overreaction can increase the stock's firm-specific return variance and reduces its return synchronicity (Peng, and Xiong, 2006; Hou, Peng, and Xiong, 2008). Accordingly, synchronicity first increases with investor attention as more firm-specific information are gathered and processed, it then decreases with the degree of the marginal investor's overreaction to firm-specific information. This confirms Teoh, Yang, and Zhang (2007) and Hou, Peng, and Xiong (2008) that a low synchronicity could be related to noise, rather than more firm-specific information released.

Moreover, stock return synchronicity is significantly and positively related to the number of analysts following. That is, firms with more analyst coverage have greater synchronicity than those with less analyst coverage. This result confirms Hypothesis 2. Similar views are provided by Hong, Lim, and Stein (2000), who posit that stocks with lower analyst coverage are ones where firm-specific information moves more slowly across the investing public. The negative and significant coefficient of $TURN*\log(1+ANALYST)$ is consistent with the results in Table 4 and Hypothesis 5, namely that investor attention has greater effects on firms with lower analysts coverage than higher analysts followings.

In addition, as Hypothesis 1, the higher synchronicity of large firms indicates that they have the richer information environments. The positive coefficients associated with size, turnover, and $\log(1+ANALYST)$ are consistent with the results of Chan and Hameed (2006). Synchronicity is also positively associated with the volatility of stock returns, $VOLATILITY$, and book-to-market ratio, BM. With regard to stock volatility, a growing body of studies has shown that more informative stock prices are associated with greater return volatility (e.g., French and Roll, 1986). The positive coefficients of $SYN1$ and $SYN2$ confirm this viewpoint. As for the book-to-market ratio, it has two potential impacts on firm-specific uncertainty. If a book-to-market is an inverse proxy of growth opportunities, a lower book-to-market implies higher growth-related uncertainty. On the other hand, book-to-market is a proxy for distress risk if it is a positive predictor of future returns. Hence, a lower book-to-market also indicates lower distress-related uncertainty, and higher synchronicity as well as lower idiosyncratic risk. From the positive coefficient of BM, growth opportunity appears the predominant implication of the book-to-market ratio.

4.4 Semi-parametric model

Above results indicate that there is a nonlinear relationship between share turnover and price informativeness. Therefore, in order to estimate the shape of the turnover–synchronicity relationship in more details, but controlling for other trading characteristics, a semi-parametric regression model is particularly appropriate. In the semi-parametric regression model, I model the turnover - synchronicity relationship nonparametrically to avoid any functional form assumption on this relationship, while the other variables enter parametrically. Specifically, I run the following semi-parametric model:

$$SYN1_{i,t} = \beta_0 + \beta_1 f(TURN_{i,t}) + \beta_2 \log(1 + ANALYST_{i,t}) + \beta_3 TURN_{i,t} * \log(1 + ANALYST_{i,t}) + \beta_4\, SIZE_{i,t-1} + \beta_5 BM_{i,t-1} + \beta_6 VOLATILITY_{i,t} + \varepsilon_{i,t}, \tag{9}$$

where f denotes a generic smooth function, which represents the synchronicity – turnover relationship after controlling for the parametric effects of other variables, which are as those defined in eq. (5). The model is estimated using Yatchew's (1997, 1998) differencing method.[4] A similar regression is also run with the dependent variable being replaced by $SYN2$.

Figure 1 presents the functional form of $f(TURN)$, which represents the relationship between turnover and synchronicity after removing the parametric effects of other variables. The results confirm Hypothesis 5. Specifically, the turnover - synchronicity relationship exhibits a S-shape. Specifically, synchronicity first decreases with share turnover, it then rises up and drops down to the end. Due to attention constraint, investors optimally allocate their attention across the multiple

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[4] Consider a semi-parametric regression:

$$f_i = f(z_i) + x_i\beta + \varepsilon_i \tag{a1}$$

where z is a random variable, x is a p-dimensional random variable, $E[y|x,z] = f(z) + x\beta$, and ε_i is i.i.d. mean-zero error term, such that $var[y|x,z] - \upsilon_i^2$. Following the methodology suggested by Yatchew (1997), the data were first arranged in order and then differenced to remove the nonparametric effect. The *mth*-order differences is expressed as :

$$\textstyle\sum_{j=1}^{m} d_j y_{i-j} = \beta\left(\sum_{j=1}^{m} d_j x_{i-j}\right) + \sum_{j=1}^{m} d_j f(z_{i-j}) + \sum_{j=1}^{m} d_j v_{i-j} \tag{a2}$$

where $d_0,\ldots,d_m$ are differencing weights satisfying the conditions:

$$\textstyle\sum_{j=1}^{m} d_j = 0 \text{ and } \sum_{j-1}^{m} d_j^2 = 1 \tag{a3}$$

This condition ensures that the differencing removes the non-parametric component in (a2) as the sample size increases. With the optimal choice of weights equation (a2) could be estimated by OLS to get the estimate of β, $\hat{\beta}_{diff}$. Then, subtract the estimated parametric part from both sides of (a1) to get:

$$y_i - x_i\hat{\beta}_{diff} = x_i(\beta - \hat{\beta}_{diff}) + f(z_i) + \varepsilon_i \cong f(x_i) + \varepsilon_i \tag{a4}$$

Finally, the estimated function form of f is obtained by employing a standard kernel regression of $y - x\boldsymbol{\beta}$ on z. The difference order here is set to 10.

sources of uncertainty. At first, limited attention leads to category-learning behavior, i.e., attention-constrained investors tend to allocate more attention to market- and sector-level uncertainty than to firm-specific uncertainty. With the increasing of attention, they allocate more attention to firm-specific information. As a consequence, the synchronicity is negatively associated with turnover (Peng, Xiong, 2006). At the second stage, as investors process more fundamental uncertainty, the information environment becomes more transparent and there is less surprise in the stock prices. Then, prices convey relative more fundamental information, and then the synchronicity improves with investor attention (Peng, and Xiong, 2006; Hou, Peng, and Xiong, 2008; Dasgupta, Gan, and Gao, 2010). However, investors could overestimate the precision of her information as attention interacts with behavioral biases, like extrapolative expectations and overconfidence (Hou, Peng, and Xiong, 2008). This introduces noise into stock prices and reduces return synchronicity.

In sum, the dynamic pattern of turnover on price synchronicity confirms the dual role of investor attention. When investors pay limited attention to the stock, stock prices incorporate less firm-specific news and stock returns move more synchronously. This relative amount market and industry-wide information decreases with investor attention. When investor attention is moderate, the stock prices are more informative about their future fundamentals, and synchronicity is positively related with investor attention. As investors pay excess attention to the stock, more idiosyncratic noise is impounded into prices, which induces a negative relationship between synchronicity and attention. Overall, the result that price synchronicity is dynamically related to investor attention implies that investor attention not only resolves fundamental uncertainty, but also introduces noise into prices.

4.5 Asymmetric lead-lag phenomenon and investors' attention

The evidence so far suggests that there is a positive relationship between stock return synchronicity and the number of analysts following the firm; firms with fewer analyst followings have higher sensitivity of investor attention to stock prices. Chan and Hameed (2006) examine the lead-lag relationship among portfolios sorted by the number of analysts while controlling for the influence of firm size. They find that the lagged returns of the high analyst-following portfolio are able to predict the returns of the low analyst-following portfolios. As a result, they posit that, for firms with more analyst coverage, their adjustment speed to market-wide information is higher.

In this section, I take a further step and investigate whether the cross lead-lag relation between firms with different analyst coverage varies with attention shocks. Table 6 reports the lead-lag results of high- and low- analyst following firms. Panel A is the results of equal-weighted portfolios, and Panel B provides the results of value-weighted portfolios. After controlling for firm size and the lagged returns of low-analyst following, it's found from the coefficients β_2 in Panel A that, for all sizes, the relation between the low-analyst following returns and lagged high-analyst following returns occur when high-analyst following stocks receive extensive attention. Low-analyst following portfolio's shocks can explain the variation in the cross-serial relation between high and low analysts following only within large-sized firms. For large-sized firms, though both high- and low- analyst following portfolio's shocks are capable of explaining the variation in the cross-serial relation, Their magnitude seems substantially lower than the smaller one (0.081 < 0.419). My result that attention on high-analyst following stocks have greater effects on the lead-lag relationship is accordant with Connolly and Stivers (2003), who show that weeks with extreme turnover and return dispersion shocks tend to have more macroeconomic news releases. Overall, the positive β_2 indicates that more investors' attention, especial on firms with high analyst coverage, is helpful in enhancing the information diffusion to low analyst-following firms. This supports for Hypothesis 6.

To get a robust test, I re-estimate equation (9) using portfolio returns usig value-weighted approach. Employing value-weighed returns rather than equal-weighed returns would bias the results towards larger firms and thus alleviate the impact of microstructure effects like nonsynchronous trading and bid-ask spread that are usually related with smaller firms (Hou and Moskowitz, 2005). Similar results are found from value-weighted portfolios. One exception is that market portfolio's shocks do enhance diffusion of common information when portfolios are value-weighted. Once the attention effect is accounted for, the cross predictability (β_1) for equal-weighted portfolio returns between low- and high-analyst following stocks only occur within small and median size-portfolios. This confirms above finding that smaller firms depend more on investors' attention to transit information released by analyst following. Interestingly, all β_1 for value-weighted portfolios are insignificantly different from zero. This is in line with the prediction that the lead-lag effect is predominantly an investor attention and analyst coverage phenomenon: returns on high analyst-following firms lead returns on low analyst-following firms when investors are attentive.

I also test whether the lead-lag relationship among the size-sorted portfolios is associated with investors' attention, and whether the large portfolio's shocks or the small portfolio's shocks are more important in explaining the variation in the cross-serial relation. A similar procedure is taken. In particular, to control the potential effects of analyst coverage on information transmission, for each year, firms are first divided into four analyst-following sub-portfolios (zero, low, medium, high) on the basis of the number of analysts following. The firms within each analyst-following portfolio are further ranked into three portfolios according to the firm size at the end of the prior year. This method ensures that firms in different size but in the same analyst-following portfolios vary only in terms of the firm size but not in terms of the number of analysts. Thus, within a given analyst-following portfolio, I estimate the following model between small and large size portfolios:

$$R_{S,t} = \beta_0 + (\beta_1 + \beta_2 MRTO_{k,t})R_{L,t-1} + \beta_3 R_{S,t-1} + \varepsilon_t, \tag{10}$$

where $R_{S,t}$ is the excess weekly return of small-sized portfolio at week *t*, $MRTO_{k,t}$ is the $MRTO$ of portfolio *k* in week *t*, *k* is either market portfolio, *M*, small-sized portfolio, *S*, and large-sized portfolio, *L*.

In light that size is also a measure of information diffusion rate, Table 7 reports the attention shocks and asymmetric lead-lag relation between small- and large-size portfolios. While controlling for the numbers of analyst following and the lagged small-firm returns, it's found from Panel A that the lead-lag relation between the small-firm equal-weighted returns and lagged large-firm equal-weighted returns exist only when firms have analyst coverage, and the large-firm portfolio's shocks can explain the variation in the cross-serial relation for firms with analyst following. For those with high analyst coverage, both the large-firm portfolio's shocks and the small-firm portfolio's shocks are capable of explaining the variation in the cross-serial relation. In comparison, the magnitude of the large-firm portfolio's shocks seems substantially larger than the small-firm portfolio's shocks (0.623 > 0.189). This indicates that attention on larger firms has a greater influence on the lead-lag relationship than on smaller firms. Overall, the positive β_2 indicates that more investors' attention is helpful in enhancing the information impounded into small firms. By contrast, for firms without analyst coverage, no attention shock from market, large firms, and small firms can affect the lead-lag relationship.

Similar results are obtained from value-weighed returns. That is, when past returns on the value-weighted portfolio of large firms catch investors' attention, they still reliably predict current returns on the value-weighted portfolio of small firms. One exception is that market portfolio's shocks become enhancing diffusion of common information when portfolios are value-weighted. Overall, returns on big firms lead returns on small firms when investors are attentive and analysts provide earnings forecasts of these firms. Without these two effects, there is little evidence of cross predictability in small and large stock returns (β_1 is insignificantly positive).

Above results are consistent with the argument that slow diffusion of common information is a leading cause of the lead-lag effect in stock returns (Lo and MacKinlay, 1990; Hou and Moskowitz, 2005). Chordia and Swaminathan (2000) provide a similar finding, namely that low volume firms adjust more slowly to market-wide information, which cause a lead-lag effect. This paper extends Chordia and Swaminathan (2000) and contributes to the above literature by showing that the lead-lag effect between large- and small-sized portfolios is caused by relative more attention to large stocks, and relative slower diffusion of information about small firms. Likewise, the lead-lag effect between stocks with high- and low-analyst coverage is also associated with relative more attention paid to stocks with more analyst coverage. Above result confirms Hypothesis 6, namely that more attention on higher analyst following stocks strengthens the lead-lag relationship between high and low analyst following portfolios.

5. Conclusion

This paper provides empirical evidence that attention is a crucial factor in investors' reaction to information provided by financial analysts. In particular, stock prices of firms that attract more investors' attention contain more information. However, as argued by Teoh, Yang, and Zhang (2007) and Hou, Peng, and Xiong (2008), when attention interacts with investors' behavioral biases, such as extrapolative expectations and overconfidence, investors might overreact to firm-specific information. This overreaction can increase the stock's firm-specific return variance and reduces its return synchronicity, which in turn leads to a negative relationship between price synchronicity and investor attention. As a result, the relative firm-specific information conveyed in prices dynamically changes with investors' attention. This is in line with the well-known knowledge that stock prices not only reflect market-level, industry-level and firm-specific information, but also noise due to investors' behavioral biases (Roll, 1988; Hou, Peng, and Xiong, 2008).

Information diffuses more slowly for stocks with slower analyst coverage. After controlling for firm size, investors' attention has more effects on firms with low analyst following. That is, firms that are followed by more analysts, the degree of investors' attention has little effect on the magnitude of firm-specific information incorporated into their stock prices; however, firms that have smaller analyst following, the magnitude of firm-specific information can be incorporated into their stock prices only when it catches investors' attention. This is in line with the attention argument of Klibanoff et al. (1998) and Huberman and Regev (2001).

To ascertain whether investors' attention indeed has effects on the role played by analyst coverage or firm size on the speed of price adjustment, I test whether the cross-serial lead-lag relation also varies with investors' attention shocks. As expected, when investors pay abnormal attention to the market, the cross-sectional lead-lag relationship becomes strong, and the high analyst-following portfolio's shocks, instead of the low analyst-following portfolio's shocks, are more important in explaining the variation in the cross-serial relation. Likewise, the cross-serial correlation between small-firm portfolio returns and lagged large-firm portfolio returns is more prevalent when people keep their eyes on the large-firm portfolio.

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Table 1 Summary Statistics

R_1^2 and $SYN1$ refer to the R^2 statistic and the stock price synchronicity measures, respectively, that are estimated using eq. (1), while R_2^2 and $SYN2$ refer to the same measures that are estimated using eq. (3). N is the number of firm-year observations in the group, $RMSE1$ and $RMSE2$ are the volatility of the residual return from eq. (1) and eq. (3), respectively. $ANALYST$ is the number of analysts following the stock, $SIZE$ is the market capitalization in billions, BM is the book to market ratio, $TURN$ is the trading volume divided by shares outstanding, and $VOLATILITY$ is the standard deviation of weekly stock returns.

Variables	N	Mean	Q1	Median	Q3	Stdev
R_1^2	122855	0.171	0.049	0.123	0.251	0.156
R_2^2	130254	0.217	0.079	0.153	0.292	0.194
$SYN1$	122855	-2.119	-2.961	-1.968	-1.093	1.467
$SYN2$	129044	-1.664	-2.463	-1.727	-0.916	1.321
$RMSE1$	122855	0.062	0.036	0.052	0.076	0.041
$RMSE2$	129012	0.205	0.017	0.026	0.038	2.316
$SIZE$	121039	2.032	0.054	0.187	0.794	11.395
$TURN$	130767	0.615	0.002	0.008	0.034	5.466
$VOLATILITY$	130583	0.067	0.039	0.057	0.083	0.046
BM	77985	0.722	0.303	0.532	0.877	1.435
$ANALYST$	76443	23.806	5.000	13.000	31.000	30.028

Table 2 Synchronicity for various portfolios

This table reports the average synchronicity for portfolios formed based on size ($SIZE$), number of analyst following ($ANALYST$), and share turnover ($TURN$). "Small" are stocks in the smallest 30 percent, "medium"includes the middle 40 percent, and "large" includes the largest 30 percent. * denotes significant at the 10% significance level; ** denotes significant at the 5% significance level; *** denotes significant at the 1% significance level.

	$SIZE$	$ANALYST$	$TURN$
		Panel A: $SYN1$	
Small	-2.447	-2.328	-2.467
Median	-1.536	-2.192	-1.830
Large	-1.058	-1.335	-1.786
Difference	1.388	0.993	0.681
t-value	8.155***	5.731***	4.094***
		Panel B: $SYN2$	
Small	-1.915	-1.846	-1.846
Median	-1.470	-1.237	-1.237
Large	-1.365	-1.047	-1.047
Difference	0.550	0.799	0.799
t-value	3.707***	4.774***	4.511***

Table 3 Synchronicity over size and analyst coverage portfolios

Average synchronicity on portfolios sorted by size and numbers of analyst following are reported over the period from January 1984 to December 2011. All stocks on NYSE/AMEX/NASDAQ are ranked into three portfolios by their market value at the end of the previous year. For every calendar year, I first sort firms into three groups based on their market value at the end of the last December. I then sort firms within each size groups into to four groups on the basis of analyst coverage, like *Zero*, *Low*, *Medium*, or *High* analyst following. Panel A reports the synchronicity ($SYN1$) from regression (1), and Panel B reports the synchronicity ($SYN2$) from regression (3). T1 is the t statistics of difference in large and small portfolios; T2 is the t statistics of difference in high and low analyst following portfolios; T3 is the t statistics of difference in high and zero analyst following portfolios. * denotes significant at the 10% significance level; ** denotes significant at the 5% significance level; *** denotes significant at the 1% significance level.

				$ANALYST$					
		Low	Median	High	Zero	High-Low	T2-value	High-Zero	T3-value
				Panel A: $SYN1$					
$SIZE$	Small	-2.535	-2.575	-1.955	-2.793	0.580	3.24***	0.837	4.94***
	Median	-1.665	-1.523	-1.432	-1.586	0.233	1.19	0.154	0.80
	Large	-1.156	-1.042	-0.985	-1.089	0.171	0.99	0.105	0.56
	Large-Small	1.379	1.533	0.970	1.703				
	T1-value	9.13***	9.17***	5.12**	11.18***				
				Panel B: $SYN2$					
$SIZE$	Small	-1.906	-1.917	-1.588	-2.048	0.319	1.93*	0.460	3.03***
	Median	-1.282	-1.233	-1.206	-1.148	0.077	0.36	-0.058	-0.28
	Large	-1.099	-1.078	-0.965	-1.061	0.134	0.67	0.096	0.46
	Large-Small	0.807	0.839	0.622	0.987				
	T1-value	5.81***	5.40***	2.98***	7.93***				

Table 4 Synchronicity over three-sorted portfolios

Average synchronicities on three-way sorted portfolios are reported over the period from January 1984 to December 2011. For every calendar year, I first sort firms into three groups based on their market value at the end of the last December. I then sort firms within each size groups into to four groups on the basis of analyst coverage, like *Zero*, *Low*, *Medium*, or *High* analyst following. Finally, the firms within each size-analyst following portfolio are further are divided into three portfolios on the basis of turnover. The left part reports the synchronicity ($SYN1$) from regression (1), and the right part reports the synchronicity ($SYN2$) from regression (3). T-value is the t statistics of difference in high and low turnover portfolios. * denotes significant at the 10% significance level; ** denotes significant at the 5% significance level; *** denotes significant at the 1% significance level.

$SIZE$	$ANALYST$	$SYN1$					$SYN2$				
		$TURN$					$TURN$				
		Low	Median	High	High-Low	t-value	Low	Median	High	High-Low	t-value
Small	Zero	-1.042	-0.985	-1.089	-0.047	-0.28	-1.078	-0.965	-1.060	0.020	0.10
	Low	-2.535	-2.575	-1.955	0.580	3.24***	-1.906	-1.917	-1.588	0.319	1.93*
	Median	-2.793	-1.665	-1.523	1.269	7.61***	-2.048	-1.282	-1.230	0.820	5.32**
	High	-1.432	-1.586	-1.156	0.276	0.20	-1.206	-1.148	-1.100	0.110	0.08
Median	Zero	-2.079	-2.051	-1.520	0.559	2.47**	-1.578	-1.603	-1.070	0.510	2.53**
	Low	-2.030	-2.055	-1.615	0.416	2.01**	-1.708	-1.606	-1.242	0.467	2.36**
	Median	-2.019	-2.096	-1.481	0.539	2.34**	-1.584	-1.627	-1.210	0.380	1.91*
	High	-1.855	-2.076	-1.426	0.429	0.31	-1.680	-1.613	-1.200	0.480	0.34
Large	Zero	-1.320	-2.054	-1.080	0.241	1.19	-1.595	-1.597	-1.040	0.550	3.04***
	Low	-1.574	-2.059	-1.150	0.423	2.02**	-1.598	-1.615	-1.070	0.520	2.79***
	Median	-1.375	-2.094	-1.040	0.336	1.61	-1.426	-1.601	-1.100	0.328	1.48
	High	-1.486	-2.069	-0.990	0.501	0.35	-1.370	-1.607	-0.970	0.400	0.29

Table 5 Determinants of stock return synchronicity

This table presents coefficients from model (5) to model (6). $SYN1$ and $SYN2$ refer to the stock price synchronicity measures, that is estimated using eq. (1) and eq. (3), respectively. $\log(1+ANALYST)$ is the log of the number of analysts, $TURN$ is the log of trading turnover, $SIZE$ is the log market capitalization, BM is the book to market ratio, $VOLATILITY$ is the standard deviation of the stock return. The coefficients are estimated by GMM, with t-statistics in parentheses that are calculated with autocorrelation- and heteroskedastic-consistent standard errors by the Newey and West method. *, **, and *** denote significant at the 10%, 5%, and 1% significance level, respectively.

			$SYN1$
Intercept	-3.940	-3.953	-3.948
	(-130.03)***	(-131.88)***	(-131.45)
$TURN$	0.138	0.155	0.169
	(19.58)***	(19.76)***	(17.35)***
$TURN^2$		0.025	0.018
		(4.61)***	(3.00)***
$TURN^3$			-0.007
			(-2.66)***
$\log(1+ANALYST)$	0.109	0.109	0.109
	(21.53)***	(21.68)***	(21.69)***
$TURN * \log(1+ANALYST)$	-0.041	-0.040	-0.041
	(-5.51)***	(-5.39)***	(-5.54)***
$SIZE$	0.290	0.291	0.291
	(63.47)***	(63.80)***	(63.79)***
BM	0.028	0.027	0.027
	(2.33)**	(2.33)**	(2.33)**
$VOLATILITY$	1.762	1.669	1.672
	(12.12)***	(11.53)***	(11.55)***
Adjusted R^2	0.2245	0.2247	0.2248
			$SYN2$
Intercept	-3.290	-3.324	-3.321
	(-105.84)***	(-109.24)***	(-109.18)***
$TURN$	0.024	0.058	0.066
	(3.79)***	(8.21)***	(7.26)***
$TURN^2$	0.1906	0.056	0.051
		(11.94)***	(10.09)***
$TURN^3$		0.1925	-0.004
			(-1.69)*
$\log(1+ANALYST)$	0.098	0.099	0.099
	(19.45)***	(19.73)***	(19.73)***

$TURN * \log(1 + ANALYST)$	-0.033	-0.028	-0.027
	(-4.15)***	(-3.63)***	(-3.53)***
$SIZE$	0.233	0.236	0.236
	(50.06)***	(50.96)***	(50.97)***
BM	0.019	0.018	0.018
	(1.57)	(1.52)	(1.51)
$VOLATILITY$	2.517	2.356	2.359
	(14.13)***	(13.50)***	(13.50)***
Adjusted R^2	0.1906	0.1925	0.1926

Table 6 Attention shocks and lead-lag relation between analyst following portfolios

This table reports on the effects of $MRTO$ on the cross-serial relation between the returns of small-firm portfolio and lagged large-firm portfolio. The model is as follows:

$$R_{L,t} = \beta_0 + (\beta_1 + \beta_2 MRTO_{k,t})R_{H,t-1} + \beta_3 R_{L,t-1} + \varepsilon_t,$$

where $R_{L,t}$ is the excess weekly return of low-analyst following portfolio in week t, $MRTO_{k,t}$ is the $MRTO$ of portfolio k in week t, k is either market portfolio, M, or high-analyst following portfolio, H, and low-analyst coverage portfolio, L. The coefficients are estimated by OLS, with t-statistics in parentheses that are calculated with autocorrelation- and heteroskedastic-consistent standard errors by the Newey and West method. The sample period is January 1984 to December 2012. * denotes significant at the 10% significance level; ** denotes significant at the 5% significance level; *** denotes significant at the 1% significance level.

		β_0		β_1		β_2		β_3		Adj. R^2
Panel A: Equal-weighted										
Small	K=M	0.005	(8.17)***	0.088	(1.78)*	0.245	(1.21)	0.032	(0.44)	0.024
	K=L	0.005	(8.16)***	0.090	(1.82)*	0.010	(0.52)	0.029	(0.41)	0.023
	K=H	0.005	(8.31)***	0.097	(1.98)**	0.174	(5.27)***	0.019	(0.26)	0.041
Median	K=M	0.005	(8.68)***	0.135	(2.77)***	0.220	(1.09)	-0.036	(-0.57)	0.025
	K=L	0.005	(8.69)***	0.138	(2.85)***	0.031	(1.55)	-0.038	(-0.60)	0.025
	K=H	0.005	(8.88)***	0.134	(2.82)***	0.478	(8.59)***	-0.035	(-0.57)	0.070
Large	K=M	0.005	(8.27)***	0.011	(0.22)	0.275	(1.24)	0.125	(2.07)**	0.02
	K=L	0.005	(8.39)***	0.017	(0.36)	0.081	(3.04)***	0.117	(1.94)*	0.025
	K=H	0.005	(8.32)***	0.004	(0.08)	0.419	(5.84)***	0.133	(2.22)**	0.041
Panel B: Value-weighted										
Small	K=M	0.006	(8.91)***	0.077	(1.52)	0.136	(3.41)***	0.002	(0.03)	0.016
	K=L	0.006	(8.95)***	0.082	(1.61)	-0.003	(-0.17)	-0.010	(-0.15)	0.009
	K=H	0.006	(9.02)***	0.082	(1.61)	0.163	(4.83)***	-0.009	(-0.13)	0.024
Median	K=M	0.006	(9.04)***	0.076	(1.46)	0.129	(3.21)***	0.006	(0.09)	0.016
	K=L	0.005	(7.11)***	-0.013	(-0.26)	0.033	(0.82)	0.114	(2.78)***	0.010
	K=H	0.005	(7.14)***	-0.017	(-0.34)	0.204	(3.61)***	0.117	(2.87)***	0.018
Large	K=M	0.006	(9.13)***	-0.019	(-0.35)	0.132	(2.61)**	0.128	(1.99)8*	0.011
	K=L	0.006	(9.24)***	-0.013	(-0.23)	0.098	(2.97)***	0.117	(1.82)*	0.013
	K=H	0.006	(9.18)***	-0.024	(-0.44)	0.446	(4.81)***	0.134	(2.08)**	0.022

Table 7 Attention shocks and lead-lag relation between size portfolios

This table reports on the effects of $MRTO$ on the cross-serial relation between the returns of small-firm portfolio and lagged large-firm portfolio. The model is as follows:

$$R_{S,t} = \beta_0 + (\beta_1 + \beta_2 MRTO_{k,t})R_{L,t-1} + \beta_3 R_{S,t-1} + \varepsilon_t,$$

where $R_{S,t}$ is the excess weekly return of small-sized portfolio in week t, $MRTO_{k,t}$ is the $MRTO$ of portfolio k in week t, k is either market portfolio, M, small-sized portfolio, S, and large-sized portfolio, L. The coefficients are estimated by OLS, with t-statistics in parentheses that are calculated with autocorrelation- and heteroskedastic-consistent standard errors by the Newey and West method. * denotes significant at the 10% significance level; ** denotes significant at the 5% significance level; *** denotes significant at the 1% significance level.

		β_0		β_1		β_2		β_3		Adj. R^2
Panel A: Equal-weighted										
Low	K=M	0.005	(8.17)***	0.056	(1.31)	0.275	(1.13)	0.103	(2.31)**	0.021
	K=S	0.005	(8.19)***	0.056	(1.31)	0.017	(0.62)	0.104	(2.32)**	0.023
	K=L	0.005	(8.21)***	0.052	(1.21)	0.108	(3.53)***	0.108	(2.43)**	0.030
Median	K=M	0.004	(7.37)***	0.008	(0.18)	0.218	(0.87)	0.156	(3.34)***	0.025
	K=S	0.004	(7.36)***	0.008	(0.17)	0.058	(1.80)*	0.156	(3.36)***	0.027
	K=L	0.004	(7.37)***	0.002	(0.05)	0.166	(3.97)***	0.165	(3.54)***	0.035
High	K=M	0.001	(1.59)	0.037	(0.63)	0.501	(1.54)	0.061	(1.18)	0.008
	K=S	0.001	(1.51)	0.040	(0.70)	0.189	(3.62)***	0.061	(1.17)	0.015
	K=L	0.001	(1.63)	0.029	(0.51)	0.623	(5.94)***	0.068	(1.32)	0.030
Zero	K=M	0.004	(8.37)***	-0.016	(-0.48)	0.060	(0.28)	0.243	(5.89)***	0.050
	K=S	0.004	(8.39)***	-0.014	(-0.42)	0.043	(1.73)	0.242	(5.86)***	0.052
	K=L	0.005	(8.37)***	-0.017	(-0.52)	0.051	(0.81)	0.243	(5.89)***	0.051
Panel B: Value-weighted										
Low	K=M	0.006	(9.00)***	0.055	(1.16)	0.148	(2.66)***	0.061	(1.46)	0.013
	K=S	0.006	(9.05)8**	0.055	(1.17)	0.005	(0.14)	0.056	(1.33)	0.008
	K=L	0.006	(9.09)***	0.052	(1.10)	0.119	(3.29)8**	0.057	(1.37)	0.015
Median	K=M	0.005	(7.12)***	-0.015	(-0.31)	0.167	(2.71)***	0.118	(2.88)***	0.014
	K=S	0.005	(7.11)***	-0.013	(-0.26)	0.033	(0.82)	0.114	(2.78)***	0.008
	K=L	0.005	(7.14)***	-0.017	(-0.34)	0.204	(3.61)***	0.117	(2.87)***	0.018
high	K=M	0.002	(2.73)***	-0.006	(-0.10)	0.198	(2.87)***	0.083	(1.80)*	0.009
	K=S	0.002	(2.71)***	-0.001	(-0.02)	0.156	(2.75)***	0.078	(1.68)*	0.009
	K=L	0.002	(2.77)***	-0.006	(-0.11)	0.656	(5.19)***	0.083	(1.80)*	0.013
Zero	K=M	0.005	(7.36)***	-0.092	(-2.19)**	0.142	(2.60)***	0.193	(4.96)***	0.021
	K=S	0.005	(7.36)***	-0.084	(-2.00)**	0.029	(0.92)	0.185	(4.76)***	0.017
	K=L	0.005	(7.35)***	-0.082	(-1.97)**	-0.001	(-0.03)	0.184	(4.73)***	0.017

Figure 1 Turnover and synchronicity

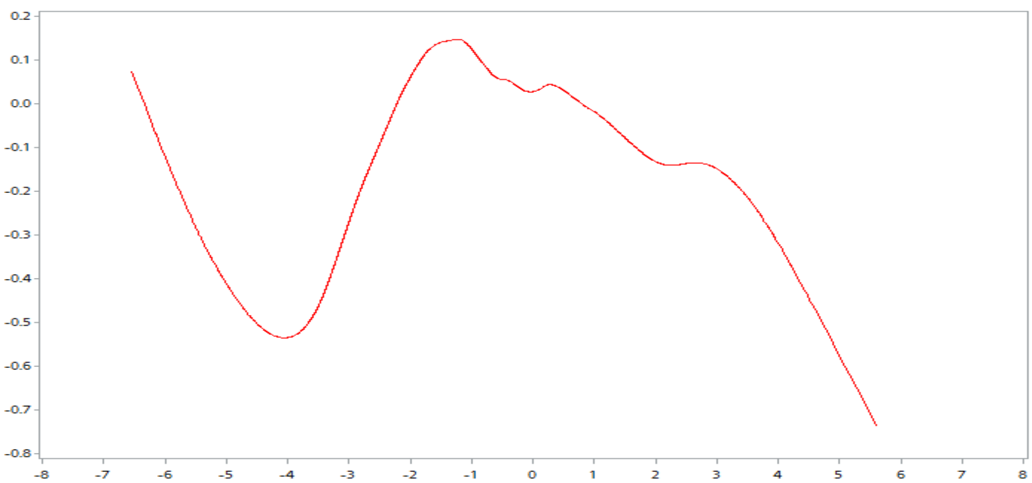
This figure plots the estimated functional form of $f(TURN)$ in the model:

$$SYN1_{i,t}\ (SYN2_{i,t}) = \beta_0 + \beta_1 f(TURN_{i,t}) + +\beta_2 \log(1 + ANALYST_{i,t}) + \beta_3 TURN_{i,t} * \log(1 + ANALYST_{i,t}) + \beta_4 SIZE_{i,t-1} + \beta_5 BM_{i,t-1} + \beta_6 VOLATILITY_{i,t} + \varepsilon_{i,t}$$

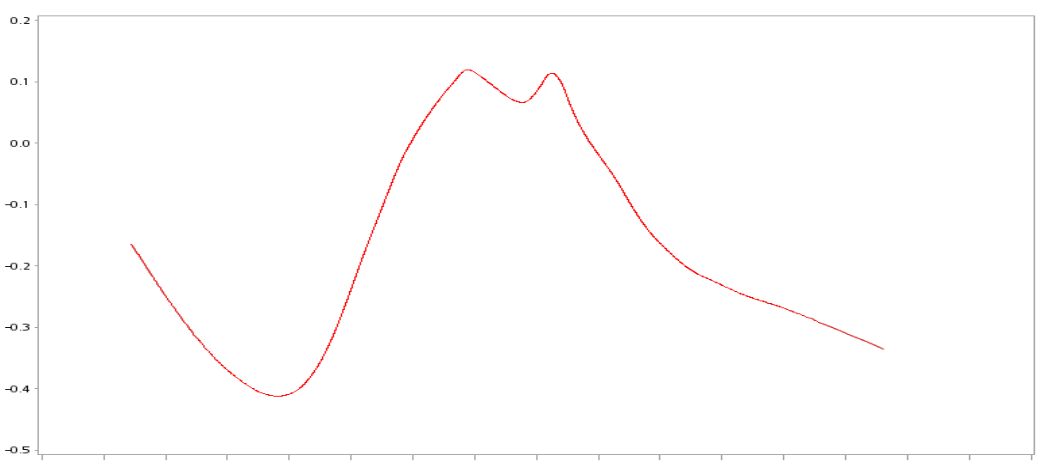
,

where *SYN1* refer to the stock price synchronicity measures, that is estimated using eq. (1), while *SYN2* refer to the same measure that is estimated using eq. (3). $\log(1 + ANALYST_{i,t})$ is the log of the number of analysts covering company *i* in year *t*, $TURN_{i,t}$ is the log of trading turnover of firm *i* inyear*t*, $SIZE_{i,t}$ is the log market capitalization of firm *i* at year *t*, $VOLATILITY_{i,t}$ is the standard deviation of the stock return of firm *i* in year *t*. The model is estimated using Yatchew's (1998) differencing method.

Panel A: $SYN1$



Panel A: $SYN2$



三、活動照片

報到並領取會議資料

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進行口頭報告