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Private information and corporate earnings: Evidence from big data

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Abstract

Utilizing multiple big-data sources, firm-level indices intended to track foot traffic to US retailer stores are constructed. The foot-traffic index significantly predicts quarterly sales growth, revenue surprises, earnings surprises, as well as excess returns around quarterly earnings announcements. The average excess return difference between stocks with high and low index values during the five-day period around earnings announcement dates is 3.44%. Using the index as a proxy for managerial private information, we find evidence that managers smooth earnings by increasing discretionary accruals amid high prospects for future revenues. However, announcement returns are negatively related with the level of discretionary accruals, implying investors downplay firm announcements when the level of discretionary accruals is high. In addition, the foot-traffic index for the period beginning after the fiscal-quarter end and ending prior to the earnings announcement date strongly predicts the post-earnings-announcement drift, implying that this anomaly is partly due to delayed arrival of new information rather than underreaction.

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1. Introduction

"Data is not information, information is not knowledge, knowledge is not understanding, understanding is not wisdom." – Clifford Stoll

The paper demonstrates that big data provide a valuable tool for financial economists to understanding of the information diffusion process around corporate earnings announcements. Big data, unstructured but containing anything from consumer/investor behavior and point of sales transactions of products and services offered online, is one of the fastest growing themes in many disciplines such as marketing and healthcare, but has not been utilized much in the finance literature. However, there are many anecdotes that sophisticated investors have begun to harness the power of big data. A consulting firm sells satellite images of construction sites in Chinese cities to hedge funds, with the goal of giving traders independent data so they don't need to rely on government statistics.[1] Hedge fund analysts hired consultants to count cars in retailers' car parks in order to project revenues during intense shopping seasons. And, a UBS analyst was reported to have purchased satellite images of Walmart car parks to estimate its business activity ahead of the release of its quarterly earnings (Ozik and Sadka, 2013). Thus, innovative investors have opportunity to achieve an informational edge by systematically obtaining and analyzing unique data to generate excess returns.

In addition to their benefits for the investment community, big data provide a unique opportunity for academic research on the information asymmetry and diffusion process. Such data sets contain information on firms' fundamentals, capturing sales volumes of firms' products and services, number of visitors to stores, thus eventually firms' revenue and earnings. Although firm insiders have access to this information in real time through their operational systems, investors do not have a tool that provides direct access to this information until it is publicly available through various news and corporate events, such as quarterly earnings announcements. Therefore, by analyzing the information content of big data regarding firms' fundamentals, researchers are able to reasonably estimate managerial private information, and study how managers utilize this information with respect to earnings management and how this information is impounded into stock prices.

[1] Hope, Bradley, (2014, Nov 20). Startups Mine Market-Moving Data From Fields, Parking Lots—Even Shadows. Wall Street Journal. Retrieved from http://www.wsj.com/articles

In this paper, we investigate the relation between managers' private information and earnings announcements and subsequent returns, utilizing proprietary data sources. We show that unstructured big data is a powerful source in predicting firm fundamentals and future returns. We construct a foot-traffic index for each firm, by estimating the amount of foot traffic to retail stores. We focus on US retail firms whose main revenue source is their retail stores. The innovation of this index is twofold. First, we are capturing activities of real economy that track consumption of customers, which therefore is correlated with the fundamental of the firms. Recently, social media has become a popular topic in financial studies. Our foot-traffic index is distinct from social media variables, because the index tracks real, as opposed to financial, activities. Second, since the management of a firm is most likely to collect the information on the firm fundamentals frequently, we can use the foot-traffic index to proxy managers' private information with respect to firms' future revenue and earnings.

We obtain the foot-traffic data pertaining to large US retailers collected from approximately 350 million mobile phones, tablets, as well as desktop computers. The foot-traffic is defined to be an event associated with consumer intention to visit a particular retail store. These events are counted and aggregated per retailer over quarter. For example, a search for driving direction to a geographical location of a Walmart store is counted toward the Walmart foot-traffic. Then, the foot-traffic index (FTI) for quarter t and firm i is obtained from the quarterly growth rate of the events, by taking log difference between the number of events aggregated over the quarter t and the quarterly average of the number of events aggregated over quarter $t-1$ to quarter $t-4$.

We focus on earnings announcements to examine managers' private information and its diffusion process. First, earnings announcement is most anticipated piece of events that all the market participants carefully watch and where the disagreement is resolved through newly released information. Second, earnings are arguably the single most important determinants for stock prices that investors follow. Therefore, there are strong incentives for corporate executives to manage earnings. For example, they may report higher earnings by increasing discretionary accruals, if the prospect for future earnings is high.

Our main results are following. First, we demonstrate the informativeness of the FTI. The foot-traffic index significantly predicts firms' fundamentals. R^2 from a regression of quarterly revenue growth on FTI is 39%. In addition, the FTI strongly predicts standardized unexpected revenue (SUR) and standardized unexpected earnings (SUE). The predictive power of the FTI for

SUE is statistically significant even after considering SUR and the persistence of SUE (Bernard and Thomas (1990), Abarbanell and Bernard (1992)).

The FTI also has strong predictive power for excess returns around quarterly earnings announcements. We calculate announcement returns in excess of the market return for the period between one day prior to the earnings announcement date and three days afterward. The average announcement return for stocks in the highest FTI quintile is 2.21%, while that for stocks in the lowest quintile is -1.24%, resulting in economically significant return differential of 3.44% for the five-day period between stocks with high and low FTI values.

After we establish the predictability of FTI for fundamentals and announcement returns, we reconstruct the foot-traffic index to proxy for managements' private information. Specifically, we use the FTI for the period beginning the fiscal-quarter $t+1$ and ending prior to the announcement date for quarter-t earnings, as a proxy for the private information with respect to the quarter $t+1$. The idea is that although this information is not required to be released during the earnings announcement for quarter t, insiders of firms have access to this information, collecting real-time through their operational system. Since the FTI has strong predictability for earnings and revenue, this measure is a valid proxy for managements' private information with respect to quarter $t+1$ and thus provide an interesting tool for studying behavior of informed insiders toward earnings announcements.

We examine how managements' expectation for quarter $t+1$ revenue and earnings, proxied by FTI, affect earnings for quarter t. Literature discusses about whether managers use their reporting discretion to signal private information (Subramanyam (1996), Louis and Robinson (2005)). Also, evidence shows that earnings management can be detected through investigating discretionary accruals (Dechow, Sloan, and Sweeney, 1995). Therefore, we study the relation between discretionary accruals for quarter t, estimated by the modified Jones (1991) model, and managers' expectation for quarter $t+1$. We find that regressions of discretionary accruals on FTI yield significant positive coefficients on FTI, implying that managers smooth earnings by increasing discretionary accruals amid high prospects for future revenues. However, evidence shows that investors do not take corporate earnings for granted as it is reported. Announcement returns are negatively related with the level of discretionary accruals, implying investors downplay firms' announcements when the level of discretionary accruals is high.

Finally, we use the FTI to study further how managements' private information is disseminated. Especially, we study the relation between post-earnings-announcement-drift (PEAD) and the private information proxied by FTI. We show that the proxy for private information strongly predicts the PEAD, implying that managements' private information is slowly diffused to market participants. This result suggests that PEAD is partly due to delayed arrival of new information rather than underreaction.

Our paper contributes to a few strands of the literature. First, a number of studies on social networks demonstrate the potential mechanisms by which private information is disseminated among investors. Literature provides evidence that such information flows through various channels, such as education networks (Cohen, Frazzini and Malloy, 2008, 2010), geographical proximity (Coval and Moskowitz (2001), Hong, Kubik, and Stein (2005)), and social interaction (Hong, Kubik, and Stein, 2004). Second, there is a growing literature on media coverage or social media. This strand of literature studies the relation between stock returns and investor sentiments or coverage intensity obtained by analyzing various media sources. Fang and Peress (2009) study media coverage and cross-section of stocks and show that high coverage stocks have lower cost of capital. Numerous studies apply textual analysis on media to extract the sentiment and relate it to firms' earnings and future returns (Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008), Loughran and McDonald (2011)). Chen, De, Hu, and Hwang (2015) use social media, such as Seeking Alphas, to obtain sentiments to predict earnings announcements and future returns. Bartov, Faurel, and Mohanram (2015) use Tweeter feeds to extract aggregate sentiments before earnings announcements. Da, Engleberg, and Gao (2011) shows that the google search volume is related with future stock returns and the subsequent reversal.

The approach of our paper, however, has major distinctions from previous works on social networks or media coverage, providing several advantages. First, the previous literature is mostly concerned about the relation between stock prices and investors' behavior towards information flows. Although investors' network connection or the sentiment of various media sources predict stocks returns, at least part of the relation between returns and those variables maybe due to investors' biases or irrational behaviors. For example, attention grabbing stocks provide higher short-term returns but display more significant return reversals (Da, Engleberg, and Gao, 2011). Contrary to the literature, our paper is the first to create a measure that is directly related with the real consumption activities in retail stores, which in turn is correlated with firms' fundamentals. Thus, the measure is likely to be independent from investors' sentiments in social media or their social networks.

Second, our FTI variable provides a unique experimental setting for studying information asymmetry with respect to fundamentals. Previous literature studies the information flow in investors' community and its effect on stock prices. Even though the private information on fundamentals may be disseminated through various channels, such as management connections or words of mouths, the media or social network variables cannot be considered as proxies for managers' private information. Our variable, on the contrary, directly measures fundamental activities that are not yet publicly announced, thus can proxy for managers' private information.

Our paper also adds to the literature on private information and earnings management. Subramanyam (1996) provides evidence that discretionary accruals are positively related with future returns, implying that managers use accruals to communicate their private information. Louis and Robinson (2005) argue that the accrual signal is perceived to be more credible by investors, if the signal is accompanied by other signals, such as stock splits. In addition, a few papers discusses about various managers' incentives, such as dividend smoothing, for earnings management (Kasanen, Kinnunen, and Niskanen (1996), Benard and Skinner (1996)). Studies on this topic typically examine the relation between the current accruals and future returns or operating performance, and deduce the information content of accruals from the observed relation. Compared to the literature, our approach is more explicit in measuring private information and provides more direct evidence. Our analysis shows that managers may use excess level of accruals to signal positive outlook, but it is regarded as opportunistic by investors.

Finally, our study has interesting implication for market efficiency. Traditional asset-pricing models assume that information is instantaneously incorporated into prices upon arrival. However, recent evidence shows that information production and its diffusion process takes place with a delay. For example, McLean and Pontiff (2015) show that investors learn about and trade against mispricing known to public through the publications of academic papers. Therefore, investors expand their knowledge base and utilize newly available information, implying that trading activities of sophisticated investors gradually increase market efficiency. The big data sources that we use in this paper are public in nature. However, generating information using those data is costly, since it requires human resources and computing power to extract useful information from the seemingly irrelevant data.[2] Therefore, big data suggests tremendous opportunity for innovative

[2]Grossman and Stiglitz (1980) introduce the concept of near efficiency, arguing that because information production

investors and for researchers on financial markets as well.

The paper is organized as follow. In the next section, we describe our sample and the main variable, the FTI. Section 3 provides evidence of predictability of FTI for fundamentals as well as returns. In Section 4, we study earnings management and announcement returns, using FTI as a proxy for private information. In Section 5, we provide our conclusion remarks.

2. Data and Variables

We use CRSP to obtain stock market variables, including stock returns, prices, and number of shares outstanding for the firms in our sample. IBES detail history file is used to obtain analyst forecasts and earnings announcement dates. And, firms' financial statements are obtained from Compustat.

2.1. Foot-Traffic Index

MKT MEDIASTATS, LLC shared their weekly foot-traffic data pertaining to the cross section of large US retailers for the time period of March 2009 to July 2014. The data is collected from millions of consumer devices, including approximately 350 million mobile phones, tablets, as well as desktop computers. However, the data only includes large big-box retailers whose main revenue source comes from their physical retail stores, and does not include online shops or other types of retailers, such as telecommunication companies or restaurants. Therefore, the sample consists of 50 US bog-box retail firms.

Table 1 provides the list of the firms in the sample, and their tickers and revenue as of year 2014. 29 firms in the sample makes the list of the top 100 US retailer by National Retail Federation (NRF), which includes private firms, online retailers, restaurants, and telecommunication companies, as well as big-box retailers. Total US revenue of the sample firms is $1.2 trillion as of 2014, and the average (median) revenue is $24.4 billion ($7.3 billion). The total revenue of the sample firms is more than 64% of total revenue of NRF 100 firms.

The foot-traffic data is records of specific types of events. Specifically, individual events are associated with consumer intention to visit a particular retail store. These events are counted and

is costly, prices only partially reflect information.

aggregated per retailer each week. For example, a search for driving direction to a geographical location of a Walmart store is counted toward the Walmart foot-traffic for the week. Some retailers have multiple brand name stores. For example, GAP has several brand name stores, including Gap, Banana Republic, Old Navy, Piperlime, Athleta and INTERMIX. Thus, the total events for GAP involves with the aggregation of all the events for each brand name stores.

Finally, the foot-traffic indices (FTI) are derived using the weekly foot-traffic data described above. First, individual events are aggregated over a quarter per firm. Then, the FTI for quarter t and firm i is obtained from the quarterly growth rate of the events over the previously four quarters, by taking log difference between the number of events aggregated over the quarter t and the quarterly average of the number of events aggregated over quarter $t-1$ to quarter $t-4$.[3]

Figure 1 illustrates an example of one of the data sources that are used to construct foot-traffic data. The first panel provides a daily time series of individual events pertaining to GAP locations over the period of Dec. 2012 to Nov. 2013, while the second panel shows the time series of events for the entire sample firms. These events are derived from data extracted from Andoid mobile devices in the United States. The figure shows that patterns observed are correlated with consumption. For example, the spikes of number of events in both panels coincides with holidays and weekends. Also, the mid-year spike in GAP indicates a mid-year sale event.

2.2. Variable Definitions and Summary Statistics

Table 2 shows the summary statistics of main variables. The variables are defined as follow; The quarterly revenue growth for firm i as of fiscal quarter t is calculated as $S_{i,t}/S_{i,t-1}-1$, where $S_{i,t}$ is the quarterly revenue as of fiscal quarter t for firm i; To estimate the standardized unexpected earnings (SUR), we assume that the revenue follows a seasonal random walk with a drift. Specifically, the SUR for stock i in quarter t is defined as $[(S_{i,t}-S_{i,t-4})-r_{i,t}]/\sigma_{i,t}$ where $\sigma_{i,t}$ and $r_{i,t}$ are the standard deviation and average, respectively, of $(S_{i,t}-S_{i,t-4})$ over the preceding eight quarters; The standardized unexpected earnings (SUE) is estimated as $(AE_{i,t}-FE_{i,t})/P_{i,t}$, where $AE_{i,t}$ is quarterly earnings per share announced for quarter t of stock i, $FE_{i,t}$ is mean analysts' forecasted EPS, and $P_{i,t}$ is quarter-end price; The announcement return is calculated as the return in excess over the market during the period of one day before the earnings announcement date and three

[3]Our results are robust to various way of calculating growth rate, for example, the growth rates of the number of events during quarter t over the number of events during quarter $t-1$.

days after the announcement date; The post-earnings-announcement-drift (PEAD) is the return of each firm in excess over the market for the period beginning on four days after the announcement dates for fiscal quarter-t earnings and ending on 60 days after the announcement dates.

Panel A shows the descriptive statistics of main variables, including the mean and standard deviations as well as quartiles of each variable. The FTI has slightly higher average, median, and standard deviation compared to revenue growth. The mean (median) of FTI is 0.034 (0.024) with the standard deviation of 0.316, while the revenue growth has the mean (median) of 0.027 (0.015) and standard deviation of 0.209. Announcement returns are positive on average, having the mean of 0.7% and the median of 0.3%. The average PEAD is also slightly positive being 0.2%, but the median of PEAD has a negative value of -0.2%.

Panel B reports correlations of the variables. The upper right corner of Panel B reports Pearson correlations and the lower left corner of the table provides Spearman's rank correlations. The FTI has significant and positive correlations with revenue growth, SUR, SUE, and announcement return. The correlation between FTI and PEAD is significantly positive at 10% level using Pearson correlation and 1% using Spearman's rank correlation. As expected, revenue growth and SUR have significantly positive correlations with SUE, and announcement returns, and a positive correlation with PEAD, implying that revenue growth and surprises are important sources for SUE and announcement returns, as well as post-earnings-announcement drift.

3. Predictability of FTI

In this section, we examine the informativeness of FTI in predicting firms' fundamentals. We create FTI with the intention of tracking customers' traffic to US retailers. We assume that this index is directly related with the real consumption activities in retail stores, which in turn is correlated with firms' sales and earnings. Thus, we test the validity of FTI as a predictor of revenue and earnings as well as announcement returns beyond the market expectation.

3.1. Sales and Earnings

Table 3 shows the predictability of FTI for revenue growth and surprises. Panel A shows the regressions of the quarterly revenue growth on the quarterly foot-traffic index (FTI). Models (1) to (4) show the results of pooled time-series cross-sectional regressions. For Models (2) to (4), we include time (year-quarter) fixed effect, firm fixed effect, and both time and firm fixed effect. Model (5) shows the result of Fama-MacBeth regressions. Specifically, each quarter, we estimate cross-sectional regressions of revenue growth on FTI. Then we calculate the time-series average of coefficients of regressions and its t-value. For Models (1) to (4), we report the adjusted R^2, while the average R^2 is reported for Model (5). The sample consists of firm-quarters of US retailers with fiscal quarter ending between March 2009 and July 2014.

Panel A shows a strong predictability of FTI for revenue growth. The simple regression (Model 1) shows that R^2 of the regression is 39%. The FTI has a coefficient of 0.4 with a significant t-value of 24, implying that 1% increase in FTI is associated with 0.4% increase in revenue. This predictability is robust to firm and time fixed effects. Fama-MacBeth regression in Model (5) also shows consistent results. The average R^2 of each cross-sectional regression is 23%. The magnitude of coefficient is somewhat smaller being 0.29, but showing a significant t-value of 8.62.

Figure 2 shows the results of Table 3 graphically. The figure scatter-plots revenue growth on foot-traffic index. The vertical axis is revenue growth and the horizontal axis is foot-traffic index. The red line is the predicted value of revenue growth using foot-traffic index. As in Table 3, the slope of the fitted line is less than one, which implies that not all traffic to stores leads to actual consumption. However, the scatter plot shows a strong correlation, confirming the predictability of revenue growth using FTI.

FTI also has a strong predictability for revenue surprises. Panel B reports the results of regressions of the SUR on the foot-traffic index. We use the same specifications as in Panel A, except for using SUR as a dependent variable. The significant coefficients are robust to firm and time fixed effects. For example, the specification with both time and firm fixed effect (Model 4) yields a coefficient of positive 0.7 on FTI with a t-value of 2.92. Fama-MacBeth regression model provides very similar results, implying that the predictability of FTI is unlikely due to specific periods in time or unobserved firm characteristics.

Now, we examine earnings and FTI. Table 4 shows that FTI has a predictive power for earnings, beyond revenue surprises. Model (1) shows the result of simple regression of SUE on FTI. FTI enters the model with a significant and positive coefficient with t-value of 2.32. In Model (2), we analyze the effect of revenue surprises on earnings surprises. Jagadeesh and Livnat (2006) shows that stock price reaction on the earnings announcement date and drift after announcements is significantly related to revenue surprises. Ertimur, Livnat, and Martikainen (2003) study different sources of earnings surprises and find that investors value more highly revenue surprise than expense surprise. Consistent with these studies, we find that SUR is highly correlated with SUE, implying SUR is important source of earnings surprises.

Model (3) includes both FTI and SUR. Although the magnitude of both SUR and FTI become slightly smaller, both variables remain statistically significant. Model (4) controls the lag of SUE to address the persistence of SUE (Bernard and Thomas 1989, 1990, Arbarnell and Bernard, 1992). Consistent with previous literature, the SUE at $t-1$ has a positive relation with the current SUE. However, the lag of SUE do not subsume FTI and SUR, both of which remain statistically significant.

Models (5) to (8) examine whether time-specific effects or firm-specific heterogeneity drive the results. Specifically, we add time and firm fixed effects or use Fama-MacBeth method. The results are generally robust except for the Fama-McBeth regressions. For example, regression of SUE on FTI and SUR as well as time and firm fixed effects (Model 7) provides the coefficient of 0.172 with a t-value of 2. Interestingly, after the significance of lagged SUE is not robust to various specifications, implying that the persistence of SUE is trivial in our sample. Overall, the analysis in Table 4 shows the predictability of earnings surprises using FTI.

3.2. Return Predictability

Now, we turn our attention to announcement returns. Table 5 examines the return predictability of FTI around earnings announcements. We use five-day event window around earnings announcement beginning one day prior to the announcement date and ending three days afterward. Berkman and Troung (2009) document that the proportion of Russell 3000 firms which make after-hours earnings announcements is more than 40%. For after-hours announcements, earnings related price changes are not observed on day 0 but observed on day one. Therefore, we choose this period to make sure there is enough time for stock prices to capture all the price changes due to announcements.[4]

Panel A shows the average announcement returns during the event window by quintiles of foot-traffic index (FTI). Returns are calculated in excess of the market returns of the corresponding

[4]Choosing different event windows does not alter the main results.

periods. Quintiles of FTI are calculated using the following process. In month t, we group the firms that have fiscal quarter ending during the three-month rolling period starting month $t-2$ and ending t. Using the group of firms, we rank the firms based on FTI to obtain quintile cutoff values. Then, we use the quintile cutoff values to assign quintile ranks for the firms that have fiscal quarter ending in month t. Thus, each quintile can have different number of events. We follow this process to make sure that we pool all the firms in our sample in ranking firms in quintiles. Different ways to assign quintile scores – for example, each month t, rank firms only using firms that have fiscal quarter end at t – does not change our results.

Panel A shows the significant relation between FTI and announcement returns. The average announcement returns are monotonic with the quintiles of FTI. The average return around the earnings announcements of firms in the lowest quintile is negative 1.24%, and statistically significant at 10% level. On the contrary, the average announcement returns of quintile 4 and 5 are 1.69% and 2.21%, respectively, and both are statistically significant at 1% level. The last column of the panel shows the result of hypothesis testing for the mean difference between highest and lowest quintiles. The difference between the highest and the lowest quintile is 3.44% for the five-day holding period, and this is not only statistically significant with t-value of 3.45, but also economically significant.

In Panel B, we take a regression approach to address the concern whether specific time period or small group of firm drive the return predictability. Thus, we estimate various regression models of announcement returns on foot-traffic index. Models (1) to (4) show the results of pooled regressions, while Model (5) uses the method of Fama-MacBeth. For Models (1) to (4), we report the adjusted R^2, while the average R^2 is reported for Model (5).

Consistent with Panel A, results in Panel B show there is a significant relation between announcement returns and FTI. In Model (1), FTI enters the regression with a significant positive coefficient of 0.035 with a t-value of 3.86. This significant predictability of FTI for announcement returns is robust to time (year-quarter), firm, and both time and firm fixed effects. The Fama-MacBeth regression model also gives consistent results. The magnitudes of the coefficients on FTI from all the specifications are very similar around 0.035. This is economically significant, implying that an one standard deviation increase in FTI is related with about an 1.1% increase in announcement return.

The informativeness of FTI in predicting announcement returns is apparent in Figure 3. The figure plots the average buy-and-hold returns during the event window from 10 days prior to the earnings announcement date (day 0) to 10 days afterward. Returns are calculated in excess of the market returns of corresponding periods. The first panel shows the average buy-and-hold return of firms in the lowest quintile, while the second panel shows the results of the highest quintile. The graph shows the power of FTI as a predictor of earnings surprises. The pattern of event time returns for firms in the lowest quintile is strikingly contrasting to that of firms in the highest quintile. There is a statistically significant negative jump around announcement dates for firms in the lowest quintile, while there is a positive jump around announcements for firms in quintile five. This result reinforces the predictive power of FTI for earnings surprises and announcement returns.

4. Earnings Management, Private Information, and Its Dissemination

Previously, we demonstrate that FTI is strongly correlated with firms' fundamentals, thus has strong predictive power for earnings surprises and announcement returns. In this section, we examine how managements' expectation for quarter $t + 1$ affect quarter-t earnings, using FTI as a proxy for managers' private information. Due to this predictability for firms' fundamentals, FTI can be a reliable proxy for managers' expectation with respect to the quarter $t + 1$. And, the reliability of FTI as proxy for managers' private information provide unique opportunity for studying managerial behavior toward earnings reports.

4.1. Earnings Management and Private Information

we reconstruct the foot-traffic index to proxy managers' private information on firms' future revenue and earnings. Specifically, we use the FTI for the period beginning the fiscal-quarter $t + 1$ and ending prior to the announcement date for quarter-t earnings, as a proxy for the private information of management with respect to the quarter $t + 1$. We denote this newly constructed foot-traffic index for this period as PI. Thus, PI is calculated the growth rate of the weekly average number of foot traffic during the pre-announcement period over the weekly average foot traffic during past 12-month period. Since the management of a firm collects the information on the firm's fundamentals real-time through their operational system and owing to the predictability of FTI, it is reasonable to assume that PI is reliably correlated with managers' expectation for quarter

$t+1$. Although the information content of PI is not required to be released during the earnings announcement for quarter t, insiders of firms have access to this information at the time of earnings announcement. Thus, investigating the PI and announced earnings provides useful insights on managerial behavior toward earnings announcements.

A few papers investigate whether discretionary accruals are managers' tool to communicate their private information, or simply opportunistic and mislead investors (For example, Subramanyam (1996) and Louis and Robinson (2005)). Therefore, we study the relation between discretionary accruals for quarter t and managers' expectation for quarter $t+1$, proxied by PI. Each quarter, discretionary accruals are estimated following the modified Jones (1991) model from a cross-section regression as follow.[5]

$$TA_{i,t} = \alpha_0 + \alpha_1(1/A_{i,t-1}) + \alpha_2(\Delta REV_{i,t} - \Delta REC_{i,t}) + \alpha_3 PPE_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $TA_{i,t}$ is total accruals of firm i at t scaled by lagged total assets; $A_{i,t-1}$ is total assets at $t-1$; $PPE_{i,t}$ is gross property plant and equipment in quarter t scaled by total assets at $t-1$; $\Delta REV_{i,t}$ is the change in revenue from quarter $t-1$ to t scaled by total asset at $t-1$; and $\Delta REC_{i,t}$ is net receivables in quarter t less net receivables in $t-1$ scaled by total assets at $t-1$. The discretionary accruals for firm i at quarter t is obtained from the residuals of the regressions, $\varepsilon_{i,t}$.

Table 6 reports the regression results of discretionary accruals (DA) on the proxy for managements' private information (PI) and other control variables. Model (1) shows the result of a simple regression of DA on FTI, and suggest that FTI for quarter t is not significantly related with the level of discretionary accruals. The insignificance of FTI is sensible because FTI is strongly correlated with revenue growth and the revenue growth is already accounted for when discretionary accruals are estimated. Model (2) regresses DA on PI. PI enters the model with a significant and positive coefficient with a t-value of 2.84. This implies that managers tend to borrow from future earnings to increase the current earnings if they have high expectation for the next quarter. On the contrary, managers reduce the current earnings to smooth future earnings if their expectation is low.

Model (3) includes both FTI and PI, and provides the consistent result with the previous specifications. As in the first two models, FTI is indistinguishable from zero while PI is significantly

[5]We use the modified Jones model, because Dechow, Sloan, and Sweeney (1995) show that the model exhibits the most power in detecting earnings management. Analysis using the Jones model provides similar results.

positive. For Models (4) to (6), we control SUE, lags of SUE and FTI, and SUR. None of variables enter with significant coefficient except PI, which stays significantly positive even after controlling earnings and revenue surprises. Model (7) to (10) are the same specification as Model (3), but include fixed effects or use Fama-MacBeth model. Significance of PI is robust to these specifications.

In sum, Table 6 shows that regressions of discretionary accruals on PI yield significant positive coefficients on PI, and the significance of PI is robust to various specifications. This implies that managers smooth earnings by increasing (decreasing) discretionary accruals amid high (low) prospects for the next quarter. Since discretionary accruals are related with strong fundamentals for the next quarter, this is consistent with the notion that managers use discretionary accruals to signal private information, rather than simply being opportunistic.

If discretionary accruals are the tools that managers use to signal their private information, then the question that follows is how investors react to this signals? First, are investors able to identify managerial signals and decompose discretionary accruals from the reported earnings? Second, do investors takes discretionary accruals as optimistic signals or managerial opportunism? We try to answer these questions in Table 7 by extending the regression models in Table 5. Specifically, the following regression model is estimated.

$$AR_{i,t} = \alpha + \beta_1 FTI_{i,t} + \beta_2 PI_{i,t+1} + \beta_3 DA_{i,t} + \gamma^{'} \mathbf{X}_{i,t} + \varepsilon_{i,t} \tag{2}$$

where $AR_{i,t}$ is the announcement return for firm i and quarter t, and is calculated as the return in excess over the market during the period of one day before the earnings announcement date and three days after the announcement date; $FTI_{i,t}$ the foot-traffic-index for quarter t; $PI_{i,t+1}$ is the proxy for managers' private information for quarter $t+1$, measured prior to the announcement dates for quarter t; and $\mathbf{X}_{i,t}$ is the control variables.

First, we comment on control variables. Size is the natural logarithm of the market capitalization as of fiscal quarter-t end. BE/ME is the natural logarithm of the book-to-market ratio as of the most recent fiscal year ending at least three month prior to fiscal quarter-t end. PastReturn is the cumulative return in excess over the market from thirty to three days prior to the earnings announcement. Consistent with literature, size has significant and negative coefficients and the relation is robust to various specifications. BE/ME has positive coefficients and they are significant for the most specifications. PastReturn is negatively related with announcement return, albeit often insignificant, implying that there is return reversal after announcements. This is consistent with the notion that market makers demand higher expected returns (thus, higher return reversal) around earnings announcements (So and Wang, 2014). Overall, examining control variables suggests that our sample, despite of small size, share the common characteristics of asset pricing relation with bigger samples of other finance researches.

Now, we turn our attention to main explanatory variables. Consistent with Table 5, FTI has a positive and significant relation with announcement returns even after various firm characteristics, SUE, and SUR are controlled for, and this positive relation is robust to various specifications. Interestingly, PI enters the regression models with a significant and negative coefficient. However, the significance disappears when time and firm fixed effects are included. Most importantly, DA has a negative and significant coefficient consistently throughout different specifications, implying that investors do not take earnings announcements favorably if the level of DA is high. This suggests that although discretionary accruals may be valid signals by managers for future fundamentals, it is regarded as rather opportunistic and misleading by investors.

For Model (7) includes contemporaneous SUE and SUR. As expected, SUE and SUR both are significantly related with announcement returns. For the most specifications, however, we exclude SUE and SUR to examine the pure effect of FTI, PI, and DA, since FTI and PI as well as DA affect the level of SUE and SUR. We also control the lags of SUE and FTI to address the persistence of earnings surprises (Bernard and Thomas, 1990). Lag of FTI enters the regressions with a negative coefficient, but is insignificant for the most specifications. Lagged SUE also has a negative coefficient, although the negative coefficient is not robust to various specifications.

In sum, Table 7 shows that investors take corporate earnings announcements critically and are able to detect the level of earnings management from reported earnings. The only variables that have consistently significant throughout various specifications are FTI and DA. FTI is positively related with announcement returns, while announcement returns are negatively related with the level of discretionary accruals. This implies that while price reactions to announcements are justified by the changes in fundamentals but investors downplay firms' announcements when the level of discretionary accruals is high. Thus, at least around earnings announcements, investors see discretionary accruals as managerial opportunism rather than a positive signal for future fundamentals.

4.2. Post-Eearnings-Announcement-Drift

In this section, we study the diffusion of managers' private information. Previously, we show that despite a positive correlation of discretionary accruals and managers' expectation for future earnings and revenue, investors do not take discretionary accruals as favorable news. So, stock price reaction around earnings announcements do not reflect managers' private information, even though managers may signal this using excess level of discretionary accruals. Thus, we examine when managers' private information is disseminated to investors and reflected in stock prices, by investigating stock price movement after earnings announcements.

Table 8 reports the regression results of the post-earnings-announcement-drift (PEAD) on FTI, PI, DA and other control variables. PEAD is defined as the return of each firm in excess over the market for the period beginning on four days after the announcement dates for fiscal quarter-t earnings and ending on 60 days after the announcement dates.

Model (1) shows that FTI is positive and significant at 10% level, while Model (2) displays a significant and positive coefficient on PI. However, Model (3) shows that FTI is subsumed by PI, while PI remains statistically significant. Thus, managers' private information on quarter $t + 1$ is not immediately observed by investors at earnings announcement dates, but is gradually disseminated to investors and reflected in stock prices over an extended period of time.

Models (4) and (5) study the relation between PEAD and SUE and SUR. We include lags of SUE and SUR, since various studies show that lags of SUE and SUR have predictive power for PEAD (Bernard and Thomas (1990), Jagadeesh and Livnat (2006)). As expected both SUE and SUR have positive coefficients although SUE is not significant for some specifications. Interestingly, that Lagged SUE and SUR have negative coefficient despite positive auto-correlations of these variables. However, the significance is not robust to fixed effects, or Fama-MacBeth method (Models 9 and 10). Model (6) control DA. Despite insignificance of DA, controlling DA somewhat weakens PI, indicating a positive correlation between DA and PI, as reported in Table 5. However, PI enters regression models with a significant and positive coefficient, when controlling DA with other variables and fixed effects.

Model (7) includes all the explanatory variables except DA. The result shows that PI and SUE remain significantly positive. We may interpret this result consistent with both underreaction and near market efficiency (Grossman and Stiglitz, 1980). On one hand, the observed predictability of

SUE is consistent with the underreaction explanation for PEAD. On the other hand, the positive coefficient on PI implies a rational process where prices perform a role in conveying information from the informed to the uninformed. Grossman and Stiglitz (1980) introduce the concept of near efficiency where prices reflect the information of informed individuals but only partially, so that those who expend resources to obtain information do receive compensation. The significant and positive relation between PI and PEAD is consistent with this explanation, implying that PEAD is at least partly due to new information with respect to the next quarterly earnings.

Overall, Table 8 shows that across various specifications, PI is the most consistent variables in predicting PEAD. These results suggest that there may be underreaction of investors with respect to earnings announcements, but also part of PEAD may be due to the dissemination of new information. We show previously that although there is evidence that managers signal their private information through the excess level of accruals, this signal is unfavorably met by investors, fails to be priced immediately. However, managers' private information is gradually diffused and reflected in stock prices over an extended period of time.

5. Conclusion

In this paper, we study the relation between managers' private information and its diffusion process utilizing a proprietary data set constructed from multiple sources of big data. First, we demonstrate the usefulness of the data set in predicting firms' fundamentals and future returns. We construct firm-level foot-traffic indices for US retail stores and show that the FTI has strong predictive power for revenue surprises, earnings surprises, and excess returns around quarterly earnings announcements. We show that there is a significant return differential of 3.44% around earnings announcement dates between high and low FTI firms.

Second, we show that our FTI measure provides a practical setting to study the information asymmetry and diffusion process. We use FTI as proxy for managers' private information and study their behavior toward earnings announcements. We provide evidence that managers smooth earnings through discretionary accruals amid high prospects for future revenues. Although discretionary accruals may be considered as a signal of managers' private information, our analysis suggests that discretionary accruals are regarded as opportunistic by investors.

Finally, we study post-earnings-announcement-drift to further study the diffusion process of managers' private information. We show that the proxy for private information strongly predicts the PEAD, implying that managements' private information is slowly diffused to market participants. This result suggests that PEAD is partly due to delayed arrival of new information.

References

Abarbanell, Jeffry S. and Victor L. Bernard, 1992, Tests of Analysts' Overreaction/Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behavior, *Journal of Finance* 47, 1181–1207.

Bartov, Eli, Lucile Faurel, and Partha Mohanram, 2015, Can Twitter Help Predict Firm-Level Earnings and Stock Returns?, *Working paper*.

Berkman, Henk and Cameron Troung, 2009, Event Day 0? After-Hours Earnings Announcements, *Journal of Accounting Research* 47, 71–103

Bernard, Victor L., and Douglas J. Skinner, 1996, What motivates managers' choice of discretionary accruals?, *Journal of Accounting and Economics* 22, 313–325.

Bernard, Victor L., and Jacob K. Thomas, 1989, Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?, *Journal of Accounting Research* 27, 1–36.

Bernard, Victor L., and Jacob K. Thomas, 1990, Evidence That Stock Prices Do Not Fully Reflect The Implications of Current Earnings For Future Earnings, *Journal of Accounting and Economics* 13, 305–304.

Chen, Hailiang, Prabuddha De, Yu Hu, and Byoung-Hyoun Hwang, 2015, Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media, *Review of Financial Studies*, forthcoming.

Cohen, Lauren, Andrea Frazzini and Christopher Malloy, 2008, The Small World of Investing: Board Connections and Mutual Fund Returns, *Journal of Political Economy* 116, 951–979.

Cohen, Lauren, Andrea Frazzini and Christopher Malloy, 2010, Sell-Side School Ties, *Journal of Finance* 65, 1409–1437.

Coval, Joshua D. and Tobias J. Moskowitz, 2001, The Geography of Investment: Informed Trading and Asset Prices, *Journal of Political Economy* 109, 811–841.

Da, Zhi, Joseph Engleberg, and Pengjie Gao, 2011, In Search of Attention, *Journal of Finance* 66, 1461–1499.

Dechow, Patricia M., Richard G. Sloan, and Amy P. Sweeney, 1995, Detecting Earnings Management, *The Accounting Review* 70, 193–225.

Ertimur Yonca, Joshua Livnat, and Minna Martikainen, 2003, Differential Market Reactions to Revenue and Expense Surprises, *Review of Accounting Studies* 8, 185–211

Fang, Lily and Joel Peress, 2009, Media Coverage and the Cross-section of Stock Returns, *Journal of Finance* 64, 2023–2052.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393–408.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2004, Social Interaction and Stock-Market Participation, *Journal of Finance* 59, 137–163.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2005, Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers, *Journal of Finance* 60, 2801–2824.

Hope, Bradley, 2014, Nov 20., Startups Mine Market-Moving Data From Fields, Parking Lots—Even Shadows, *Wall Street Journal*.

Jagadeesh, Narasimhan and Joshua Livnat, 2006, Revenue Surprises and Stock Returns, *Journal of Accounting and Economics* 41, 147–171.

Jagadeesh, Narasimhan and Joshua Livnat, 2006, Post-Earnings-Announcement Drift: The Role of Revenue Surprises, *Financial Analysts Journal* 62, 22–34.

Jones, Jennifer J., 1991, Earnings Management During Import Relief Investigations, *Journal of Accounting Research* 29, 193–228.

Kasanen, Eero, Juha Kinnunen, and Jyrki Niskanen, 1996, Dividend-based earnings management: Empirical evidence from Finland, *Journal of Accounting and Economics* 22, 283–312.

Loughran, Tim and Bill McDonald, 2011, When is a liability not a liability? textual analysis, dictionaries, and 10-ks, *Journal of Finance* 66, 35–65.

Louis, Henock and Dahlia Robinson, 2005, Do managers credibly use accruals to signal private information? Evidence from the pricing of discretionary accruals around stock splits, *Journal of Accounting and Economics* 39, 361–380.

McLean R. David and Jeffrey Pontiff, 2015, Does Academic Research Destroy Stock Return Predictability?, *Journal of Finance*, forthcoming.

Ozik, Gideon and Ronnie Sadka, 2013, Big data and information edge, *Hedge Funds Review* December 2013/January 2014, 32–34.

So Eric C., and Sean Wang, 2014, News-driven Return Reversals: Liquidity Provision Ahead of Earnings Announcements, *Journal of Financial Economics* 114, 20–35

Subramanyam K.R., 1996, The pricing of discretionary accruals, *Journal of Accounting and Economics* 22, 249–281.

Tetlock, Paul C., 2007, Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62, 1139–1168.

Tetlock, Paul C., Maytal Saar-Tsechansky, and Sofus Macskassy, 2008, More Than Words: Quantifying Language to Measure Firms' Fundamentals, *Journal of Finance* 63, 1437–1467

Table 1: Sample Firms

This table provides the list of firms in the sample, their tickers, headquarter locations, and US sales amounts as of 2014. US sales amounts are obtained from National Retail Federations and Yahoo! Finance.

No	Ticker	Name	HQ	US Retail Sales (Million)
1	AEO	American Eagle Outfitters, Inc.	Pittsburgh, PA	3,282.9
2	ANF	Abercrombie & Fitch Co.	New Albany, OH	3,744.0
3	ANN	Ann Inc.	New York, NY	2,533.5
4	ASNA	Ascena Retail Group Inc.	Suffern, NY	4,713.0
5	BBBY	Bed Bath & Beyond Inc.	Union, NJ	11,708.0
6	BBY	Best Buy Co., Inc.	Richfield, MN	35,957.0
7	BIG	Big Lots Inc.	Columbus, OH	5,177.0
8	CASY	Casey's General Stores, Inc.	Ankeny, IA	7,767.2
9	CHS	Chico's FAS Inc.	Fort Myers, FL	2,675.2
10	COST	Costco Wholesale Corporation	Issaquah, WA	79,694.0
11	CVS	CVS Health Corporation	Woonsocket, RI	67,974.0
12	DDS	Dillard's Inc.	Little Rock, AR	6,490.0
13	DKS	Dick's Sporting Goods Inc.	Coraopolis, PA	6,811.0
14	DLTR	Dollar Tree, Inc.	Chesapeake, VA	8,390.0
15	DSW	DSW Inc.	Columbus, OH	2,496.1
16	EXPR	Express Inc.	Columbus, OH	2,165.5
17	FDO	Family Dollar Stores Inc.	Matthews, NC	10,489.0
18	GES	Guess' Inc.	Los Angeles, CA	2,417.7
19	GNC	GNC Holdings Inc.	Pittsburgh, PA	2,613.2
20	GPS	The Gap, Inc.	San Francisco, CA	13,071.0
21	HD	The Home Depot, Inc.	Atlanta, GA	74,203.0
22	HTSI	Harris Teeter Supermarkets Inc.	Matthews, NC	4,710.0
23	JCP	J. C. Penney Company, Inc.	Plano, TX	12,184.0
24	JOSB	Joseph A. Bank Clothiers, Inc.	Hampstead, MD	3,252.5
25	JWN	Nordstrom Inc.	Seattle, WA	13,259.0
26	KORS	Michael Kors Holdings Limited	London, UK	4,371.5
27	KR	The Kroger Co.	Cincinnati, OH	103,033.0
28	KSS	Kohl's Corp.	Menomonee Falls, WI	19,023.0
29	LL	Lumber Liquidators Holdings, Inc.	Toano, VA	1,047.4
30	LB	L Brands	Columbus, OH	10,303.0
31	M	Macy's, Inc.	Cincinnati, OH	28,027.0
32	MW	The Men's Wearhouse, Inc.	Houston, TX	3,252.5
33	PIR	Pier 1 Imports, Inc.	Fort Worth, TX	1,865.8
34	RAD	Rite Aid Corporation	Camp Hill, PA	26,528.0
35	RH	Restoration Hardware Holdings, Inc.	Corte Madera, CA	1,867.4
36	ROST	Ross Stores Inc.	Pleasanton, CA	11,032.0
37	SHLD	Sears Holdings Corporation	Hoffman Estates, IL	25,763.0
38	SIG	Signet Jewelers Limited	Hamilton, Bermuda	5,736.3
39	SKS	Saks Inc.	New York City, NY	3,147.6
40	SVU	SUPERVALU Inc.	Eden Prairie, MN	11,499.0
41	SWY	Safeway Inc.	Pleasanton, CA	36,330.0
42	TFM	The Fresh Market, Inc.	Greensboro, NC	1,753.2
43	TGT	Target Corp.	Minneapolis, MN	72,618.0
44	TIF	Tiffany & Co.	New York, NY	4,249.9
45	TJX	The TJX Companies, Inc.	Framingham, MA	22,206.0
46	URBN	Urban Outfitters Inc.	Philadelphia, PA	3,323.1
47	WBA	Walgreens Boots Alliance, Inc.	Deerfield, IL	72,671.0
48	WFM	Whole Foods Market, Inc.	Austin, TX	13,642.0
49	WMT	Wal-Mart Stores Inc.	Bentonville, AR	343,624.0
50	WSM	Williams-Sonoma Inc.	San Francisco, CA	4,591.0
			Total	1,219,282.4
			Average	24,385.6
			Median	7,289.1

Table 2: Summary Statistics

Panel A shows the descriptive statistics of main variables, and Panel B reports correlations. The upper right corner of Panel B reports Pearson correlations and the lower left corner of the table provides Spearman correlations. The quarterly revenue growth for firm *i* as of fiscal quarter *t* is calculated as $S_{i,t}/S_{i,t-1}$ minus one, where $S_{i,t}$ is the quarterly revenue as of fiscal quarter *t* for firm *i*. The SUR for stock *i* in quarter *t* is calculated as $[(S_{i,t} – S_{i,t-4}) – r_{i,t}]/\sigma_{i,t}$ where $\sigma_{i,t}$ and $r_{i,t}$ are the standard deviation and average, respectively, of $(S_{i,t} – S_{i,t-4})$ over the preceding eight quarters. The SUE is estimated as $(AE_{i,t} – FE_{i,t}) /P_{i,t}$, where $AE_{i,t}$ is quarterly earnings per share announced for quarter *t* of stock *i*, $FE_{i,t}$ is mean analysts' forecasted EPS, and $P_{i,t}$ is quarter-end price. The announcement return is calculated as the return in excess over the market during the period of one day before the earnings announcement date and three days after the announcement date. The post-earnings-announcement-drift (PEAD) is the return of each firm in excess over the market for the period beginning on 4 days after the announcement dates for fiscal quarter-*t* earnings and ending on 60 days after the announcement dates. p-values of correlations are reported in square brackets.

Panel A: Descriptive Statistics

Variable	FTI	Rev. Growth	SUR	SUE	Ann. Return	PEAD
N	918	894	890	869	918	914
Mean	0.0336	0.0271	0.0194	0.0011	0.0066	0.0018
Std Dev	0.3164	0.2091	1.6619	0.0073	0.0887	0.1290
25^{th} Pctl	-0.0960	-0.0723	-0.8717	0.0000	-0.0409	-0.0762
Median	0.0237	0.0148	0.0950	0.0005	0.0028	-0.0017
75^{th} Pctl	0.1675	0.1174	0.9837	0.0016	0.0519	0.0678

Panel B: Correlations

	FTI	Rev. Growth	SUR	SUE	Ann. Return	PEAD
FTI		0.628	0.140	0.082	0.127	0.064
		[0.000]	[0.000]	[0.013]	[0.000]	[0.054]
Rev. Growth	0.627		0.232	0.086	0.164	0.051
	[0.000]		[0.000]	[0.010]	[0.000]	[0.131]
SUR	0.137	0.205		0.069	0.175	0.067
	[0.000]	[0.000]		[0.039]	[0.000]	[0.046]
SUE	0.065	0.099	0.235		0.059	0.111
	[0.048]	[0.003]	[0.000]		[0.076]	[0.001]
Ann. Return	0.154	0.164	0.126	0.261		0.066
	[0.000]	[0.000]	[0.000]	[0.000]		[0.046]
PEAD	0.091	0.046	0.051	0.054	0.035	
	[0.006]	[0.173]	[0.126]	[0.103]	[0.286]	

Table 3: Regressions of Revenue growth and SUR on Foot-traffic Index

Panel A shows the regressions of the quarterly revenue growth on the quarterly foot-traffic index (FTI). Panel B reports the results of regressions of the standardized unexpected revenue (SUR) on the foot-traffic index. The quarterly revenue growth for firm *i* as of fiscal quarter *t* is calculated as $S_{i,t}/S_{i,t-1}$ minus one, where $S_{i,t}$ is the quarterly revenue as of fiscal quarter *t* for firm *i*. The SUR for stock *i* in quarter *t* is calculated as $[(S_{i,t} - S_{i,t-4}) - r_{i,t}]/\sigma_{i,t}$ where $\sigma_{i,t}$ and $r_{i,t}$ are the standard deviation and average, respectively, of $(S_{i,t} - S_{i,t-4})$ over the preceding eight quarters. Models (1) to (4) show the results of pooled regressions, while Model (5) shows the result of Fama-MacBeth regressions. Adjusted R^2 (for pooled regressions) and the average R^2 (for Fama-MacBeth regressions) are reported. The sample includes firm-quarters of US retailers with fiscal quarter ending between March 2009 and July 2014.

Panel A: Regressions of Revenue Growth on FTI

Model	(1)	(2)	(3)	(4)	(5)
Coefficient	0.414	0.307	0.417	0.310	0.290
t value	[24.11]	[15.12]	[23.67]	[14.74]	[8.62]
Adj (Average) R^2	39.38%	47.03%	37.07%	44.98%	23.33%
Fixed Effect	N	Time	Firm	Firm+Time	Fama-MacBeth

Panel B: Regressions of SUR on FTI

Model	(1)	(2)	(3)	(4)	(5)
Coefficient	1.155	0.800	1.128	0.706	0.795
t value	[5.33]	[3.43]	[5.06]	[2.92]	[2.24]
Adj (Average) R^2	2.98%	18.93%	4.11%	21.07%	3.78%
Fixed Effect	N	Time	Firm	Firm+Time	Fama-MacBeth

Table 4: Regression of SUE on Quarterly FTI

This table reports the regression results of standardized unexpected earnings (SUE) on the quarterly foot-traffic index (FTI). The SUE is estimated as $(AE_{i,t} - FE_{i,t}) / P_{i,t}$, where $AE_{i,t}$ is quarterly earnings per share announced for quarter *t* of stock *i*, $FE_{i,t}$ is mean analysts' forecasted EPS, and $P_{i,t}$ is quarter-end price. Firm quarters with stock prices below $5 are excluded. The SUR for stock *i* in quarter *t* is calculated as $[(S_{i,t} - S_{i,t-4}) - r_{i,t}]/\sigma_{i,t}$ where $\sigma_{i,t}$ and $r_{i,t}$ are the standard deviation and average, respectively, of $(S_{i,t} - S_{i,t-4})$ over the preceding eight quarters. Adjusted R^2 (for pooled regressions) and the average R^2 (for Fama-MacBeth regressions) are reported. The sample includes firm-quarters of US retailers with fiscal quarter ending between March 2009 and July 2014.

Variables\Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FTI(t) × 100	0.167		0.148	0.158	0.201	0.180	0.172	0.070
	[2.37]		[2.08]	[2.14]	[2.42]	[2.18]	[2.00]	[1.12]
SUR(t) × 100		0.026	0.021	0.021		0.037	0.043	0.031
		[2.32]	[1.80]	[1.74]		[2.91]	[3.18]	[3.15]
SUE(t-1)				-0.013			-0.046	0.346
				[-0.60]			[-2.13]	[2.46]
Adj (Average) R^2	0.53%	0.49%	0.79%	0.75%	11.07%	11.90%	12.38%	33.72%
Fixed Effect	N	N	N	N	Time + Firm	Time + Firm	Time + Firm	Fama-MacBeth

Table 5: Returns Around Earnings Announcement Dates

Panel A shows the average returns during the event window by quintiles of foot-traffic index (FTI). The event window is the period between one day prior to the earnings announcement date and three days afterward. Returns are calculated in excess of the market returns of the corresponding periods. Quintiles of FTI are calculated using the following process. In month *t*, we pool firms that have fiscal quarter ending during the three-month rolling period of *t-2* to *t*, and rank the firms based on FTI to obtain quintile cutoff values. Then, we use the quintile cutoff values to assign quintile ranks for the firms that have fiscal quarter ending in month *t*. The last row of Panel A reports the results of the hypothesis testing for the mean difference between the highest and the lowest quintiles. Panel B reports the regressions of event returns on foot-traffic index. Models (1) to (4) show the results of pooled regressions, while Model (5) shows the results of Fama-MacBeth regressions. Adjusted R^2 (for pooled regressions) and the average R^2 (for Fama-MacBeth regressions) are reported. The sample includes firm-quarters of US retailers with fiscal quarter ending between March 2009 and July 2014.

Panel A: Announcement Returns by FTI Quintile

Quintile	N	Mean	Std Dev	Median	t Value
Low (Short)	159	-1.24%	9.62%	-1.23%	-1.62
2	185	-0.14%	8.38%	-0.40%	-0.23
3	192	0.49%	8.51%	0.90%	0.79
4	201	1.69%	8.85%	0.55%	2.71
High (Long)	181	2.21%	8.77%	1.86%	3.39
HT: High – Low	340	3.44%	9.18%		3.45

Panel B: Regressions of Announcement Returns on Quarterly FTI

Model	(1)	(2)	(3)	(4)	(5)
Coefficient	0.035	0.035	0.033	0.032	0.033
t value	[3.86]	[3.79]	[2.85]	[2.75]	[2.35]
Adj (Average) R^2	1.49%	2.76%	3.02%	4.34%	4.22%
Fixed Effect	N	Firm	Time	Firm+Time	Fama-MacBeth

Table 6: Regressions of Discretionary Accruals on Foot-traffic Index

This table reports the regression results of discretionary accruals on SUE, foot-traffic index, and a proxy for managements' private information (PI). Discretionary accruals are estimated using the modified Jones model, by estimating a cross-section regression each quarter. The PI(t+1) is a proxy for managements' private information on the revenue for the fiscal quarter *t+1*. The PI(t+1) is obtained from the foot-traffic index for the period beginning after the fiscal-quarter-*t* end and ending prior to the announcement date for quarter-*t* earnings. The SUE is estimated as $(AE_{i,t} – FE_{i,t}) /P_{i,t}$, where $AE_{i,t}$ is quarterly earnings per share announced for quarter *t* of stock i, $FE_{i,t}$ is mean analysts' forecasted EPS, and $P_{i,t}$ is quarter-end price. The SUR for stock *i* in quarter *t* is calculated as $[(S_{i,t} – S_{i,t-4}) – r_{i,t}]/\sigma_{i,t}$ where $\sigma_{i,t}$ and $r_{i,t}$ are the standard deviation and average, respectively, of $(S_{i,t} – S_{i,t-4})$ over the preceding eight quarters. Adjusted R^2 (for pooled regressions) and the average R^2 (for Fama-MacBeth regressions) are reported. The sample includes firm-quarters of US retailers with fiscal quarter ending between March 2009 and July 2014.

Variables\Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FTI(t)	0.001		-0.003	-0.003	-0.003	-0.003	0.000	-0.003	0.001	-0.011
	[0.36]		[-0.78]	[-0.80]	[-0.69]	[-0.69]	[0.04]	[-0.79]	[0.11]	[-1.67]
FTI(t-1)					0.000	0.000				
					[-0.01]	[-0.01]				
PI(t+1)		0.009	0.010	0.010	0.011	0.011	0.008	0.011	0.008	0.013
		[2.84]	[2.84]	[2.84]	[2.93]	[2.92]	[1.86]	[2.81]	[1.78]	[2.54]
SUE(t)				0.000	0.000	0.000				
				[0.23]	[-0.05]	[-0.06]				
SUE(t-1)					0.001	0.001				
					[0.60]	[0.61]				
SUR(t)						0.000				
						[0.07]				
Adj (Average) R^2	-0.11%	0.95%	0.90%	0.77%	0.69%	0.55%	-0.71%	0.75%	-0.52%	5.10%
Fixed Effect	N	N	N	N	N	N	Time	Firm	Time + Firm	Fama-MacBeth

Table 7: Announcement Returns and Foot-traffic Index

This table reports the regression results of announcement returns on foot-traffic index, a proxy for managements' private information (PI), and other control variables. The dependent variable is the returns around earning announcement dates for fiscal quarter *t*. The announcement return is calculated as the return in excess over the market during the period of one day before the earnings announcement date and three days after the announcement date. The PI(t+1) is a proxy for managements' private information on the revenue for the fiscal quarter *t+1*. The PI(t+1) is obtained from the foot-traffic index for the period beginning after the fiscal-quarter-*t* end and ending prior to the announcement date for quarter-*t* earnings. The DA is discretionary accrual estimated using the modified Jones model, by estimating a cross-section regression each quarter. The SUE is estimated as $(AE_{i,t} - FE_{i,t}) / P_{i,t}$, where $AE_{i,t}$ is quarterly earnings per share announced for quarter *t* of stock i, $FE_{i,t}$ is mean analysts' forecasted EPS, and $P_{i,t}$ is quarter-end price. The SUR for stock *i* in quarter *t* is calculated as $[(S_{i,t} - S_{i,t-4}) - r_{i,t}]/\sigma_{i,t}$ where $\sigma_{i,t}$ and $r_{i,t}$ are the standard deviation and average, respectively, of $(S_{i,t} - S_{i,t-4})$ over the preceding eight quarters. Size is the natural logarithm of the market capitalization as of fiscal quarter-*t* end. BE/ME is the natural logarithm of the book-to-market ratio as of the most recent fiscal year ending at least three month prior to fiscal quarter-*t* end. PastReturn is the cumulative return in excess over the market from thirty to three days prior to the earnings announcement. Adjusted R^2 (for pooled regressions) and the average R^2 (for Fama-MacBeth regressions) are reported. The sample includes firm-quarters of US retailers with fiscal quarter ending between March 2009 and July 2014.

Variables\Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
FTI(t)	0.074				0.075	0.080	0.053	0.063	0.069	0.084	0.083
	[5.27]				[4.71]	[4.57]	[3.31]	[3.61]	[3.56]	[3.89]	[3.01]
FTI(t-1)					-0.011	-0.014	-0.025				
					[-0.80]	[-0.84]	[-1.74]				
PI(t+1)	-0.041				-0.034	-0.029	-0.028	-0.017	-0.012	-0.012	0.083
	[-3.41]				[-2.41]	[-1.97]	[-2.11]	[-1.24]	[-0.75]	[-0.74]	[3.01]
DA		-0.537			-0.683	-0.706	-0.804		-0.590	-0.644	-0.666
		[-4.43]			[-5.00]	[-4.72]	[-5.96]		[-4.33]	[-4.26]	[-3.03]
SUE(t)			5.691				7.052				
			[10.95]				[10.62]				
SUE(t-1)			-0.809			-0.068	-2.836			-0.580	-1.782
			[-2.39]			[-0.11]	[-4.53]			[-1.44]	[-0.72]
SUR(t)				[0.01]			[0.01]				
				[5.79]			[2.54]				
SUR(t-1)				[-0.00]		0.001	[-0.00]			0.000	0.002
				[-1.85]		[0.23]	[-0.69]			[0.01]	[0.51]
Size	-0.008	-0.006	-0.004	-0.008	-0.005	[-0.01]	[-0.00]	-0.044	-0.049	[-0.05]	[-0.00]
	[-3.20]	[-2.40]	[-1.87]	[-3.62]	[-1.90]	[-1.73]	[-1.81]	[-4.41]	[-4.40]	[-4.09]	[-0.74]
BE/ME	0.009	0.005	-0.003	-0.001	0.011	[0.01]	[0.00]	0.022	0.022	[0.03]	[0.01]
	[2.08]	[1.13]	[-0.66]	[-0.36]	[2.19]	[2.19]	[0.43]	[2.68]	[2.45]	[2.62]	[1.05]
PastReturn	-0.027	-0.037	-0.032	-0.034	-0.057	[-0.06]	[-0.04]	-0.060	-0.073	[-0.09]	[-0.03]
	[-0.81]	[-1.10]	[-1.01]	[-1.07]	[-1.50]	[-1.57]	[-1.16]	[-1.71]	[-1.95]	[-2.21]	[-0.37]
Adj (Average) R^2	4.99%	3.29%	13.86%	4.46%	8.10%	7.88%	25.46%	7.97%	7.26%	12.95%	41.05%
Fixed Effect	N	N	N	N	N	N	N	Time+Firm	Time+Firm	Time+Firm	Fama-MacBeth

Table 8: Post-Earning-Announcement Drift and Foot-traffic Index

This table reports the regression results of the post-earnings announcement drift (PEAD) on foot-traffic index, a proxy for managements' private information (PI), and other control variables. The dependent variables are the return of each firm in excess over the market for the period beginning on 4 days after the announcement dates for fiscal quarter-*t* earnings and ending on 60 days after the announcement dates. The PI(t+1) is a proxy for managements' private information on the revenue for the fiscal quarter *t+1*. The PI(t+1) is obtained from the foot-traffic index for the period beginning after the fiscal-quarter-*t* end and ending prior to the announcement date for quarter-*t* earnings. The SUE is estimated as $(AE_{i,t} – FE_{i,t}) / P_{i,t}$, where $AE_{i,t}$ is quarterly earnings per share announced for quarter *t* of stock i, $FE_{i,t}$ is mean analysts' forecasted EPS, and $P_{i,t}$ is quarter-end price. The SUR for stock *i* in quarter *t* is calculated as $[(S_{i,t} – S_{i,t-4}) – r_{i,t}]/\sigma_{i,t}$ where $\sigma_{i,t}$ and $r_{i,t}$ are the standard deviation and average, respectively, of $(S_{i,t} – S_{i,t-4})$ over the preceding eight quarters. The DA is discretionary accrual estimated using the modified Jones model, by estimating a cross-section regression each quarter. Size is the natural logarithm of the market capitalization as of fiscal quarter-*t* end. BE/ME is the natural logarithm of the book-to-market ratio as of the most recent fiscal year ending at least three month prior to fiscal quarter-*t* end. PastReturn is the cumulative return in excess over the market from thirty to three days prior to the earnings announcement. Adjusted R^2 (for pooled regressions) and the average R^2 (for Fama-MacBeth regressions) are reported. The sample includes firm-quarters of US retailers with fiscal quarter ending between March 2009 and July 2014.

Variables\Models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
FTI(t)	0.029		0.011			0.004	0.038	0.037	-0.032	-0.015	-0.030
	[1.73]		[0.49]			[0.18]	[1.63]	[1.45]	[-1.25]	[-0.48]	[-0.65]
PI(t+1)		0.037	0.033			0.037	0.032	0.035	0.051	0.045	0.073
		[2.33]	[1.79]			[1.92]	[1.55]	[1.63]	[2.50]	[1.95]	[2.54]
SUE(t)				1.050		1.474		1.593		-1.922	3.551
				[1.25]		[1.65]		[1.81]		[-1.91]	[1.08]
SUE(t-1)				-1.054		-0.616		-0.657		-1.327	-1.375
				[-1.94]		[-1.08]		[-1.18]		[-2.32]	[-0.46]
SUR(t)					0.008	0.005		0.003		0.002	-0.006
					[2.63]	[1.48]		[0.75]		[0.57]	[-1.09]
SUR(t-1)					[-0.01]	[-0.01]		[-0.01]		[-0.00]	[-0.00]
					[-2.32]	[-1.68]		[-1.87]		[-0.78]	[-0.11]
DA							0.027	0.066		[0.27]	[-0.20]
							[0.14]	[0.30]		[1.26]	[-0.58]
Size	-0.005	-0.007	-0.007	-0.006	[-0.01]	[-0.01]	-0.005	-0.005	-0.095	-0.120	-0.001
	[-1.45]	[-1.83]	[-1.83]	[-1.67]	[-2.08]	[-1.75]	[-1.34]	[-1.13]	[-6.50]	[-6.52]	[-0.27]
BE/ME	0.015	0.017	0.017	[0.01]	0.008	0.018	0.022	0.024	0.012	-0.003	0.009
	[2.35]	[2.54]	[2.56]	[1.52]	[1.20]	[2.34]	[3.12]	[2.97]	[1.00]	[-0.17]	[0.65]
PastReturn	-0.029	-0.025	-0.026	[-0.02]	-0.016	-0.042	-0.047	-0.062	-0.059	-0.163	-0.091
	[-0.61]	[-0.50]	[-0.52]	[-0.47]	[-0.33]	[-0.77]	[-0.89]	[-1.09]	[-1.15]	[-2.81]	[-1.01]
Adj (Average) R^2	0.97%	1.75%	1.66%	0.91%	1.27%	2.51%	2.53%	3.44%	13.80%	17.17%	46.16%
Fixed Effect	N	N	N	N	N	N	N	N	Time + Firm	Time + Firm	Fama-MacBeth

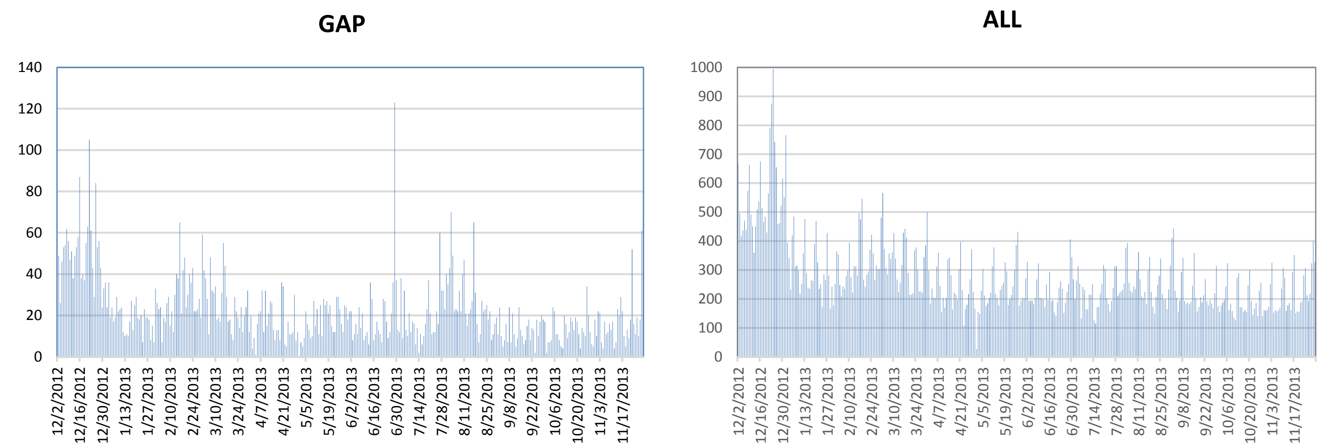

Figure 1. Daily time-series of foot traffic obtained from Android device. The figure plots one of the data sources that are used to construct the foot-traffic index. The first panel provides a daily time series of foot traffic to GAP locations over the period of Dec. 2012 to Nov. 2013, while the second panel shows the time series of traffic to the entire sample firms. This data is extracted from Andoid mobile devices in the United States.

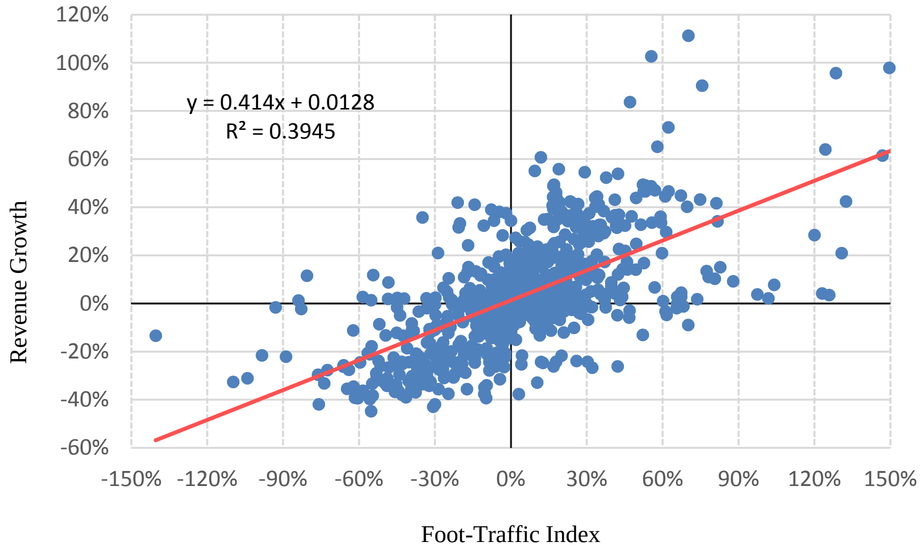

Figure 2. Revenue growth vs. foot-traffic index. The figure scatter plots revenue growth on foot-traffic index. The vertical axis is revenue growth and the horizontal axis is foot-traffic index. The red line is the predicted value of revenue growth using foot-traffic index. The sample includes US retail firms of fiscal quarter ending between Mar 2009 and July 2014.

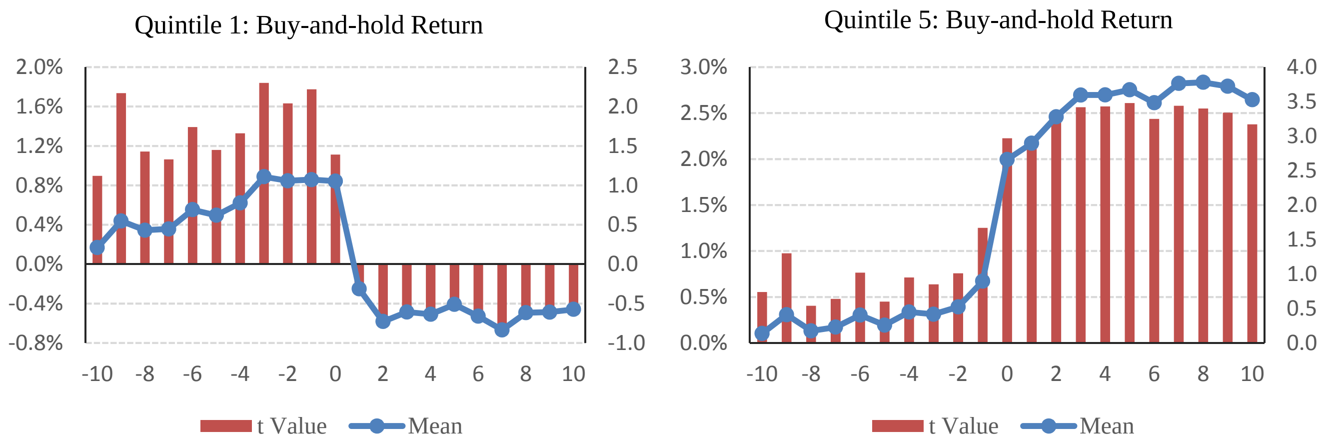

Figure 3. Excess returns around earnings announcement dates. This figure plots the average buy-and-hold returns during the event window from 10 days prior to the earnings announcement date (day 0) to 10 days afterward. Returns are calculated in excess of the market returns of corresponding periods. The first panel shows the average buy-and-hold return of firms in quintile 1 of foot-traffic index, while the second panel shows the results of firms in quintile 5. The sample includes US retail firms of fiscal quarter ending between Mar 2009 and July 2014.