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Information Acquisition and Expected Returns: Evidence from EDGAR Search Traffic*

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Abstract

Using a novel dataset containing investors' access of company filings through the SEC's EDGAR system, we show that the abnormal number of IPs searching for firms' financial statements strongly predicts future stock returns and firm fundamentals. A long-short portfolio based on our measure of information acquisition activity generates a monthly abnormal return of 80 basis points that is not reversed in the long-run. Consistent with theories of endogenous information acquisition, the return predictability is more pronounced for firms with larger and lengthier financial filings that are more costly to process, and for IPs searching current and historical filings simultaneously. Our findings suggest investors' costly information acquisition activities reveal their private expectation of firm value.

JEL classification: G12, G14

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1 Introduction

Information acquisition and dissemination is key to understanding asset price movements and market efficiency. When information is costly to acquire and price is only partially revealing, economic agents will expend resources and effort to become informed (Grossman and Stiglitz (1980); Verrecchia (1982)), and in doing so, will move prices closer to the fundamental value. A central prediction from theories of costly information acquisition is that more investors will choose to become informed when they perceive greater benefits from doing so, holding the cost of information acquisition constant.[1] Although theories offer clear and rich predictions, empirical evidence of the relation between information acquisition behavior and the value of information is sparse in financial markets, potentially due to the difficulty of directly measuring the information acquisition activities of investors.

In this paper, we take advantage of a novel dataset containing investors' access of regulatory filings through the Securities and Exchange Commission (SEC)'s EDGAR (Electronic Data Gathering, Analysis, and Retrieval) system to study the implications of information acquisition activities on firm value. Because the EDGAR system is the main source of firms' regulatory filings, and the SEC maintains a log file of all activities performed by users on EDGAR, we are able to directly observe investors' information acquisition activity for a broad cross-section of firms over a sample period of more than 10 years.

Our research objectives in this paper are twofold. First, we examine the determinants of investors' information acquisition through the EDGAR website. Motivated by theories of information acquisition,[2] we posit that information acquisition activities should be negatively related to the cost of gathering and analyzing information, and positively related to the (perceived) benefits of information. To test this, we use the number of unique IP addresses searching for SEC filings through EDGAR as a proxy for investors' information acquisition activities. We then run cross-sectional regressions of our information acquisition proxy on several firm characteristics associated with the costs and benefits of information acquisition. Specifically, we hypothesize that firms with higher investor visibility and attention will attract more information acquisition, as these stocks are more accessible in investors' minds and less costly to analyze. We conjecture that the strength of firms' information environments would affect information acquisition, although the direction of the effect is not clear ex-ante.[3] We also expect investors to have stronger incentives to acquire information about firms with higher valuation uncertainty (Mele and Sangiorgi (2015)). Using firm size as a proxy for investor visibility, trading volume as a proxy for investor attention (Gervais, Kaniel, and Mingelgrin (2001); Barber and Odean (2007)), analyst coverage as a proxy for information environment (Hong, Lim, and Stein (2000)), and idiosyncratic volatility as a proxy for valuation uncertainty (Zhang (2006)), we find evidence

[1] The definition of "information acquisition", as is commonly used in the literature, not only includes cost of acquiring information, but also the cost of analyzing and interpreting information.

[2] There is a large body of theoretical literature on information acquisition, e.g., Grossman and Stiglitz (1980), Diamond and Verrecchia (1981), Verrecchia (1982), Hellwig (1980), Admati (1985), Veldkamp (2011) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016).

[3] On one hand, firms with better public information environments will be less costly to analyze, so we expect information acquisition to increase with the quality of a firm's information environment. On the other hand, more disclosure of public information may reduce benefits from private information acquisition and hence crowd out private information acquisition activities (Goldstein and Yang (2017)).

consistent with the theories. These four firm characteristics explain 55% of the cross-sectional variation of information acquisition activities across firms. Further tests show that information acquisition through EDGAR also increases following negative stock returns, for firms belonging to the S&P 500 index, held by more institutional investors and during earnings announcement months, but these additional characteristics do not dramatically improve the explanatory power of our baseline model.

After implementing a simple characteristic-based model of expected information acquisition, we proceed to examine our second research question, that information acquisition activities reveal the arrival of unobservable private information. A number of papers make such predictions, including Van Nieuwerburgh and Veldkamp (2009), Van Nieuwerburgh and Veldkamp (2010) and Cziraki, Mondria, and Wu (2021). The main insight from this framework is that, when an investor has a small initial information advantage about a given asset, this information advantage leads them to acquire more public information about that asset.[4] Therefore, when investors increase their attention to some assets relative to others, it implies that investors have received private news. In theory, the direction of the unobservable private information can be either positive or negative. In reality, however, investors will more likely engage in costly information acquisition when they receive positive information, due to the high cost of short selling and the asymmetry in buying and selling decision. Barber and Odean (2007) argue that when deciding which stocks to buy, investors have to choose from thousands of available stocks, hence information acquisition becomes an important part of decision-making. On the other hand, unless using short selling, investors can only sell the stocks they currently own, and the selling decision is more likely motivated by liquidity and tax considerations, and less likely to require information acquisition.

To that end, we extract the number of IPs unexplained by firm characteristics to infer investors' private information of asset payoffs. Consistent with the idea that information acquisition embeds the value of information, we show that an abnormal number of IPs (denoted as AIP) requesting EDGAR filings strongly predicts subsequent stock returns. An equal-weighted, monthly rebalanced, long-short strategy that buys stocks in the highest decile of AIP and sells stocks in the lowest decile of AIP generates 59 to 80 basis points per month after adjustment for the Carhart (1997) four factors and is highly significant. Adjusting for the recently proposed factor models – the Fama and French (2015) five-factor model, the Hou, Xue, and Zhang (2015) q-factor model, and the Stambaugh and Yuan (2016) mispricing-factor model – does not affect the return spread of the long-short portfolio much. The abnormal return of AIP strategy is much weaker for value-weighted portfolios. The high-minus-low AIP strategy generates approximately 30 basis points per month, which is mostly insignificant.[5] The insignificant return spread of value-weighted portfolio is expected to some extent. Since short-sale constraints are less binding for large-cap stocks, the direction of the information contained in AIP is more ambiguous for large stocks. Using several proxies of short-sale constraints including lendable

[4] In these papers, the initial information advantage comes from geographic proximity between investors and firms, but this may not be the only source of information advantage. Investors may get private information about a firm through talking to its employees or having insights about customer opinion (Huang (2018)).

[5] The value-weighted portfolio returns are dominated by the stocks with largest market cap. Subsequent analysis based on a double-sort on firm size and AIP shows that AIP can generate significant abnormal returns for value-weighted portfolios except among the largest size quintile.

supply and lending fees, we confirm that the positive expected return information embedded in EDGAR searching activities is more pronounced for stocks that are more costly to short.

With a Fama-MacBeth regression setting, we show that AIP has additional explanatory power for future stock returns when we control for the standard cross-sectional return predictors, such as firm size, book-to-market ratio, momentum, short-term reversal, idiosyncratic volatility, turnover, and institutional ownership. The return predictability of AIP persists for two quarters, and is not reversed in the subsequent 24 months. This persistence in return predictability alleviates concerns that our finding is the result of temporary price pressure caused by noise traders, which should reverse over the long-run (Da, Engelberg, and Gao (2011)). Furthermore, we show that within-firm change of AIP (relative to its 12-months moving average) also significantly predict future returns, suggesting that our result is unlikely driven by unobserved risk exposure which should be persistent at the firm level. The return predictability of AIP is also *not* explained by alternative channels including investor recognition, media coverage, firm events, extreme returns, and investor disagreement.

Looking into different types of EDGAR filings, we find that the return predictability of AIP comes mainly from those searching for firms' annual reports 10-Ks (AIP_10K). As analyzing 10-Ks is more costly than other types of SEC filings and those searching activities are more indicative of deliberate information acquisition, the stronger predictability of AIP for 10-Ks is consistent with theories of costly information acquisition.[6] To further substantiate our argument, we conduct two tests that explore the heterogeneity in information acquisition costs. First, we use the filing size and word count of 10-Ks as proxies for the complexity of financial filings (Loughran and McDonald (2014)), and find that the return predictability of AIP is significantly stronger among firms with larger and lengthier 10-Ks that are more costly to process. Second, we show that the return predictability of AIP is more pronounced when we focus on IPs searching for the current and historical 10-Ks simultaneously. The evidence supports the hypothesis that in equilibrium, the expected value of information are proportional to the cost of acquiring and analyzing information, as predicted by theories of endogenous information acquisition.

Having established the robustness of the return predictability of the abnormal number of IPs, we examine the sources of return predictability. The key assumption in this paper is that under short-sale constraints, investors rationally allocate more effort and attention to stocks that they have received positive private news. This assumption is generally difficult to test, since the sources of private information is unobservable to an econometrician. We conduct two tests to shed light on the nature of the unobservable information that motivates investors' information acquisition through EDGAR. First, investors' information acquisition decision could reflect their private knowledge of firm fundamentals that are not fully priced in the market yet.[7] Consistent with the first channel, we find that AIP strongly predicts the future *changes* in firms' fundamentals such as quarterly Return-on-Assets (ROA), standardized unexpected earnings (SUE), and *revisions* in analyst consensus EPS forecast. Moreover, AIP

[6] Cohen, Malloy, and Nguyen (2020) document that the length of the average 10-K has grown 6 times longer over the last 20 years.

[7] Investors may get informed about firm fundamentals, for example, by being exposed to advertisement on firms' product or major events in economically-linked firms (Liaukonyte and Zaldokas (2019); Madsen (2017)).

significantly predict future earnings announcement returns, suggesting that the information contained in AIP is not immediately incorporated into stock prices and is (partially) revealed during earnings announcements.

Secondly, investors may observe negative shocks to stock prices that are not warranted by firms' fundamental changes. Supporting the second channel, we show that the abnormal number of IPs searching for EDGAR filings increases significantly after firms' stocks experiencing mutual fund outflow-induced fire sale (Coval and Stafford 2008; Edmans, Goldstein and Jiang 2012). Taken together, our evidence suggests that the return predictability of AIP arises because information acqusition activities reveal the arrival of positive private information about a firm.

This paper contributes to several strands of the existing literature. First, our results offer strong empirical evidence supporting information acquisition theories that information acquisition is endogenous to the value of information. Using the novel EDGAR log file dataset, we construct a direct measure of investors' information acquisition activity, and show its strong predictability for firms' future returns and fundamentals. Several recent studies examine a specific type of market participants' access of SEC filings through EDGAR website, including institutional investors (Chen, Cohen, Gurun, Lou, and Malloy (2020); Drake, Johnson, Roulstone, and Thornock (2020)), financial analysts (Gibbons, Iliev, and Kalodimos (2021)), the Federal Reserve (Li, Lind, Ramesh, and Shen (2018)), and hedge funds (Crane, Crotty, and Umar (2018)). Lee and So (2017) study the information content of analysts' selective coverage decisions and show that an abnormal amount of analyst coverage reflects analysts' favorable expectation of firms' fundamental performances. By extracting the information acquisition activities of all internet users through the EDGAR site, our measure captures the expected return information embedded in the collective behavior of a much larger set of market participants, i.e., millions of unique end-users of financial information. In addition, analysts' incentives have been found to be distorted by generating underwrting revenues (Lin and McNichols (1998)) or trading commissions for their brokerage houses (Cowen, Groysberg, and Healy (2006)); such distortions are less likely among EDGAR users. Empirically, we construct the AIP measure by controlling for analyst coverage proxies.

This paper also contributes to the growing literature on the effect of investor attention and information acquisition on asset prices and capital market efficiency. Da, Engelberg, and Gao (2011) show that the abnormal attention of retail investors, as captured by Google search volume, causes transitory price pressures on attention-grabbing stocks. Using news-searching activity via the Bloomberg terminal as a proxy for institutional investors' attention, Ben-Rephael, Da, and Israelsen (2017) find that institutional attention facilitates the timely incorporation of fundamental information into asset prices. More pertinent to this study, Drake, Roulstone, and Thornock (2015) show that EDGAR-based information acquisition affects the efficient pricing of earnings-related news. However, the aforementioned papers mainly examine the effect of information acquisition on the pricing of *publicly* announced news, while this paper directly infers investors' *private* expectations of firm value through their collective actions.[8] Empirically, we find more EDGAR-based informtion acqusition activities are associated with a larger fraction

[8] Our approach complements a recent paper by Kadan and Manela (2019), which use option price changes around public news announcements to infer the value of information.

of firm-specific information reflected in stock prices, and also higher information asymmetry as measured by bid-ask spread and $GPIN$.

The remainder of this paper is organized as follows. Section 2 describes the data, presents summary statistics, and examines the cross-sectional determinants of information acquisition through EDGAR. Section 3 tests the relation between abnormal level of information acquisition and future stock returns. In Section 4, we shed light on the nature of unobservable information that are revealed by EDGAR-based information acquisition activities. Section 5 presents a battery of robustness tests and conducts additional analyses. Section 6 concludes the paper.

2 Data and Methodology

2.1 Data

Our IP search volume data comes from the Securities and Exchange Commission's (SEC) EDGAR log file database, which has recorded all website search traffic for SEC filings since 2003.[9] Each search record contains information about the user's unique Internet Protocol (IP) address (partially anonymized)[10], timestamp, searched company (identified by the Central Index Key (CIK)) and searched specific filing (identified by the unique SEC accession number).[11] Following Lee, Ma, and Wang (2015) and Ryans (2017), we first filter the raw log data to eliminate the requests made by robots or automated webcrawlers, since such numerous and indiscriminate requests are uninformativeness for our research question.[12] Next, we match the CIK in the EDGAR log filings to that in COMPUSTAT to identify public companies, and retrieve the filing type and filing date for each requested file by linking the accession number to the Master Index files maintained by the SEC.[13] We classify these filings into six groups: 10-K, 10-Q, 8-K, insider, registration, and proxy.[14] Finally, we calculate the monthly IP search

[9] The data is available for download at https://www.sec.gov/data/edgar-log-file-data-set.html.

[10] The EDGAR log file dataset provides the first three octets of the IP address with the fourth octet obfuscated with a three character string that preserves the uniqueness of the last octet without revealing the full identity of the IP.

[11] The detailed log file record elements are described at https://www.sec.gov/files /EDGAR_variables_FINAL.pdf.

[12] First, following Lee, Ma, and Wang (2015), we exclude the searching records of those users who download more than 50 unique firms' filings in one day. The user is identified by their unique IP address. Second, following Ryans (2017) and Drake, Roulstone, and Thornock (2015), we remove log records that reference an "index" (idx=1), as index pages only provide the links to filings rather than the filings themselves. Third, following Ryans (2017), we keep the request records with successful document delivery (code=200). We then further exclude the search records of users who make more than 25 filing requests per minute or more than 500 requests per day, or with more than three unique CIKs searching per minute. Finally, we only keep one search record for a specific filing (unique accession number) to each user in a given day. This step is to avoid duplicated records due to users viewing the same document multiple times, a particular concern after the adoption of XBRL filing in 2009. For users who view the financial reports of XBRL-adopted firms in interactive data format, every click on a different footnote will generate a new search record, although it references the same document.

[13] Further details of the EDGAR index files can be found at https://www.sec.gov/edgar/searchedgar/accessing-edgar-data.htm

[14] We define the 10-K category as the filing type in "10-K", "10-K/A", "10-K405", "10-K405/A", "10-KSB", "10KSB", "10-KSB-A", "10KSB/A", "10-KT", "NT 10-K", and "10-KSB40"; the 10-Q category as the filing type in "10-Q", "10-Q/A", "10QSB", "10-QSB", "10QSB-A", and "NT 10-Q"; the 8-K category as the filing type in "8-K" and "8-K/A"; the insider category as the filing type in "SC 13G", "SC-13D", "SC 13G/A", "SC 13D/A", "3", "4", and "5"; the registration category as the filing type in "S-1", "S-1/A", "S-3", "S-3/A", "S-3ASR", "424B5", "424B4", "424B3", "424B2", and "FWP"; and the proxy category as the filing type in "DEF 14A", "DEF 14C", "DEFA14A", "DEFM14A", "DEFR14A", and "DEFM14C".

volume for each filing category at firm level by counting the total number of unique IP addresses that searched one category of SEC filings of a specific company within a one-month window. We define IP_total as the total number of unique IP addresses searching all six types of SEC filings. Drake, Roulstone, and Thornock (2015) report that periodic accounting reports are the type of SEC filings most frequently requested by investors through the EDGAR website. We therefore also construct two additional measures of information acquisition specifically targeting firms' periodic accounting reports. IP_funtl (IP_10K) is the total number of unique IP addresses searching 10-K, 10-Q, and 8-K (10-K) filings. Our sample runs from January 2003 to December 2014.[15]

It is important to note that there are other ways for investors to access financial filings, such as a firm's investor relations website and Yahoo! Finance. Data vendors such as Bloomberg and FactSet also provide investors with access to these financial statements. As a result, our analysis of the EDGAR server log cannot capture all the views/downloads that the entire universe of investors are conducting on company filings. However, the EDGAR server still possesses several advantages over other information sources. First, it is questionable that investors primarily use the company website to retrieve SEC filings. As an example, Monga and Chasan (2015) quote General Electric (GE) CFO Jeffrey Bornstein, who noted that GE's 2013 annual report was downloaded from their investor relations website just 800 times.[16] However, for the same annual report, the EDGAR logs record 21,987 (4,325) downloads in the year (two months) following its filing. Second, other sources of company information often condense income-statement and balance-sheet information into pre-specified bins. As a result, some critical components of firms' financial information may be misrepresented. Third, many important accounting information such as information regarding operating lease is only available from annual reports' footnotes, not from a Bloomberg terminal or the Yahoo Finance web page. Finally, investors could better assess a firm's future prospects by reading the qualitative information contained in 10-K filings, which is not freely available in these data consolidators (Loughran and McDonald (2011)).

We obtain monthly stock returns from the Center for Research in Security Prices (CRSP), and annual accounting data from Compustat. Our sample of stocks starts with all common stocks traded on the NYSE, Amex, and NASDAQ. We adjust the stock returns by delisting. If a delisting return is missing and the delisting is performance-related, we set the delisting return at -30% (Shumway (1997)). We remove stocks with month end price less than $3.

We use standard control variables in our empirical analysis. $LnME$ is defined as the natural logarithm of market capitalization at the end of June in each year. $LnBM$ (Book-to-market ratio) is the most recent fiscal year-end report of book value divided by the market capitalization at the end of calendar year t-1. Book value equals the value of common stockholders' equity, plus deferred taxes and investment tax credits, and minus the book value of preferred stock. MOM (Momentum) is defined as the cumulative holding-period return from month t-12 and t-2. We follow the literature by skipping the most recent month's return when constructing the MOM variable. REV (short-term reversal measure) is the prior month's return. *Turnover12* is the monthly trading volume over shares outstanding, averaged from the past 12 months.

[15] There are significant gaps in the data between September 2005 and May 2006, due to lost or corrupt log file. As a result, we exclude these months from our sample in our analysis.

[16] https://www.wsj.com/articles/the-109-894-word-annual-report-1433203762.

Since the dealer nature of the NASDAQ market makes its turnover difficult to compare with the turnover observed on NYSE and AMEX, we follow Gao and Ritter (2010) by adjusting the trading volume for NASDAQ stocks.[17] IO (Institutional ownership) is the sum of shares held by institutions from 13F filings in each quarter divided by total shares outstanding. $IVOL$ (Idiosyncratic volatility) is the standard deviation of the residuals from the regression of daily stock excess returns on the Fama and French (1993) three-factor returns within a month (Ang, Hodrick, Xing, and Zhang (2006)). Institutional ownership data of stocks are available from the Thomson Reuters (formerly CDA/Spectrum) Institutional Holdings database (13F). *Coverage* is the log one plus the number of analysts following a firm. Both the analyst coverage and recommendation data are from I/B/E/S. We get the filing size and number of words of the 10-Ks for all publicly-traded firms from WRDS SEC Analytics.

Finally, we obtain stock lendable supply (lendable shares divided by shares outstanding) and stock lending costs from the Markit Securities Finance (formerly Data Explorer) database.[18] We use the Markit provided $DCBS$ score (Daily Cost of Borrowing Score) to measure short selling costs. $DCBS$ is a score from 1 to 10 created by Markit using their proprietary information. This score is intended to capture the cost of borrowing the stock: A score of 1 represents the cheapest to short and 10 represents the most difficult.

2.2 Summary Statistics

Table 1 displays the time-series average of the cross-sectional means and standard deviations of the variables for the full sample. The average number of unique IPs searching for all six types of SEC filings of a firm is 155 in a month. The cross-sectional standard deviation is 317, indicating a large cross-sectional variation among firms. Consistent with Drake, Roulstone, and Thornock (2015), the annual report 10-K is the most frequently searched type of SEC filings, with an average of 60 IPs requesting it in a month. IPs searching for 10-Q and 8-K are relatively less frequent. The average institutional ownership in our sample is 55%, reflecting the rapid growth of assets managed by institutional investors during our sample period. The remaining summary statistics are well known and do not require additional discussion.

Table A.1 reports the pairwise rank correlation among our variables. The three IP variables are highly correlated. This is expected as periodic accounting reports consist of the largest fraction of EDGAR search requests. The number of IPs is also positively correlated with firm size, analyst coverage, and turnover, suggesting that firms with high investor visibility and attention have more EDGAR users. The number of IPs is negatively correlated with stock idiosyncratic volatility. However, this is mainly due to the size effect: small firms with high return volatility attract less EDGAR searching. As will be shown later, once we control for firm size, the number of IPs becomes positively correlated with idiosyncratic volatility, potentially because the incentives of acquiring information are greater when stock price is noisier (Grossman and Stiglitz (1980)).

Figure A.1 plots the average number of IPs searching for EDGAR filings in each calendar

[17] Specifically, we divide NASDAQ volume by 2.0, 1.8, 1.6, and 1.0 for the periods before February 2001, between February 2001 and December 2001, between January 2002 and December 2003, and after January 2004, respectively.

[18] See Saffi and Sigurdsson (2010) for a detailed account of Markit equity lending database.

month. The average is first calculated across stocks within a particular year-month and then averaged across all years. As we can see, there is no large seasonal variation for IP_total. The number of IPs searching for 10-Ks do spike during March and April. This could be explained by more investors searching for 10-Ks during earnings season as most public firms file annual report in these two months. In our subsequent analysis, we design tests to rule out the alternative explanation that our result is simply driven by earnings announcement.

2.3 Cross-sectional Determinants of Number of IPs

Theories of endogenous information acquisition suggest that information acquisition activity is a function of both the cost of acquiring information and the benefits of trading on acquired information. In order to isolate investors' expected benefits from information acquisition activity, we need a model of expected information acquisition activities. To this end, we develop and implement a simple characteristics-based model of expected information acquisition, and identify the discrepancies between the realized and expected level of information acquisition. Calculating these discrepancies requires proxies for information acquisition and firm characteristics useful in estimating the expected level of information acquisition activities.

Our proxy for information acquisition activity is the number of unique IP addresses searching for EDGAR filings for each firm in a given month. To mitigate data mining concerns, we use three measures capturing information acquisition activities for different types of SEC filings. IP_total is the total number of unique IPs searching for all types of SEC filings, and IP_funtl (IP_10K) is the total number of unique IPs searching for 10-K, 10-Q and 8-K (10-K) filings. Our choice of firm characteristics is guided by information acquisition theories. Specifically, we hypothesize that firms with higher visibility and investor attention would attract more information acquisition, as these firms are more accessible in investors' minds. We also conjecture that the strength of firms' information environments would affect information acquisition, although the direction of the effect is not clear. On one hand, firms with abundant public information will be less costly to analyze, so we expect information acquisition to increase with the quality of a firm's information environment. On the other hand, disclosure of public information may reduce benefits from private information acquisition and hence crowd out private information acquisition activities (Goldstein and Yang (2017)). Finally, we expect investors to have stronger incentives to acquire information about firms with higher valuation uncertainty. Following prior literature, we use firm size as a proxy for investor visibility, trading volume as a proxy for investor attention (Gervais, Kaniel, and Mingelgrin (2001); Barber and Odean (2007)), analyst coverage as a proxy for information environment[19] (Hong, Lim, and Stein (2000)), and idiosyncratic volatility as a proxy for valuation uncertainty (Zhang (2006)).

We calculate the abnormal number of IPs by fitting monthly cross-sectional regressions of the raw number of IPs to isolate the components of the number of IPs not attributable to firms' size, turnover, analyst coverage, and idiosyncratic volatility. To mitigate the effect of outliers, we use the log of one plus the number of IPs when estimating the abnormal number of IPs for

[19] Another motivation for including analyst coverage is that according to Lee and So (2017), analyst coverage contains information about future stock return. By including analyst coverage as a regressor, any expected return information embedded in the number of IPs will be incremental to that contained in analyst coverage proxies.

firms. Specifically, we calculate the abnormal number of IPs for firm i in month t by estimating the following cross-sectional regression[20]:

$$Log(1 + IP_{i,t}) = \beta_0 + \beta_1 LnME_{i,t} + \beta_2 Coverage_{i,t} + \beta_3 Turnover12_{i,t} + \beta_4 IVOL_{i,t} + \epsilon_{i,t} \quad (1)$$

where $LnME$ is the log of market capitalization, $Coverage$ is the log of one plus analyst coverage, $Turnover12$ is the monthly turnover averaged over the past 12 months, and $IVOL$ is the daily idiosyncratic volatility calculated following Ang, Hodrick, Xing, and Zhang (2006). We define the abnormal number of IPs for each firm-month as the regression residuals from equation (1). We use the notation AIP to refer to the abnormal number of IPs, where higher values correspond to firms that have greater number of IPs searching for their SEC filings given their size, trading volume, analyst coverage, and idiosyncratic volatility.

Table 2 reports the time-series average coefficients and Fama-MacBeth t-statistics from estimating equation (1). The dependent variable used is the IP_total. To see the improvement of R^2, we add the explanatory variables one by one from Column (1) to Column (9). Consistent with our hypothesis, information acquisition activities increase with firm size (t-stat=69.44), as larger firms are more visible to investors. Size alone explains 40% of the cross-sectional variation of the number of IPs. Columns (2) and (3) show that information acquisition increases with the strength of firms' information environments and investor attention, proxied by analyst coverage and turnover, respectively. Column (4) further shows that the number of IPs increases with return volatility after controlling for firm size. This finding suggests that investors' demand for information is larger for firms with more uncertain value. Column (4) also shows that these four firm characteristics explain 55% of the cross-sectional variation of the number of IPs on average. The results are similar in the two panels of Table A.2, where the dependent variables are IP_fundl and IP_10K, respectively.

The four firm characteristics used in equation (1) were selected based on theories and parsimony, and may therefore omit other firm characteristics that drive variation in the expected level of information acquisition activity. For example, investors may be attracted to firms with extreme past returns and glamour characteristics (Barber and Odean (2007)). In addition, firms included in S&P 500 index may attract more attention from investors. To examine the explanatory power of other firm characteristics, we add the stock's past 12-month return, book-to-market ratio, institutional ownership, a dummy indicating whether it belongs to S&P 500 index, and a dummy indicating quarterly earnings announcement month iteratively from Column (5) to Column (9). The results suggest that more investors search for EDGAR filings when the firm has performed poorly over the past year, has high B/M ratio, is held by more institutional investors, belongs to S&P 500 index, and is announcing earnings. However, adding these additional characteristics improves the average R^2 of equation (1) by only 3 percentage points, suggesting the limited incremental explanatory power of these additional characteristics. In the robustness test below, we show that the inclusion of other firm characteristics in equation (1) does not significantly affect the return predictability of AIP.

[20] We run pure cross-sectional regression in the first stage so that the abnormal number of IPs (regression residuals) we use later on does not have look-ahead bias.

3 Information Acquisition and Future Stock Returns

Models of information acquisition (Van Nieuwerburgh and Veldkamp (2009)) predict that when an investor has a small initial information advantage about a given asset, this information advantage leads them to acquire more information about that asset. Although in theory, the direction of information could be either positive or negative, in reality we expect investors to engage in costly information acquisition activities when they receive positive information due to short-sale constraints. Hence a key testable implication is that information acquisition activities reveal the arrival of unobservable positive information. In addition, the positive return predictability of AIP should be stronger for smaller firms with more binding short-selling constraints. In this section, we test the relationship between information acquisition proxies and future returns using both portfolio sorts and the Fama-MacBeth regression.

3.1 Portfolio Sorts

In this section, we conduct portfolio sorts to test the return predictability of information acquisition proxies. At the end of each month, we sort stocks into deciles by their AIP. We then compute the average return of each decile portfolio over the next month, which provide a time series of monthly returns for each decile. We use these time series to compute the average excess return of each decile over the entire sample. As we are most interested in the return spread between the two extreme portfolios, we also report the return to a long–short portfolio (i.e., a zero-investment portfolio that longs the stocks in the highest AIP decile and shorts the stocks in the lowest decile).[21]

Table 3 reports the average monthly excess return and alphas of each decile portfolio. Panel A reports results for the equal-weighted portfolios, and Panel B reports the results for the value-weighted portfolios. We show the portfolio results based on the abnormal number of IPs searching for three different types of SEC filings. Panel A shows a strong positive relation between AIP and future returns, regardless of which IP variables are used. For sorts based on AIP_total, firms in the highest decile outperform the firms in the lowest decile by 71 basis points per month on an equal-weighted basis (t-stat=3.18). The results are stronger when we do the portfolio sorts based on AIP_funtl and AIP_10K.[22] Specifically, the high-minus-low monthly return spread is 100 basis points (t-stat=4.70) based on AIP_10K, which corresponds to an annualized return of 12%.[23] The result suggests that information acquisition activities aggregated across EDGAR users reveal an economically large source of predictable return across

[21] The advantage of conducting analysis at monthly frequency is that it is easier to correct for known determinants of expected returns (size, book-to-market and momentum) using factor regressions, and the estimates of alpha thus obtained have a clear interpretation in terms of asset pricing theory.

[22] The larger return spread based on IPs searching for 10-K compared with IPs searching for other types of SEC filings is consistent with information acquisition theories. A firm's annual report is among the lengthiest and most difficult-to-read SEC filings. Annual reports contain detailed annual operating and financial performance and metrics, suggesting that digesting these reports requires a large amount of effort and time from investors. Compared with 10-Ks, 10-Q and 8-K files are usually much shorter and easier to digest, and investors driven to these types of filings are more likely to respond to current news events, and less likely to reflect a deliberate information acquisition choice. Given the substantially higher cost of acquiring and analyzing 10-Ks, the expected benefits perceived by investors should also be larger, which is consistent with our results.

[23] A caveat is that the large abnormal returns based on EDGAR searching data is only hypothetical. Investors without access to the real-time EDGAR searching data cannot trade on the information.

firms.

The return spread of the high-minus-low-AIP portfolio is considerably smaller and less significant when returns are value weighted. The high-minus-low return is only about 30 basis points per month, and mostly insignificant. This is consistent with our prior that for large-cap stocks with less binding short-sale constraints, the information embedded in EDGAR searching could be either positive or negative. Investors could take (less costly) short positions on large-cap stocks to benefit from the negative information they obtained privately. This implies that, ex-ante, we do not have a clear *directional* prediction of a relationship between the abnormal number of IPs and future returns.

Columns (2), (4) and (6) of Table 3 report the relation between the abnormal number of IPs and firms' future return after controlling for the portfolios' exposure to standard asset-pricing factors. We use the Carhart (1997) four-factor model to adjust portfolio risk exposure. Panel A shows that AIP predicts a strong positive return spread cross-sectionally for equal-weighted portfolios. The four-factor alphas of the long/short portfolio range from 52 to 82 basis points per month and are highly significant. Panel B shows the alphas for value-weighted portfolios. Again, we find the results are generally weaker, both economically and statistically. The four-factor alpha of the long/short portfolio ranges from 14 to 42 basis points, which are either insignificant or only marginally significant.

In Table A.3 in the Online Appendix, we show portfolio sorting results are robust when using alternative asset pricing models, examining subperiod performance, and removing microcap stocks. In Table A.4 in the Online Appendix, we show the portfolio results are not sensitive to the specific model of calculating the abnormal number of IPs. In Table A.5 in the Online Appendix, we use changes in AIP relative to its 12-month average as the sorting variable and find similar results, with monthly equal-weighted alphas ranging from 0.63% to 0.88%. In Table A.6 in the Online Appendix, we examine the within-industry return predictability of AIP_10K, as defined by the Fama-French 12 industry classification. In the end of each month, we sort all stocks within each industry into quintile portfolios and calculate the Carhart (1997) four-factor alpha of the long-short portfolio. AIP_10K generates significant and positive abnormal returns for 10 out of 12 industries, with a monthly alpha ranging from 0.48% for Financial industry to 1.06% for Energy industry. In sum, we conclude that the return predictability of AIP is robust and pervasive across the entire universe of US equity market.

To emphasize the importance of measuring the abnormal level of information acquisition activity when uncovering expected return information, we conduct a parallel portfolio test when ranking firms into deciles based on the raw number of IPs searching for EDGAR filings, as shown in Table A.7 in the Online Appendix. Panel A reports the equal-weighted excess returns and Panel B reports the equal-weighted four-factor alphas. The results show that the raw number of IPs is not significantly correlated with firms' future returns, regardless of which IP variable we use. The monthly four-factor alpha of the long-short portfolio based on the raw number of IPs ranges from -20 to 9 basis points, which are always insignificant. The lack of significant predictive power of the raw number of IP suggests that it is important to control for the expected level of information acquisition activities when inferring the arrival of private information.[24]

3.2 Cross-sectional Heterogeneity

3.2.1 The Role of Firm Size and Limits to Arbitrage

The results in section 3.1 show that the long/short portfolio alpha is only significant for equal-weighted returns, but not for value-weighted returns. This raises the concern that AIP is only useful to infer the arrival of priviate news for small stocks. To take a closer look at the role of firm size, we report the portfolio sorting results based on AIP by size quintiles in Table A.8 in the Online Appendix. For each month, we group all stocks into size quintiles based on the NYSE size breakpoints. We then *independently* sort stocks into quintiles based on AIP_10K. The table reports the Carhart (1997) four-factor alpha for the 25 portfolios: equal-weighted returns in Panel A and value-weighted returns in Panel B. We also report the alpha for each size quintile of the high-minus-low AIP portfolios. The result shows that the return predictability of AIP is strongest among the smallest size quintile, but is not limited to only the microcap stocks. The high-minus-low AIP portfolio generates a significant four-factor alpha of approximately 0.40% among the three middle-sized quintiles, both equal-weighted and value-weighted. The alpha is insignificant in the largest size quintile.

The fact that AIP loses its predictive power among the largest-cap stocks could be explained by two non-mutually exclusive channels. First, the private news that drive investors information acquisition activities could be either positive or negative when short selling is less costly. Given that large firms have few short-sale impediments, the direction of return predictability of AIP for large firms is more ambiguous. A second channel that could reinforce the weak return predictability among these stocks is that whatever information is contained in the EDGAR searches, they are impounded into stock prices more quickly due to less arbitrage frictions (e.g., liquidity and non-fundamental volatility) among large firms. We next explore how the return predictability of AIP varies across firms with different level of arbitrage frictions and short-sale constraints.

Following the literature, we investigate the role of three general limits-to-arbitrage measures: idiosyncratic volatility (Stambaugh, Yu, and Yuan (2015); Pontiff (2006)), residual institutional ownership (Nagel (2005)), and residual analyst coverage (Hong, Lim, and Stein (2000)). In addition, to substantialize the short-sale constraints argument in particular, we use the lendable supply and lending fee measure provided by Markit to measure short-selling costs. At the end of each month, we sort all stocks into terciles based on each limits-to-arbitrage and short-sale constraints variable X except lending fee, for which we sort into two groups based on whether a stock's DCBS score is above or below 2.[25] We then *independently* sort stocks into quintiles based on the abnormal number of IPs searching for 10-Ks. Table 4 displays the equal-weighted four-factor alphas of the lowest and highest AIP portfolios in the lowest and highest X groups. Consistent with the limits-to-arbitrage predictions, the alpha of the high-minus-low portfo-

[24] The rational is that large raw number of IPs could be driven by low cost of information acquisition, which is not predictive of future stock returns.

[25] This treatment follows the short selling literature. Stocks with a DCBS score less than or equal to 2 are usually cheap to borrow and are called ”general collateral”. Stocks with DCBS larger than 2 are more costly to short and are called ”special” stocks.

lio is more pronounced among stocks with higher idiosyncratic volatility, lower institutional ownership, and fewer analyst coverage. For example, the high-minus-low portfolio generates 1.24% (t-stat=4.44) monthly alpha for high-volatility stocks, and only 0.23% (t-stat=1.76) for low-volatility stocks. The difference of alphas between stocks with high and low idiosyncratic volatilty is 1.01% (t-stat=3.74). The results based on measures of short-sale constraints also support our hypothesis: the alpha of the high-minus-low portfolio is more pronounced among stocks with lower lendable supply and higher lending fees. For example, the high-minus-low portfolio generates 1.14% (t-stat=2.85) monthly alpha for high-lending fee stocks, and only 0.26% (t-stat=1.39) for low-lending fee stocks. The difference of alphas between stocks with high and low lending fee is 0.88% (t-stat=2.07).

3.2.2 Variation in Information Acquisition Costs

The key hypothesis we test in this paper is that investors' costly information acquisition activity should reveal the arrival of positive private information. One cross-sectional prediction is that the predictive relation should strengthen when the costs of information acquisition is higher. The intuition is that when information acquisition cost is higher, investors need more positive and accurate private information to justify their information acquistion activities. To test this prediction, we first use the complexity of a firm's annual report as a proxy for the cost of information acquisition. The idea is intuitive, as more complex filings require more effort and time for investors to process and digest. Following the recent literature (Loughran and McDonald (2014); You and Zhang (2009)), we use the natural log of the gross 10-K file size (complete submission text file) and the number of words contained in 10-K as a proxy for filing complexity.[26]

To this end, we first obtain the file size and number of words contained in firms' most recent 10-Ks. However, as big firms have more business lines and more diverse sets of operations, they would naturally have lengthier and larger 10-K filings.[27] To remove the confounding effect of firm size, we regress the logarithm of filing size and number of words on the logarithm of firms' market capitalizations, and use the regression residual as our proxy of filing complexity. At the end of each month, we sort all stocks into terciles based on either the residual file size or the residual word count. We then *independently* sort stocks into quintiles based on AIP_10K. Panels A and B of Table 5 show the equal-weighted four-factor alphas of the lowest and highest AIP_10K portfolios in the highest and lowest groups of filing complexity. Consistent with our prediction, the alpha of the high-minus-low portfolio is indeed economically larger and more significant for firms with more complex 10-Ks. For example, Panel A shows that the high-minus-low AIP_10K portfolio generates 1.24% (t-stat=4.88) monthly alpha among firms with the largest residual file sizes, and 0.66% (t-stat=3.30) among firms with the smallest file sizes. The difference of alphas between stocks with large and small file size is 0.58% (t-stat=2.29). The result is similar when we use the word count in 10-K as a proxy for the complexity of

[26] Loughran and McDonald (2014) report that the 10-K file size is positively associated with high return volatility in a one-month period following 10-K filings, supporting the use of file size as a proxy for the linguistic complexity of 10-K disclosure. You and Zhang (2009) find that investors' underreaction to information contained in 10-Ks is stronger for 10-Ks with larger numbers of words.

[27] The rank correlation is 0.34 between 10-K file size and firm size, and 0.40 between word count and firm size.

financial filings, as shown in Panel B.

Our second measure of information acqusition cost is whether the IP searched both the current and historical 10-K filings. As analyzing information in historical 10-Ks is more costly and more indicative of deliberate information acquisition, we expect a stronger return predictability among IPs searching both the current and historical 10-K filings. To test this, for each stock-month, we compute the number of unique IPs that searched only the current 10-Ks and those searched both the current and historical 10-Ks. We define current (historical) 10-Ks as those filed after (before) the most recent 10-K filing date. We then sort stocks into deciles based on the abnormal number of IPs within each category and report the results in Panel C of Table 5. The result shows that the return predictability of AIP is stronger when we isolate IPs that searched both the current and historical 10-Ks. Specifically, the alpha of the high-minus-low portfolio generates 0.61% (t-stat=3.08) monthly alpha for IPs that searched only the current 10-Ks, while that figure is 1.00% (t-stat=5.28) for IPs that searched both the current and historical 10-Ks. The difference of alphas between the two groups is 0.39% (t-stat=2.53). In addition to supporting the information acquisition theories, this test could help further distinguish the information acquisition story from the news-announcements explanation. On one hand, if the return predictability of AIP is entirely driven by news announcements, the result should be stronger when we focus on IPs only searching for current 10-K filings as investors rush to understand the implications of current news on firm value. On the other hand, although historical filings are unlikely to provide any news to investors, they still make up an important component of the information mosaic assembled by investors, and thus should be valuable to acquire.[28]

Overall, the evidence supports our hypothesis that the more costly information acquistion is, the larger the private information revealed by the equilibrium amount of information acquisition activity.

3.3 Fama-MacBeth Regression

We now test the return predictability of AIP using the Fama and MacBeth (1973) regression methodology. One advantage of this methodology is that it allows us to examine the predictive power of AIP while controlling for other known predictors of cross-sectional stock returns. This is important because, as shown in Table A.1, AIP is correlated with some of these predictors. We conduct the Fama-MacBeth regressions in the usual way. For each month, starting in February 2003 and ending with December 2014, we run the following cross-sectional regression:

$$Ret_{i,t+1} = \beta_0 + \beta_1 AIP_{i,t} + \gamma X_{i,t} + \epsilon_{i,t} \tag{2}$$

where $Ret_{i,t+1}$ is the return of stock i in month $t+1$, $AIP_{i,t}$ is the abnormal number of IPs searching for firm i's EDGAR filings in month t, and X is a set of control variables known to predict returns, including the natural logarithm of the book-to-market ratio ($LnBM$), the natural logarithm of the market value of equity ($LnME$), returns from the prior month (REV), returns from the prior 12-month period excluding month $t-1$ (MOM), institutional ownership

[28] Drake, Roulstone, and Thornock (2016) document the value of historical accounting reports. Cohen, Malloy, and Nguyen (2020) show that change in firms' reporting practices conveys an important signal about future firm operations, which can only be obtained after comparing current reports to historical reports.

(IO), and idiosyncratic volatility ($IVOL$), and past 12-month turnover ($Turnover12$).

Table 6 reports the time-series averages of the coefficients of the independent variables, and the t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. Columns (1) to (3) show the coefficient of AIP without any other return predictors. The coefficients of all three AIP measures are positive and significant at 1% level. This is consistent with our portfolio sorting results in which stocks with abnormally large numbers of IPs searching for their EDGAR filings have higher future returns. In Columns (4) to (6), we add the usual controls including firm size, book-to-market ratio, past 1-month returns, and past 12-month returns. The coefficients of AIP barely change, and retain their strong predictive power. In Columns (7) to (9), we further add institutional ownership, turnover, and idiosyncratic volatility to the regression model, and AIP still positively predicts future returns. The economic magnitude is substantial. The average difference of AIP_10K between the lowest and highest decile portfolio is 2.39, which implies a monthly return spread of 105 basis points between these two extreme deciles. The magnitude estimated from the Fama-MacBeth regression is in line with our portfolio sorting results. For the control variables, the signs of the coefficients are consistent with those reported in the previous literature, except for momentum, which attracts an insignificant coefficient.[29] Due to the short and recent sample period, however, the coefficients of some control variables are not significant.

4 Sources of the Return Predictability

Having established the strong return predictability of AIP, in this section, we conduct two tests to shed light on the nature of the unobservable information that drives investors' information acquisition through EDGAR. First, investors' costly information acquisition could reveal their favorable knowledge of firms' fundamentals that are not fully priced in by the market. Secondly, investors may observe negative shocks to stock prices that are not warranted by firms' fundamental changes.

4.1 Abnormal Number of IPs and Firm Fundamentals

We first test whether information acquisition via EDGAR reveals novel information about firms' future fundamental performance. We use three measures of a firm's fundamental performance. The first is the change in quarterly Return-on-Assets ($dROA$) from four quarters ago, which takes into account of the seasonality of firms' operating performances. The second measure is the standardized unexpected earnings (SUE), defined as the change of quarterly earnings-per-share (EPS) from four quarters ago scaled by stock prices 12 months ago. The third measure is the monthly forecast revision of analysts' consensus Earnings-per-Share (EPS) forecast ($FREV$) scaled by stock prices 12 months ago, which is a higher-frequency measure of firms' fundamental performances. We run panel regressions of $dROA$, SUE, and $FREV$ on lagged AIP, controlling for other firm characteristics that are associated with firms' fundamental performances, including size, book-to-market, past 12-month returns, analyst cover-

[29] This is due to the 2009 momentum crash (see Daniel and Moskowitz (2016)). The coefficient of momentum becomes positive once we exclude the year 2009 from our sample.

age, turnover, institutional ownership, idiosyncratic volatility, and lagged quarterly ROA. Since $dROA$ and SUE are measured at quarterly frequency, we construct the AIP at quarterly frequency by averaging the monthly AIP within a quarter. We also control for time-fixed effects, and standard errors are double clustered by firm and time following Petersen (2009). If the return predictability of AIP is partially driven by its predictive power for firm fundamentals, the coefficient of AIP should be significantly positive.

Table 7 reports the results of predicting fundamental performance based on AIP. The dependent variable is the change in quarterly ROA from Columns (1) to (3), SUE from Columns (4) to (6), and analyst forecast revision from Columns (7) to (9). We show the predictability result for all three AIP measures. The coefficients of AIP are significantly positive for all three measures of fundamental performance, regardless of which AIP measures we use. The economic magnitude is non-trivial. For example, Column (3) shows that an interquartile increase in AIP_10K is associated with an increase of 0.22 percentage points in $dROA$, which is about 17% of the interquartile range of quarterly change in ROA. Overall, the evidence supports the first channel that information acquisition via EDGAR contains investors' private knowledge of firms' future operating performances.

4.2 Mutual Fund Outflows and Information Acquisition

A second channel through which investors can identify the arrival of positive news is observing large negative shocks to stock prices that is not attributable to firm fundamentals. In this section, we use mutual fund outflow-induced selling pressure as an exogeneous shock to stock prices. Coval and Stafford (2007), Khan, Kogan, and Serafeim (2012), and Edmans, Goldstein, and Jiang (2012) find that mutual funds sell a firm's shares roughly in proportion to its portfolio weights when the funds are facing severe outflows. The forced selling behavior results in significant downward price pressure that persists for more than a year. This is a relatively exogenous and clean measure of stock price shock as it is associated with who is selling – funds facing large investor redemptions – rather than what is being sold, and so is unlikely to be driven by (unobserved) changes in firms' fundamentals.

To that end, we construct a mutual fund outflow-induced fire sale measure for each stock following Edmans, Goldstein, and Jiang (2012), which reflects fund outflow expressed as a percentage of a stock's total dollar trading volume within a quarter. Figure A.2 illustrates the magnitude and persistence of the effect of mechanically driven mutual fund fire-sale on stock prices. We define an "event" as a firm-quarter in which outflow falls below the 10th percentile value of the full sample. We then trace out the cumulative abnormal returns (CAR) over the CRSP equal-weighted or value-weighted index from 15 months before the event to 24 months after. Figure A.2 shows that the price pressure effects from fire sale are both significant in magnitude and long-lasting, persisting for over a year. Equally important, consistent with the literature, they are temporary rather than permanent, with the price recovering by the end of the 24th month.

To test whether more investors start to acquire information on firms experiencing fire-sale induced underpricing, we examine the change in AIP following outflow-induced fire sale.

Specifically, we run the following Fama-MacBeth regression:

$$dAIP_{i,q+1} = \beta_0 + \beta_1 Outflows_{i,q} + \beta_2 X_{i,q} + \epsilon_{i,q+1} \tag{3}$$

where $Outflow_{i,q}$ is the flow-induced fire sale measure calculated in accordance with Edmans, Goldstein, and Jiang (2012). Our dependent variable $dAIP_{i,q+1}$ is the within-firm change of AIP in quarter $q+1$ following mutual fund outflows. X is a set of firm characteristics that may affect the change of AIP.

Table 8 reports the result using all three AIP measures. Columns (1), (3), and (5) show that the coefficients of $Outflow_{i,q}$ are significantly negative without other controls, for all three AIP measures. The negative coefficient means that more IPs begin to search the SEC filings of firms that are underpriced due to mutual fund fire sale. Columns (2), (4), and (6) show that the relation between outflow-induced selling pressure and change in AIP is robust after controlling for a large set of firm characteristics.

In sum, by using mutual funds outflow-induced selling pressure to identify stock-level underpricing, our test also supports the second channel that part of the return predictability we document is attributable to investors allocating greater efforts and attention to firms experiencing exogenous underpricing that is not warranted by fundamental changes.

5 Alternative Explanations and Additional Analyses

In this section, we consider several alternative explanations for the return predictability of EDGAR searching activity, including firm events, breadth of ownership, media coverage, investor recognition, and price pressure. We also conduct additional analyses on the relation between information acquisition and investor trading and the implication for price efficiency.

5.1 Alternative Explanations

5.1.1 Firm Events

EDGAR searching activity is positively related to information-rich firm events such as earnings/dividends announcements or analyst recommendation changes (Drake, Roulstone, and Thornock (2015)). Since an earnings surprise (recommendation changes) leads to post-earnings (recommendations) announcement drift (Bernard and Thomas (1989); Womack (1996)) and earnings/dividends announcement months are generally associated with positive stock returns (Lamont and Frazzini (2007); Hartzmark and Solomon (2013)), the return predictability of AIP could be driven by these announcements-related return predictability effects. As a robustness check, we add standardized unexpected earnings (SUE), an earnings-announcement month dummy (EAM), an analyst upgrade and downgrade event dummy, and a dividend month dummy (DM) in the Fama-MacBeth regression.[30] Columns (1) to (3) of Table A.10 in the On-

[30] SUE is a firm's standardized unexplained earnings, defined as the realized earnings per share (EPS) minus EPS from four quarters prior, divided by the standard deviation of this difference over the prior eight quarters. EAM is a dummy variable that equals one when a given firm announces quarterly earnings in the month. $Upgrade$ ($Downgrade$) is a dummy equals one when there is an analyst recommendation upgrade (downgrade) in the previous month. DM is a dummy variable that equals one when there is an ex-dividend event in this

line Appendix show that the coefficients on AIP are still highly significant after controlling for firm events.

To the extent that these events may not fully capture all firm news, we consider 8-K filings as a more comprehensive measure of firm-specific material events and add the log number of 8-K filings from previous month in the regression.[31] Columns (4) to (6) of Table A.10 show that the coefficients on AIP barely change. Overall, we conclude that the information contained in AIP is not driven by firm events.[32]

5.1.2 Breadth of Ownership and Extreme Returns

Chen, Hong, and Stein (2002) show that reduction of the breadth of institutional ownership is a proxy for investor disagreement when short-sale constraints are binding for some investors. To the extent that breadth of ownership is positively correlated with the number of IPs searching for EDGAR filings, our result may be explained by breadth of ownership.

To the extent that investors are being attracted to stocks with extreme daily returns (Barber and Odean (2007)), our results could also be driven by the asset pricing effect of extreme returns or return skewness (Bali, Cakici, and Whitelaw (2011)). To rule out these alternatives, we add change of breadth of ownership ($dBreadth$) and max daily return ($Maxret$) in the Fama-MacBeth regression. $Maxret$ is defined as a stock's maximum daily return in the prior month. Columns (7) to (9) of Table A.10 show that the coefficients of AIP becomes even stronger after controlling for change of breadth of ownership and extreme daily returns.

5.1.3 Media Coverage

A related concern is that higher investor attention and information acquisition activities correlate with more intensive media coverage of a firm. As a result, the return predictability of EDGAR searching behavior could be driven by news coverage and the information content of news. To directly control for the confounding effect of news coverage and news sentiment, we use data from RavenPack News Analytics, which is a leading global news database used by practitioners in quantitative and algorithmic trading and by scholars in accounting and finance research (Dang, Moshirian, and Zhang (2015)).[33] We count the number of news for each firm over a month and use the natural logarithm of this variable as the news coverage measure. We also include the event sentiment score (ESS) from RavenPack, which indicates how firm-specific news events are categorized and rated as having a positive or negative effect on stock prices by experts with extensive experience and backgrounds in linguistics, finance, and economics.

month.

[31] Section 409 of the Sarbanes-Oxley Act of 2002 requires public companies to disclose "on a rapid and current basis" material information regarding changes in financial condition or operations as the SEC, by rule, determine to be necessary or useful for the protection of investors and in the public interest. The disclosure is filed with the SEC on Form 8-K, which companies must file "to announce major events that shareholders should know about."

[32] Another piece of evidence suggesting our result is not fully driven by firm events is provided in Table 3 of Loughran and McDonald (2017). They show that only 10.1% (21.6%) of 10-K requests over a 401-day window occur in the first week (month) after the filing date. Thus, the majority of EDGAR requests for 10-Ks is not clustered around earnings announcement days.

[33] RavenPack collects and analyzes real-time, firm-level business news from leading news providers (e.g., Dow Jones Newswire, The Wall Street Journal, and Barron's) and other major publishers and web aggregators, including industry and business publications, regional and local newspapers, government and regulatory updates, and trustworthy financial websites.

Table A.11 reports the Fama-MacBeth regression results. The sample used in this test is reduced significantly due to the requirement of news coverage data. Columns (1) to (3) show that the coefficients of AIP are still highly significant after controlling for news coverage measure. Columns (4) to (6) report the results when we control for news sentiment. Unsurprisingly, the coefficients on news sentiment itself is significant and positive. Importantly, the return predictability of AIP is not affected. Overall, we conclude that the return predictability of AIP cannot be explained by media and news coverage.

5.1.4 Attention-Driven Price Pressure

We next examine the persistence of the return predictability of AIP. This test could help rule out another alternative explanation, namely that the short-run predictability is due to temporary price pressure driven by investors' excess demand for attention-grabbing stocks. Da, Engelberg, and Gao (2011) show that an increase in Google Search Volume for a stock predicts higher stock prices in the short-run that are eventually reversed within a year. As we hypothesize that AIP contains information about firms' fundamental changes, the return predictability of AIP should not be reversed in the long-run. To test this, we run Fama-MacBeth regression of cumulative returns from month $t+j$ to $t+k$ on AIP_10K in month t. The result is reported in Table A.12 in the Online Appendix. We separately show the return predictability of AIP_10K for the next-quarter return skipping the immediate month in Column (1), the second-quarter return in Column (2), the second half-year return in Column (3), and the second-year return in Column (4). The table shows that AIP significantly predicts future returns for up to two quarters, and eventually levels off for longer horizons. The coefficient of AIP is always positive, mitigating concerns that the predictive power of AIP comes from transitory price pressure that is subsequently reversed. The result suggests that investors searching firm fundamentals through the EDGAR system appear to be more sophisticated than those searching through Google Search Engine, and their aggregate information acquisition activities contain value-relevant information about firms.

5.1.5 Investor Recognition

The positive return predictability of AIP could potentially be explained by Merton (1987)'s investor recognition hypothesis. In his model, equilibrium stock return is affected by investors' recognition of a stock because investors are not aware of all securities. Stocks with lower investor recognition have higher expected returns to compensate investors who hold the stock for insufficient diversification. An increase in investor recognition of a stock will reduce its expected return going forward and lead to a contemparenous increases in stock price. This could explain why AIP predicts short-run increase in stock returns. However, several pieces of evidence are not consistent with this alternative explanation. First, a stock experiencing an increase in investor recognition should have **lower** expected returns going forward, which is inconsistent with the fact that AIP also positively predicts long-horizon returns, as presented in Table A.12. Second, the investor recognition hypothesis implies that the return predictability of AIP comes solely from the reduction in discount rate, which should have no predictability for firms' future cash flows. However, we show that part of the return predictability of AIP comes from its predictability for a firm's fundamental performance. Lastly, in untabulated analysis, we control for change of trading volume as a proxy for shocks to investor recognition in Fama-MacBeth regression (Gervais, Kaniel, and Mingelgrin (2001)), and the return predictability of AIP still holds.

5.2 Additional Analyses

5.2.1 Information Acquisition and Investor Trading

Given the large number of unique IPs (more than 3 millions) in the EDGAR log file database and the nature of the EDGAR system, we conjecture that a majority of EDGAR users should be individual investors.[34] Thus, the significant return predictability from information acquisition of EDGAR users is consistent with the recent literature that individual investors as a group exhibit stock picking ability and their aggregated trades predict future stock returns and earnings news (Boehmer, Jones, Zhang, and Zhang (2020)). To substantiate this argument, we further examine whether information acquisition through EDGAR leads to subsequent investor trading. We examine trading by two types of investors: mutual funds and retail investors.

To test, we run Fama-MacBeth regression of net purchase by mutual funds and retail order imbalance on lagged AIP, controlling for a set of firm characteristics. Specifically, in each quarter or month, we run the following cross-sectional regression:

$$NetBuy_{i,t} = \beta_0 + \beta_1 AIP_{i,t-1} + \gamma X_{i,t-1} + \epsilon_{i,t} \tag{4}$$

where $NetBuy_{i,t}$ is the net purchases by mutual funds in quarter t or retail order imbalance in month t, $AIP_{i,t-1}$ is the abnormal number of IPs searching for firm i's SEC filings in time $t-1$, and $X_{i,t-1}$ is a vector of firm characteristics observed at time $t-1$, including firm size, book-to-market, analyst coverage, volatility, turnover, institutional ownership, and momentum. Net purchase is measured as the quarterly change in mutual fund holdings on a stock, with holdings expressed as a fraction of a firm's shares outstanding.[35] Retail order imbalance is calculated as the difference between daily retail buy and sell volume, scaled by total daily retail trading volume, and then aggregated to monthly level. Retail buys and sells are classified as in Boehmer, Jones, Zhang, and Zhang (2020), who show that retail investors' trades are informative about future stock returns.[36]

Table 9 reports the time series averages of the cross-sectional regression coefficients. The dependent variable is net purchases by mutual funds in Columns (1) to (3). The insignificant coefficients on AIP indicate that EDGAR-based information acquisition activities are not re-

[34] Institutional investors, given their resources and capacity, more likely use Bloomberg terminal or other data providers for information acquisition (Ben-Rephael, Da, and Israelsen (2017)).

[35] Since mutual fund trade is inferred from quarterly holdings data, we aggregate the AIP at quarterly frequency by averaging the monthly AIP within a quarter.

[36] The Boehmer, Jones, Zhang, and Zhang (2020) approach exploits two key institutional features of retail trading. First, most equity trades by retail investors take place off-exchange, either filled from the broker's own inventory or sold by the broker to wholesalers. TAQ classifies these types of trades with exchange code "D." Second, retail traders typical receive a small fraction of a cent price improvement over the National Best Bid or Offer (NBBO) for market orders (ranging from 0.01 to 0.2 cents), while institutional orders tend to be executed at whole or half-cent increments. The BJZ approach "picks up a majority of overall retail trading activity". We thank Xiaoyan Zhang for providing us the data on retail order imbalance.

lated to subsequent mutual fund trading. In sharp contrast, when the dependent variable is retail order imbalance in Columns (4) to (6), the coefficients on AIP are highly significant and positive. The result suggests that more information acquisition activities on a stock through the EDGAR system leads to significant net buying from retail investors on this stock subsequently.

5.2.2 IPs or Searches?

Our measure of information acquisition activity essentially equal weights each IP regardless of the number of searches the IP conducted through the EDGAR system during a one-month window. An alternative measure of information acquisition activity is the total number of searches for a firm requested by investors through the EDGAR system. This measure is problematic because, as documented by Drake, Roulstone, and Thornock (2015), the number of requests through EDGAR is dominated by a small fraction of investors who access EDGAR very frequently, and their activities are over-represented in this alternative measure.[37] Under the assumption that information is dispersed among a large group of economic agents (Hayek (1945)), we believe that our measure of the abnormal number of IPs should be more powerful in terms of inferring the unobservable information embedded in "the wisdom of crowd". Nevertheless, to test which measure of information acquisition activity has the stronger return predictability, we conduct a horse race between the abnormal number of searches ($Asearch$) and abnormal number of IPs (AIP) using the Fama-MacBeth regression approach. [38]

The result is reported in Table A.14 in the Online Appendix. Columns (1), (3), and (5) show that the return predictability of $Asearch$ is generally positive but weaker than that of AIP. Columns (2), (4), and (6) show that once we control for AIP, the coefficients of $Asearch$ are no longer significant. Importantly, the coefficients of AIP are still positive and highly significant. The result supports our use of the number of IPs as a more powerful measure of information acquisition activity, and indirectly supports the underlying assumption that private information is dispersed among market participants.

5.2.3 Implications for Price Informativeness and Information Asymmetry

Our last test examines the implications of EDGAR-based information acquisition activities for stock price informativeness and information asymmetry. If as we hypothesized, costly information acquisition activities reveal the arrival of unobservable private information for a stock, AIP should be associated with more informative stock prices. In addition, the intensified information asymmetry would also predict widening bid-ask spreads for stocks with higher AIP. Following the literature (Chen, Goldstein, and Jiang (2007); Kelly and Ljungqvist (2012)), we use stock price synchronicity as a proxy for price informativeness, and use bid-ask spread and the Generalized PIN measure developed by Duarte, Hu, and Young (2020) as proxies for information asymmetry. Specifically, for each firm-quarter observation, we regress daily returns on the value-weighted market return and the value-weighted two-digit SIC industry return, with a

[37] Drake, Roulstone, and Thornock (2015) report that 86% of the users accessing EDGAR do so infrequently and only about 2% of the users access EDGAR actively during a given quarter.

[38] Using the same decomposition method, we extract the abnormal number of searches for each firm as the residual from a monthly cross-sectional regression of log one plus the raw number of EDGAR requests for SEC filings on the same set of firm characteristics used in equation (2).

minimum of 50 daily observations.

$$RET_{i,t} = \alpha + \beta_1 MKTRET_t + \beta_2 MKTRET_{t-1} + \beta_3 INDRET_{j,t} + \beta_4 INDRET_{j,t-1} + \epsilon_{i,t}$$

Following the definition in Morck, Yeung, and Yu (2000), we define $SYNCH$ as

$$SYNCH = log(R^2/(1-R^2))$$

where R^2 is the coefficient of determination from the estimation of equation. Negative adjusted R^2 numbers are trimed at 0.0001. A lower value of $SYNCH$ indicates more firm-specific information in stock prices. $Spread$ is the daily percentage bid-ask spread, defined as $Spread = \frac{ClosingAsk_t - ClosingBid_t}{(ClosingAsk_t + ClosingBid_t)/2} * 100$. We average the $Spread$ to stock-month level. $GPIN$ is a modified version of PIN measure that captures the probability of informed trading.[39] We run Fama-MacBeth regressions of $SYNCH$, $Spread$ and $GPIN$ on lagged AIP, controlling for the same set of stock characteristics as in previous tests. Table A.15 reports the results. In Columns (1)-(3), the dependent variable is stock price synchronicity ($SYNCH$), in Columns (4)-(6) it is bid-ask spread ($Spread$), and in Columns (7)-(9) it is $GPIN$. Consistent with our hypothesis, AIP is significantly negatively associated with $SYNCH$, and positively associated with $Spread$ and $GPIN$, suggesting that stocks with higher EDGAR-based information acquisitions subsequently have more informative prices and also higher information asymmetry.

6 Conclusion

In this paper, we infer the arrival of unobservable information from investors' costly information acquisition activities and study its asset pricing implications. We use the number of unique IPs searching for SEC filings through the EDGAR system as a proxy for information acquisition activities. We develop and implement a simple characteristic-based model to decompose the total number of IPs searching for SEC filings into expected and abnormal components, and show that the abnormal number of IPs strongly and positively predicts subsequent stock returns. We also find that the abnormal number of IPs predicts firms' ascending fundamental performances, and that it also increases following exogenous underpricing, suggesting that investors rationally allocate greater attention and effort to firms that they have received unobservable positive information. Taken together, our findings provide empirical support to theoretical models of endogenous information acquisition that information acquisition actions reveal investors' private expectation of firm value. Our research also highlights the promise of using the collective wisdom of investors – extracted from their EDGAR search behavior – to study expected returns and other important economic outcomes.

[39] Duarte, Hu, and Young (2020) shows that their GPIN model performs better than PIN in capturing the arrival of private information in markets.

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Table 1: **Stock-Level Descriptive Statistics**

This table presents the descriptive statistics of our variables. IP_total is the total number of unique IP addresses searching for all six types of SEC filings. IP_funtl is the total number of unique IP addresses searching for 10-K, 10-Q, and 8-K filings. AIP_10K is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for 10-K filings in the EDGAR system. For each month, we sort all stocks into deciles based on their AIP_10K. We first calculate the mean of each variable for each decile in each month, and then calculate the time-series average of cross-sectional means. LnME is the natural log of a firm's market capitalization at the end of June of each year in millions of US dollars. Cov is the natural log one plus number of analyst coverage. Turnover12 is the monthly turnover ratio averaged over the past 12 months. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. Lendable supply is the shares held and made available to lend by Markit lenders divided by total shares outstanding. DCBS is a score from 1 to 10 created by Markit using their proprietary information and is intended to capture the cost of borrowing the stock. Outflows is calculated following Edmans, Goldstein, and Jiang (2012), which reflects fund outflow expressed as a percentage of stock's total dollar trading volume within a quarter. The overall sample period is from January 2003 to December 2014.

Summary Statistics

Variable	Mean	Median	STD	P25	P75
Number of IP searching for EDGAR filings					
IP_total	155	94	317	56	159
IP_funtl	107	64	213	37	111
IP_10K	60	32	135	17	60
IP_10Q	37	24	61	13	42
IP_8K	33	19	79	10	36
Stock-level characteristics					
LnME	6.16	6.08	1.98	4.74	7.47
LnBM	-0.66	-0.56	0.84	-1.11	-0.12
Mom	16.67%	7.64%	57.57%	-12.06%	31.78%
Cov	1.49	1.59	1.01	0.59	2.30
IVOL	0.02	0.02	0.02	0.01	0.03
Turnover12	0.17	0.12	0.19	0.05	0.21
IO	55.30%	59.15%	31.41%	28.92%	80.58%
dROA (%)	0.032	-0.018	4.844	-0.684	0.599
FREV (%)	-0.106	-0.001	22.185	-0.070	0.052
Outflows	-0.10%	-0.05%	0.19%	-0.11%	-0.02%
Lendable Supply	13.96%	14.46%	8.98%	5.85%	20.89%
DCBS	1.48	1.00	1.22	1.00	1.17

Table 2: **Cross-Sectional Determinants of Number of IPs Searching EDGAR Filings**

This table presents the Fama-MacBeth regression of log number of IPs searching for SEC filings through EDGAR system. The dependent variable is log one plus the number of unique IP addresses searching for all types of SEC filings in a month. LnME is the natural log of a firm's market capitalization at the end of June of each year in millions of US dollars. Cov is the natural log one plus number of analyst coverage. Turnover12 is the average monthly turnover ratio over the past 12 months. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. SP500 is a dummy equal to one if the stock belongs to S&P500 index. EAM is a dummy variable that equals one when a given firm announces quarterly earnings in the month. The overall sample period is from January 2003 to December 2014.

Dependent Variable is log(1+# of unique IP adresses searching all EDGAR filings)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LnME	0.2713***	0.2356***	0.2475***	0.2943***	0.2992***	0.3015***	0.3026***	0.2608***	0.2628***
	(69.44)	(71.54)	(73.46)	(75.60)	(76.94)	(77.29)	(77.58)	(75.05)	(74.98)
Cov		0.1310***	0.0422***	0.0382***	0.0321***	0.0332***	0.0360***	0.0337***	0.0399***
		(32.65)	(14.39)	(14.36)	(12.17)	(12.56)	(14.17)	(13.99)	(16.86)
Turnover12			1.0083***	0.7934***	0.7862***	0.7912***	0.7877***	0.8175***	0.8113***
			(30.21)	(29.08)	(30.04)	(29.75)	(30.52)	(30.68)	(30.92)
IVOL				9.1266***	9.0159***	9.0510***	9.0215***	8.5748***	8.0871***
				(34.65)	(33.38)	(33.16)	(32.36)	(31.55)	(31.65)
MOM					-0.0518***	-0.0529***	-0.0507***	-0.0508***	-0.0513***
					(-6.00)	(-6.19)	(-5.99)	(-6.38)	(-6.43)
LnBM						0.0171***	0.0158***	0.0087***	0.0108***
						(8.19)	(7.25)	(4.06)	(5.16)
IO							-0.0299**	0.0657***	0.0575***
							(-1.99)	(4.80)	(4.37)
SP500								0.3634***	0.3591***
								(58.81)	(58.60)
EAM									0.1587***
									(9.62)
Constant	2.5352***	2.6342***	2.5357***	2.0730***	2.0483***	2.0408***	2.0449***	2.2164***	2.1892***
	(39.20)	(40.68)	(40.19)	(33.45)	(33.37)	(33.32)	(32.62)	(34.26)	(34.03)
Ave.R-sq	0.404	0.483	0.520	0.554	0.558	0.559	0.563	0.574	0.582
N.of Obs.	610651	488129	488129	488123	488123	488123	484835	484835	484835

Table 3: **Portfolio Excess Returns and Alphas Sorted by Abnormal Number of IPs**

This table reports the monthly average excess returns and Carhart (1997) four-factor alphas (both in percentage) for each of the decile portfolios, as well as the long-short portfolio (High-Low). AIP_total is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for all types of SEC filings in the EDGAR system on a set of firm characteristics (equation (1)). Similarly, AIP_funtl (AIP_10K) is constructed using the number of IPs searching for 10-K, 10-Q, and 8-K (10-K) filings in the EDGAR system. In the end of each month, all stocks are sorted into deciles based on their abnormal numbers of IPs, and a long-short portfolio is formed by buying the highest decile and shorting the lowest decile portfolio. Portfolio returns are computed over the next month. Panel A reports the results for equally weighted portfolios and Panel B shows the results for value-weighted portfolios. The sample runs from January 2003 to December 2014.

Panel A: Equal-weighted Decile Portfolio Excess Return and 4-factor alpha

	AIP_total		AIP_funtl		AIP_10K	
	ExRet	Alpha	ExRet	Alpha	ExRet	Alpha
Low	0.46	-0.36	0.50	-0.32	0.47	-0.34
2	0.78	-0.16	0.76	-0.19	0.63	-0.33
3	0.81	-0.15	0.80	-0.16	0.75	-0.22
4	1.08	0.07	1.04	0.04	0.85	-0.18
5	1.00	-0.01	1.00	-0.02	0.93	-0.09
6	1.07	0.04	0.99	-0.04	1.02	-0.02
7	1.19	0.14	1.14	0.11	1.11	0.08
8	1.12	0.06	1.06	-0.01	1.26	0.20
9	1.14	0.08	1.24	0.16	1.32	0.27
High	1.18	0.16	1.29	0.29	1.48	0.48
High - Low	**0.71**	**0.52**	**0.79**	**0.62**	**1.00**	**0.82**
t-stats	3.18	2.74	3.61	3.33	4.70	4.35

Panel B: Value-weighted Decile Portfolio Excess Return and 4-factor alpha

	AIP_total		AIP_funtl		AIP_10K	
	ExRet	Alpha	ExRet	Alpha	ExRet	Alpha
Low	0.40	-0.40	0.57	-0.17	0.48	-0.22
2	0.80	-0.07	0.72	-0.20	0.59	-0.34
3	0.76	-0.11	0.86	-0.02	0.68	-0.25
4	1.04	0.14	0.97	0.05	0.83	-0.08
5	0.85	-0.06	0.92	0.01	0.99	0.13
6	0.80	-0.07	0.89	0.00	0.75	-0.16
7	1.00	0.16	0.90	0.07	0.88	-0.01
8	0.89	0.05	0.84	-0.02	1.01	0.20
9	0.94	0.15	0.87	0.10	0.74	-0.04
High	0.71	0.02	0.66	-0.03	0.75	0.05
High - Low	0.31	0.42	0.09	0.14	0.26	0.27
t-stats	1.23	1.79	0.44	0.68	1.32	1.38

Table 4: **Variation in the Limits to Arbitrage and Short-Sales Constraints**

This table reports the return predictability results for variation in the limits to arbitrage. We sort stocks into terciles based on each limits-to-arbitrage variable X, including idiosyncratic volatility (IVOL) (Panel A), institutional ownership (IO) (Panel B), analyst coverage (Coverage) (Panel C) and lendable supply (Panel D). For lending fee measure (Panel E), we sort stocks into two groups based on whether a stock's DCBS score is above or below 2. We then independently sort stocks into quintiles based on the abnormal number of IPs searching for 10-K (AIP_10K). AIP_10K is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for 10-K filings in the EDGAR system on a set of firm characteristics. We report the Carhart (1997) four-factor alpha of the lowest and highest AIP portfolios in the lowest and highest X groups. The "High-Low" column reports the Carhart (1997) four-factor alpha (in percentage) of the high-AIP minus low-AIP portfolios. In the bottom row of each panel, we report the difference of four-factor alphas between the high and low limits-to-arbitrage groups. T-statistics are in brackets. The sample runs from January 2003 to December 2014.

	Low AIP_10K	High AIP_10K	High-Low
Panel A: Double sort on IVOL and AIP_10K			
High IVOL	-0.76	0.48	1.24
	(-3.27)	(1.95)	(4.44)
Low IVOL	0.03	0.27	0.23
	(0.30)	(3.34)	(1.76)
High IVOL Sample -			1.01
Low IVOL Sample			(3.74)
Panel B: Double sort on IO and AIP_10K			
High IO	-0.17	0.23	0.40
	(-1.61)	(1.75)	(2.36)
Low IO	-0.56	0.48	1.03
	(-3.53)	(1.91)	(4.41)
Low IO Sample -			0.63
High IO Sample			(2.52)
Panel C: Double sort on analyst coverage and AIP_10K			
High Coverage	-0.33	0.18	0.51
	(-3.08)	(1.54)	(3.07)
Low Coverage	-0.41	0.68	1.10
	(-2.59)	(3.23)	(5.77)
Low Coverage Sample -			0.58
High Coverage Sample			(2.58)
Panel D: Double sort on lendable supply and AIP_10K			
High Lendable Supply	-0.28	0.09	0.37
	(-2.55)	(0.68)	(2.05)
Low Lendable Supply	-0.52	0.43	0.95
	(-2.59)	(2.03)	(3.53)
Low Supply Sample -			0.58
High Supply Sample			(1.88)
Panel E: Double sort on lending fee and AIP_10K			
High Lending Fee	-0.66	0.49	1.14
	(-2.62)	(1.33)	(2.85)
Low Lending Fee	-0.27	-0.01	0.26
	(-2.03)	(-0.11)	(1.39)
High Fee Sample -			0.88
Low Fee Sample			(2.07)

Table 5: **Variation in Information Acquisition Costs**

This table reports the return predictability results for variation in information acquisition costs. In Panels A and B, we conduct subsample tests based on the complexity of 10-K filings. For each month, we run cross-sectional regression of the log of filing size and number of words on the log of a firm's market capitalization, and use the regression residual as our proxy for filing complexity. We sort stocks into terciles based on the residual size or residual number of words of the most recent 10-K filing. We then independently sort stocks into quintiles based on the abnormal number of IPs searching for 10-K filings (AIP_10K). In Panel C, for each stock-month, we compute the number of unique IPs that searched only the current 10-K filings and both the current and historical filings, where current (historical) 10-K is defined as 10-Ks filed after (before) the most recent 10-K filing date. AIP_10K is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for 10-K filings in the EDGAR system on a set of firm characteristics. We report the Carhart (1997) four-factor alpha (in percentage) of the lowest and highest AIP portfolios in the lowest and highest filing complexity groups. The "High-Low" column reports the Carhart (1997) four-factor alpha of the high-AIP minus low-AIP portfolios. In the bottom row of each panel, we report the difference of four-factor alphas between the high and low filing complexity groups. T-statistics are in brackets. The sample runs from January 2003 to December 2014.

Panel A: Double sort on residual file size and AIP 10K

	Low AIP_10K	High AIP_10K	High-Low
Large Filing Size	-0.65	0.59	1.24
	(-4.22)	(3.23)	(4.88)
Small Filing Size	-0.27	0.38	0.66
	(-1.84)	(2.68)	(3.30)
Large Filing Size -			0.58
Small Filing Size			(2.29)

Panel B: Double sort on word count and AIP 10K

More word count	-0.48	0.52	1.00
	(-3.29)	(2.39)	(5.06)
Lesser word count	-0.36	0.20	0.56
	(-3.02)	(1.35)	(2.93)
More word count -			0.44
Lesser word count			(1.99)

Panel C: EDGAR searching for current and historical filings

Current filings	-0.41	0.21	0.61
	(-2.29)	(1.29)	(3.08)
Both current and historical filings	-0.45	0.55	1.00
	(-4.54)	(3.63)	(5.28)
Both current and historical filings -			0.39
Current filings			(2.53)

Table 6: **Fama-MacBeth Regression**

This table reports the results of the Fama and MacBeth (1973) regression of monthly stock returns on the abnormal number of IPs searching for SEC filings through the EDGAR system (AIP). AIP_total is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for all type of SEC filings in the EDGAR system on a set of firm characteristics. Similarly, AIP_funtl (AIP_10K) is constructed using the number of IPs searching for 10-K, 10-Q, and 8-K (10-K) filings in the EDGAR system. Size (LnME) is the natural log of a firm's market capitalization at the end of June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short term reversal measure (REV) is the lagged monthly return. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Turnover12 is the monthly turnover ratio averaged over the past 12 months. All t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	Dep.Var = One-month-ahead stock return								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AIP_total	0.0060***			0.0053***			0.0050***		
	(2.68)			(2.64)			(2.88)		
AIP_funtl		0.0047***			0.0041***			0.0042***	
		(2.70)			(2.78)			(2.94)	
AIP_10K			0.0051***			0.0046***			0.0044***
			(3.73)			(3.81)			(3.74)
REV				-0.0247***	-0.0245***	-0.0247***	-0.0283***	-0.0281***	-0.0284***
				(-3.18)	(-3.16)	(-3.19)	(-3.74)	(-3.72)	(-3.75)
LnME				-0.0006	-0.0006	-0.0006	-0.0014**	-0.0014**	-0.0014**
				(-0.89)	(-0.92)	(-0.93)	(-2.59)	(-2.60)	(-2.58)
LnBM				0.0019	0.0019	0.0019	0.0014	0.0013	0.0013
				(1.64)	(1.59)	(1.58)	(1.29)	(1.24)	(1.24)
MOM				-0.0058	-0.0057	-0.0058	-0.0048	-0.0047	-0.0048
				(-0.95)	(-0.94)	(-0.94)	(-0.88)	(-0.86)	(-0.86)
IVOL							-0.0015	-0.0025	-0.0007
							(-0.02)	(-0.04)	(-0.01)
Turnover12							-0.0094	-0.0091	-0.0089
							(-1.37)	(-1.32)	(-1.28)
IO							0.0122***	0.0119***	0.0114***
							(4.00)	(3.94)	(3.86)
Constant	0.0123**	0.0122**	0.0122**	0.0122	0.0122*	0.0123*	0.0119**	0.0120**	0.0119**
	(2.18)	(2.18)	(2.18)	(1.65)	(1.66)	(1.67)	(2.33)	(2.36)	(2.35)
Ave.R-sq	0.003	0.003	0.003	0.030	0.030	0.030	0.046	0.046	0.046
N.of Obs.	483667	483667	483667	483667	483667	483667	480793	480793	480793

Table 7: **Abnormal Number of IPs and Firm Fundamentals**

This table reports the results of the panel regression of future change in firm fundamentals on the abnormal number of IPs searching for SEC filings in the EDGAR system in month *t*. AIP_total is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for all type of SEC filings in the EDGAR system on a set of firm characteristics. Similarly, AIP_funtl (AIP_10K) is constructed using the number of IPs searching for 10-K, 10-Q, and 8-K (10-K) filings in the EDGAR system. The dependent variable in Columns (1) to (3) is the change of quarterly Return-on-Assets from four quarters ago. In Column (4) to (6), the dependent variable is the standardized unexpected earnings (SUE), defined as the change of quarterly EPS from four quarters ago divided by stock prices 12 months ago. The dependent variable in Columns (7) to (9) is the monthly revision of analysts consensus forecast for annual EPS. Size (LnME) is the natural log of a firm's market capitalization at the end of June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. Cov is the natural log one plus number of analyst coverage. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). We control for the year-quarter fixed effects in Columns (1) to (6) and the year-month fixed effects in Columns (7) to (9). Turnover12 is the monthly turnover ratio averaged over the past 12 months. Standard errors are double clustered at both firm and time level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	Change of ROA			SUE			Forecast Revision		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AIP_total	0.0017*			0.0013			0.0007***		
	(1.96)			(1.42)			(2.78)		
AIP_fundl		0.0026**			0.0026**			0.0016***	
		(2.51)			(2.22)			(6.19)	
AIP_10K			0.0028***			0.0043***			0.0019***
			(2.92)			(3.57)			(5.28)
LROA	-0.3425***	-0.3428***	-0.3430***						
	(-4.71)	(-4.73)	(-4.74)						
LnME	0.0008	0.0008	0.0008	-0.0022***	-0.0021***	-0.0021***	-0.0005	-0.0005	-0.0005
	(1.27)	(1.31)	(1.33)	(-3.73)	(-3.68)	(-3.63)	(-1.51)	(-1.55)	(-1.63)
LnBM	-0.0013	-0.0012	-0.0012	-0.0009	-0.0009	-0.0008	-0.0008**	-0.0008**	-0.0009**
	(-0.87)	(-0.84)	(-0.83)	(-0.50)	(-0.48)	(-0.44)	(-2.37)	(-2.39)	(-2.47)
MOM	0.0100***	0.0099***	0.0100***	0.0220***	0.0220***	0.0219***	0.0025***	0.0025***	0.0025***
	(3.55)	(3.56)	(3.57)	(8.19)	(8.17)	(8.18)	(5.20)	(5.14)	(5.18)
Cov	0.0004	0.0004	0.0005	0.0002	0.0003	0.0003	0.0021***	0.0021***	0.0021***
	(0.29)	(0.31)	(0.32)	(0.23)	(0.27)	(0.29)	(3.30)	(3.29)	(3.28)
Turnover12	-0.0118**	-0.0117**	-0.0117**	0.0316***	0.0318***	0.0319***	-0.0082***	-0.0082***	-0.0082***
	(-2.43)	(-2.42)	(-2.43)	(3.45)	(3.47)	(3.47)	(-3.15)	(-3.16)	(-3.17)
IO	-0.0010	-0.0011	-0.0013	-0.0093***	-0.0095***	-0.0096***	0.0049***	0.0051***	0.0052***
	(-0.48)	(-0.51)	(-0.61)	(-3.75)	(-3.87)	(-3.97)	(5.47)	(5.61)	(5.73)
IVOL	-0.0777	-0.0773	-0.0775	0.2287**	0.2330**	0.2365**	-0.1111**	-0.1115**	-0.1138**
	(-1.41)	(-1.41)	(-1.42)	(2.29)	(2.32)	(2.34)	(-2.35)	(-2.37)	(-2.41)
Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj.R-sq	0.056	0.056	0.056	0.023	0.023	0.023	0.002	0.002	0.002
N.of Obs.	128504	128504	128504	150712	150712	150712	348130	348130	348130

Table 8: **Mutual Fund Outflows and Abnormal Number of IPs**

This table reports the results of the Fama and MacBeth (1973) regression of the quarterly change in the abnormal number of IPs searching for SEC filings on quarterly mutual fund outflows. Outflows is calculated following Edmans, Goldstein, and Jiang (2012). In Columns (1) and (2), the dependent variable is the quarterly change in AIP_total in the quarter in which mutual fund outflows occur. In Columns (3) and (4), the dependent variable is the quarterly change in AIP_funtl. In Columns (5) and (6), the dependent variable is the quarterly change in AIP_10K. LnME is the natural log of a firm's market capitalization at the end of June of each year in millions of US dollars. Cov is natural log one plus number of analyst coverage. Turnover12 is the monthly turnover ratio averaged over the past 12 months. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. All t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	dAIP_total		dAIP_funtl		dAIP_10K	
	(1)	(2)	(3)	(4)	(5)	(6)
Outflows	-1.9303**	-1.5459**	-1.9145***	-1.3527***	-2.4242***	-1.7256***
	(-2.06)	(-2.31)	(-3.36)	(-3.27)	(-4.02)	(-4.92)
LnME		-0.0091***		-0.0094***		-0.0093***
		(-6.03)		(-5.68)		(-5.81)
LnBM		0.0013		-0.0014		-0.0017
		(0.56)		(-0.57)		(-0.75)
Cov		0.0080***		0.0076***		0.0087***
		(4.50)		(4.28)		(3.70)
IVOL		-1.8233***		-1.9963***		-1.8354***
		(-6.48)		(-7.68)		(-6.19)
Turnover12		-0.0015		0.0158		0.0203
		(-0.09)		(1.13)		(1.56)
IO		-0.0023		-0.0141**		-0.0143**
		(-0.36)		(-2.54)		(-2.28)
MOM		-0.0336***		-0.0370***		-0.0398***
		(-5.17)		(-5.70)		(-7.68)
Constant	0.0007	0.0901***	0.0050**	0.1036***	0.0049**	0.0967***
	(0.29)	(7.79)	(2.09)	(8.54)	(2.06)	(6.54)
Ave.R-sq	0.001	0.031	0.001	0.034	0.001	0.026
N.of Obs.	131863	131041	131863	131041	131863	131041

Table 9: **Abnormal Number of IPs and Investor Trading**

This table reports the results from the Fama and MacBeth (1973) regression of investor trading on lagged abnormal number of IPs searching for SEC filings in the EDGAR system. In Columns (1) to (3), the dependent variable is quarterly net purchases by mutual funds. Net purchase is measured as the quarterly change in mutual fund holding on a stock, with holding expressed as a fraction of a firm's shares outstanding. In Columns (4) to (6), the dependent variable is monthly retail order imbalance. Retail order imbalance is defined as the difference between daily retail buy volume and retail sell volume, scaled by total daily retail trading volume, and then aggregated to monthly level. Retail buys and sells are classified as in Boehmer, Jones, Zhang, and Zhang (2020). Size (LnME) is the natural log of a firm's market capitalization at the end of June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. Coverage is log one plus analyst coverage. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Turnover12 is the monthly turnover ratio averaged over the past 12 months. All t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. The sample in Columns (1) to (3) runs from January 2003 to December 2014. The sample in Columns (4) to (6) runs from January 2010 to December 2014.

	Net Purchases by Mutual Funds			Retail Order Imbalance		
	(1)	(2)	(3)	(4)	(5)	(6)
AIP_total	0.0030			0.0090***		
	(0.52)			(7.16)		
AIP_funtl		0.0046			0.0079***	
		(0.77)			(6.89)	
AIP_10K			0.0065			0.0076***
			(1.00)			(7.81)
LnME	-0.0003	-0.0003	-0.0003	-0.0002	-0.0002	-0.0002
	(-1.07)	(-1.08)	(-1.06)	(-0.20)	(-0.22)	(-0.25)
LnBM	0.0003	0.0004	0.0003	0.0045***	0.0045***	0.0044***
	(0.32)	(0.38)	(0.34)	(4.95)	(4.96)	(4.84)
Cov	-0.0008	-0.0007	-0.0005	-0.0025***	-0.0026***	-0.0027***
	(-0.30)	(-0.26)	(-0.22)	(-3.46)	(-3.61)	(-3.76)
IVOL	-0.1965*	-0.1975*	-0.2012*	-0.3268***	-0.3257***	-0.3243***
	(-1.96)	(-1.94)	(-1.95)	(-6.41)	(-6.40)	(-6.37)
Turnover12	-0.0069**	-0.0068**	-0.0064**	-0.0350***	-0.0351***	-0.0352***
	(-2.04)	(-2.22)	(-2.38)	(-12.83)	(-12.79)	(-12.75)
IO	0.0739***	0.0736***	0.0728***	0.0109***	0.0117***	0.0124***
	(2.86)	(2.90)	(2.92)	(3.01)	(3.26)	(3.42)
MOM	0.0066***	0.0067***	0.0065***	-0.0030	-0.0031*	-0.0031*
	(6.44)	(6.29)	(7.74)	(-1.67)	(-1.73)	(-1.70)
Constant	0.0048*	0.0050*	0.0053*	0.0469***	0.0467***	0.0465***
	(1.95)	(1.91)	(1.96)	(6.63)	(6.61)	(6.58)
Ave.R-sq	0.113	0.113	0.113	0.010	0.010	0.010
N.of Obs.	131795	131795	131795	184715	184715	184715

Information Acquisition and Expected Returns: Evidence from EDGAR Search Traffic

Online Appendix

To save space in the paper, we present additional analyses in the Online Appendix. Below is a brief description of these additional tests.

Figure A.1 plots the average number of IPs searching for EDGAR filings in each calendar month.

Table A.1 reports the pairwise rank correlation among our variables.

Table A.2 presents the cross-sectional determinants of IPs searching EDGAR filings, where the dependent variables are IP_fundl and IP_10K in Panels A and B, respectively.

Table A.7 reports the portfolio alphas when ranking firms into deciles based on the raw number of IPs searching for EDGAR filings.

In Table A.3 in the Online Appendix, we examine the robustness of our portfolio sorts. For brevity, we focus on the sorts based on AIP_10K. The first row shows the return spread when returns are weighted by past month gross return, as suggested by Asparouhova, Bessembinder, and Kalcheva (2013). Rows (2) and (3) show that our results barely change when we subtract the characteristic-matched portfolio (Daniel, Grinblatt, Titman, and Wermers (1997)) or the corresponding industry return from stock return. In the fourth row, we augment the Carhart (1997) four-factors with the Pástor and Stambaugh (2003) liquidity factor. Rows (5) to (7) show that our results hold when we use the Fama and French (2015) five factors, the Stambaugh and Yuan (2016) mispricing factor and Hou, Xue, and Zhang (2015)'s q-factor model to calculate alphas, respectively. Row (8) of Table A.3 shows that our results survive when we exclude stocks whose market capitalizations are in the bottom quintile of the NYSE size distribution. Row (9) reports the long-short alphas if we implement a six-months interval between when we sort stocks and when we measure strategy returns. Rows (10) and (11) show that the long-short portfolio generates significant alpha in two subperiods: one from 2003 to 2008 and another from 2009 to 2014. In fact, the return predictability of AIP appears to be stronger in the recent period (monthly alpha of 1.07% vs. 0.62%), consistent with the fact that the average 10-Ks have become lengthier and more costly to analyze over time (Cohen, Malloy, and Nguyen (2020)). The last row shows that the portfolio alpha is not affected by removing the financial crisis period (year 2008 and 2009) from our sample.

Our results are not sensitive to the specific model of calculating the abnormal number of IPs, as shown in Table A.4. The first row shows that the long-short portfolio based on AIP_10K calculated using model (9) of equation (1) generates a four-factor alpha of 0.67% (t-stat=3.92) for the equal-weighted portfolio. In the second row, we include the square terms of the four firm characteristics when calculating AIP to account for the nonlinear relation between number of IPs and firm characteristics. The four-factor alpha is 0.69% and 0.55% for the equal- and value-weighted portfolio, respectively. In the third row, we add the lagged log number of IPs in equation (1) when calculating AIP, and the alpha is still significant.[40] In sum, we conclude that the return predictability of AIP is robust and pervasive across the entire universe of US equity market.

In Table A.6, we examine the within-industry return predictability of AIP_10K, as defined by the Fama-French 12 industry classification. In the end of each month, we sort all stocks within each industry into quintile portfolios and calculate the Carhart (1997) four-factor alpha of the long-short portfolio. AIP_10K generates significant and positive abnormal returns for 10 out of 12 industries, with a monthly alpha ranging from 0.48% for financial industry to 1.06% for energy industry.

Table A.8 reports the alphas of double-sorted portfolios based on firm size and abnormal number of AIP.

Table A.9 shows that AIP also positively predict earnings announcement returns.

Table A.10 reports Fama-MacBeth regression results when we control for the impact of firm events, change of breadth of ownership and extreme returns.

Table A.11 reports the Fama-MacBeth regression results when we account for the confounding effect of news coverage and news sentiment.

Table A.12 tests the predictability of AIP_10K for long-horizon returns.

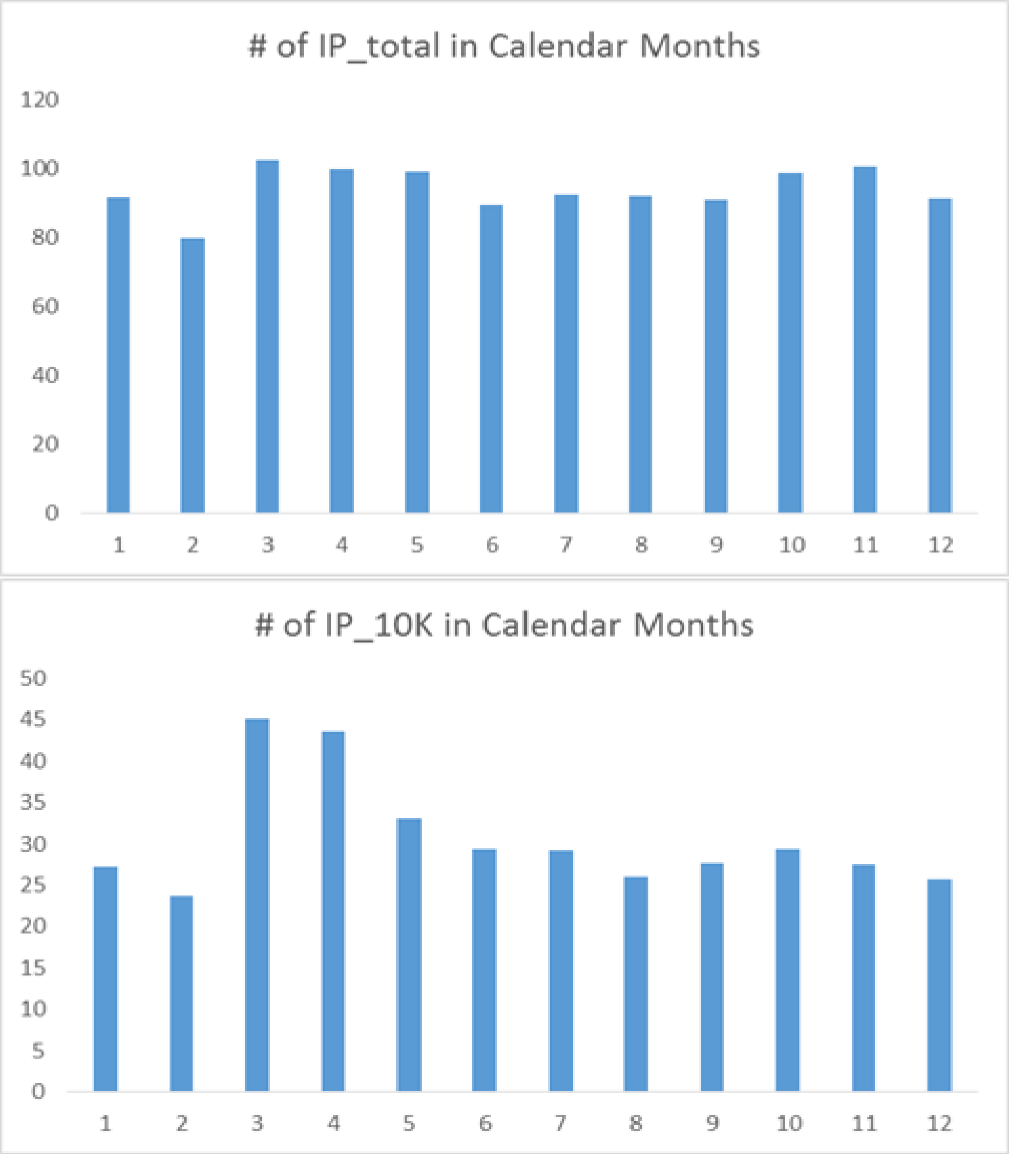
Table A.13 presents results from running a horse race by including all three AIP variables in the Fama-MacBeth regression.

Table A.14 compares the return predictability of abnormal number of IPs vs. abnormal number of searches.

Table A.15 examines the implications of EDGAR-based information acquisition activities for stock price informativeness and information asymmetry. We run Fama-MacBeth regressions of $SYNCH$ and $Spread$ on lagged AIP, controlling for the same set of stock characteristics as in previous tests.

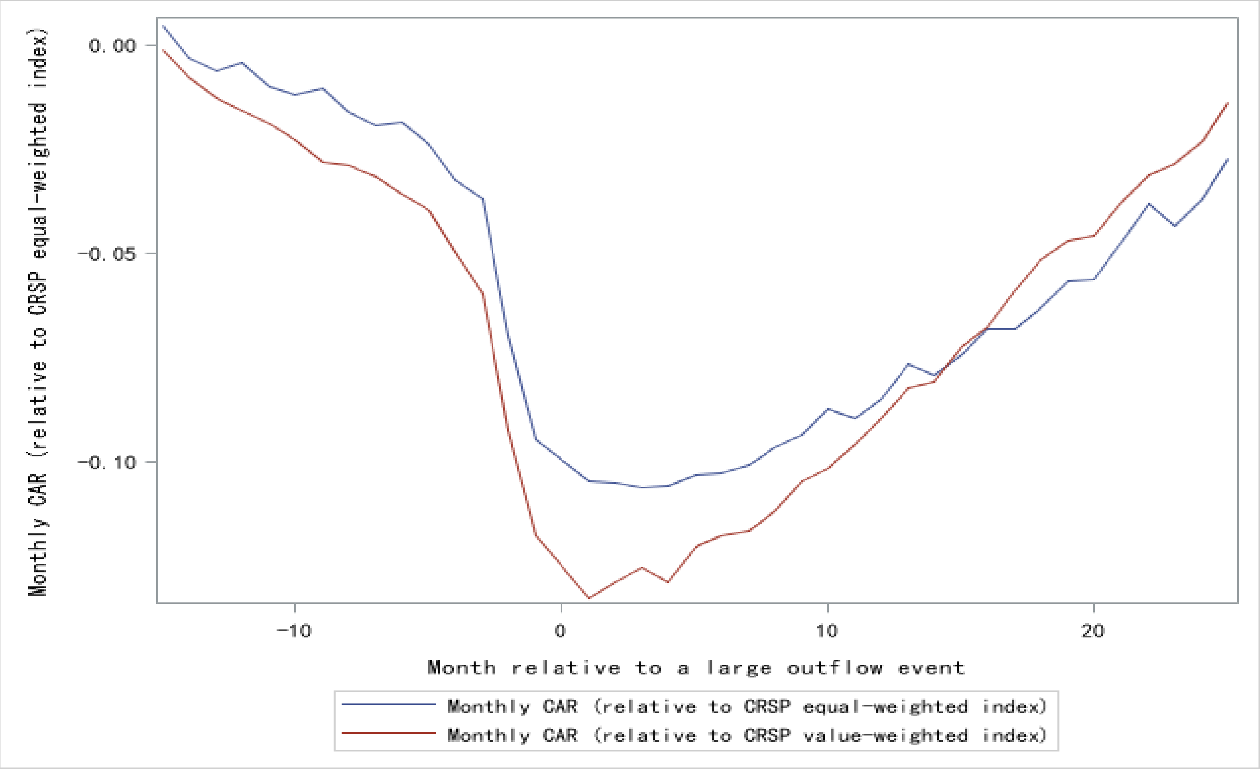
[40] This specification is equivalent to using the innovation in number of IPs to predict returns, so the return predictability of AIP is unlikely explained by any (omitted) persistent firm characteristics. In Table A.5 in the Online Appendix, we show that a positive relation between AIP and returns holds for change-based specifications, which further mitigates concerns that the return predictability of AIP is driven by an omitted firm-fixed effect not controlled for in our model of AIP.

Figure A.1: **Averge Number of IPs in Calendar Months**



This figure plots the average number of IPs searching for EDGAR filings in each calendar month. The average is first calculated across stocks within a particular year-month and then averaged across years. IP_total is the total number of unique IP addresses searching for all six types of EDGAR filings. IP_10K is the total number of unique IP addresses searching for 10-K files. The sample period is from January 2003 to December 2014.

Figure A.2: **Effect of Mutual Funds Hypothetical Sales on Stock Prices**



This figure plots the monthly cumulative average abnormal returns (CAR) of stocks around the event months, where an event is defined as a firm-quarter observation in which mutual fund fire sale induced outflows falls below the 10th percentile value of the full sample. Outflows is calculated following Edmans, Goldstein, and Jiang (2012). CAR is computed over the benchmark of the CRSP equal-weighted (blue line) or value-weighted index (red line) from 15 months before the event to 24 months after.

Table A.1: **Pairwise Correlations**

This table reports the pairwise rank correlation between our variables where they overlap. IP_total is the total number of unique IP addresses searching for all six types of SEC filings. IP_funtl is the total number of unique IP addresses searching for 10-K, 10-Q, and 8-K filings. AIP_10K is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for 10-K filings in the EDGAR system. For each month, we sort all stocks into deciles based on their AIP_10K. We first calculate the mean of each variable for each decile in each month, and then calculate the time-series average of cross-sectional means. LnME is the natural log of a firm's market capitalization at the end of June of each year in millions of US dollars. Coverage is log one plus analyst coverage. Turnover12 is the monthly turnover ratio averaged over the past 12 months. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. Lendable supply is the shares held and made available to lend by Markit lenders divided by total shares outstanding. DCBS is a score from 1 to 10 created by Markit using their proprietary information and is intended to capture the cost of borrowing the stock. Outflows is calculated following Edmans, Goldstein, and Jiang (2012), which reflects fund outflow expressed as a percentage of stock's total dollar trading volume within a quarter. The overall sample period is from January 2003 to December 2014.

Correlation Matrix

	IP_total	IP_funtl	IP_10K	LnME	Cov	Turnover12	Ivol	LnBM	Mom	IO
IP_total	1.000									
IP_funtl	0.918	1.000								
IP_10K	0.812	0.897	1.000							
LnME	0.671	0.664	0.672	1.000						
Cov	0.594	0.605	0.603	0.832	1.000					
Turnover12	0.588	0.579	0.539	0.544	0.621	1.000				
IVOL	-0.134	-0.149	-0.212	-0.523	-0.360	-0.016	1.000			
LnBM	-0.239	-0.229	-0.224	-0.319	-0.326	-0.303	0.051	1.000		
MOM	0.031	0.023	0.044	0.112	0.051	0.049	-0.117	0.008	1.000	
IO	0.469	0.494	0.514	0.650	0.647	0.615	-0.306	-0.193	0.095	1.000

Table A.2: **Cross-Sectional Determinants of Number of IPs Searching EDGAR Filings**

This table presents the Fama-MacBeth regression of log number of IPs searching for SEC filings through EDGAR system. In Panel A, the dependent variable is log one plus the number of unique IP addresses searching for 10-K, 10-Q and 8-K filings in a month. In Panel B, the dependent variable is log one plus the number of unique IP addresses searching for 10-K filings in a month. LnME is the natural log of a firm's market capitalization at the end of June of each year in millions of US dollars. Coverage is log one plus analyst coverage. Turnover12 is the average monthly turnover ratio over the past 12 months. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. SP500 is a dummy equal to one if the stock belongs to S&P500 index. EAM is a dummy variable that equals one when a given firm announces quarterly earnings in the month. The overall sample period is from January 2003 to December 2014.

Panel A: Dependent Variable is log(1+# of unique IP adresses searching 10-K, 10-Q and 8-K filings)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LnME	0.2723***	0.2355***	0.2468***	0.2931***	0.2984***	0.3015***	0.3005***	0.2563***	0.2578***
	(64.05)	(61.21)	(60.97)	(65.17)	(66.87)	(67.27)	(67.10)	(63.63)	(63.29)
Coverage		0.1405***	0.0530***	0.0492***	0.0421***	0.0436***	0.0369***	0.0343***	0.0414***
		(35.59)	(15.60)	(15.87)	(13.86)	(14.48)	(15.57)	(15.24)	(18.17)
Turnover12			0.9833***	0.7702***	0.7708***	0.7787***	0.7560***	0.7878***	0.7856***
			(29.18)	(26.62)	(27.23)	(26.95)	(27.32)	(27.66)	(28.78)
IVOL				9.0866***	8.9652***	9.0334***	9.0934***	8.6203***	7.9829***
				(36.40)	(34.66)	(34.19)	(33.54)	(32.67)	(32.41)
MOM					-0.0684***	-0.0698***	-0.0685***	-0.0687***	-0.0696***
					(-7.72)	(-8.00)	(-7.95)	(-8.50)	(-8.56)
LnBM						0.0251***	0.0223***	0.0148***	0.0172***
						(10.23)	(9.01)	(6.09)	(7.28)
IO							0.0411***	0.1421***	0.1303***
							(2.76)	(10.31)	(9.80)
SP500								0.3863***	0.3814***
								(62.83)	(62.17)
EAM									0.2092***
									(10.96)
Constant	2.2017***	2.2804***	2.1866***	1.7281***	1.7033***	1.6943***	1.6868***	1.8686***	1.8366***
	(34.86)	(36.21)	(35.81)	(28.85)	(28.72)	(28.66)	(27.97)	(30.13)	(29.99)
Ave.R-sq	0.386	0.458	0.491	0.522	0.526	0.527	0.533	0.543	0.554
N.of Obs.	610651	488129	488129	488123	488123	488123	484835	484835	484835

Table A.2 Continued

Panel B: Dependent Variable is log(1+# of unique IP adresses searching 10-K filings)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LnME	0.2979***	0.2674***	0.2765***	0.3120***	0.3169***	0.3201***	0.3155***	0.2648***	0.2678***
	(61.33)	(60.72)	(59.37)	(61.48)	(62.64)	(63.24)	(62.55)	(58.19)	(58.65)
Coverage		0.1453***	0.0729***	0.0698***	0.0637***	0.0649***	0.0431***	0.0401***	0.0482***
		(35.85)	(23.41)	(23.28)	(21.42)	(21.49)	(16.48)	(15.66)	(18.95)
Turnover12			0.8122***	0.6461***	0.6415***	0.6522***	0.5924***	0.6288***	0.6188***
			(30.68)	(28.59)	(28.59)	(28.74)	(28.38)	(28.75)	(29.59)
IVOL				6.9981***	6.9145***	7.0130***	7.2542***	6.7143***	6.2019***
				(30.56)	(29.46)	(28.94)	(29.41)	(28.15)	(27.44)
MOM					-0.0484***	-0.0510***	-0.0521***	-0.0517***	-0.0517***
					(-5.54)	(-5.93)	(-6.09)	(-6.52)	(-6.60)
LnBM						0.0267***	0.0213***	0.0127***	0.0159***
						(9.03)	(7.48)	(4.39)	(5.84)
IO							0.1600***	0.2765***	0.2654***
							(10.36)	(18.94)	(18.82)
SP500								0.4416***	0.4358***
								(53.84)	(53.85)
EAM									0.1730***
									(7.36)
Constant	1.3873***	1.4159***	1.3396***	0.9886***	0.9639***	0.9554***	0.9267***	1.1349***	1.1097***
	(25.17)	(25.47)	(24.67)	(18.65)	(18.51)	(18.43)	(17.62)	(20.88)	(20.57)
Ave.R-sq	0.388	0.467	0.486	0.501	0.504	0.506	0.511	0.522	0.532
N.of Obs.	610651	488129	488129	488123	488123	488123	484835	484835	484835

Table A.3: **Robustness of Decile Portfolio Sorts**

This table reports the results of several robustness tests for a long/short portfolio based on the abnormal number of IPs searching for 10-K filings in the EDGAR system (AIP_10K). AIP_10K is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for 10-K filings in the EDGAR system on a set of firm characteristics. For the first robustness test, we report the gross return-weighted portfolio returns, for which the weights are 1 + the stock's lagged monthly return, following Asparouhova, Bessembinder, and Kalcheva (2013). The second robustness test shows the portfolio returns adjusted using the DGTW method. The third set of robustness tests shows the Fama-French 48 industry-adjusted excess return. The fourth row shows the alpha using the Pástor and Stambaugh (2003) liquidity factor augmented with the Fama-French factors and the momentum factor. For the fifth set of tests, we report the alphas using the Fama and French (2015) Five Factor model. For the sixth and seventh sets of tests, we report the alphas using the Stambaugh and Yuan (2016) Mispricing Factors model and the Hou, Xue, and Zhang (2015) Q-factor model. For the eighth set of analyses, we exclude stocks whose market capitalizations are in the bottom quintile based on NYSE size breakpoints. In the ninth row, we skip six months between the moment an abnormal IP is constructed and the moment at which we start measuring returns. In the tenth and eleventh rows, we report the four-factor alpha for two sub-sample periods, one from 2003 to 2008 and the another from 2009 to 2014. The last row report the four-factor alpha after removing the financial crisis period (year 2008 and 2009). T-statistics are in brackets. Returns and alphas are reported in percentage.

	EW	VW
Gross return-weighed portfolio	1.096	NA
	(5.16)	
DGTW adjusted	0.910	0.410
	(4.51)	(2.22)
FF48 Industry-adjusted	0.739	0.155
	(3.26)	(1.16)
FF + Cahart + PS Factor	0.800	0.348
	(4.23)	(1.78)
FF five factor (2015)	0.685	0.248
	(3.36)	(1.19)
Mispricing factors (Stambaugh and Yuan 2017)	0.892	0.276
	(4.42)	(1.35)
Q-factor (Hou, Xue and Zhang 2015)	0.897	0.183
	(4.66)	(0.87)
Remove microcap stocks	0.518	0.276
	(2.58)	(1.35)
Skip six months	0.532	0.266
	(2.23)	(1.28)
2003-2008	0.620	0.261
	(2.41)	(0.89)
2009-2014	1.073	0.121
	(3.74)	(0.45)
Remove financial crisis period	0.733	0.116
	(3.87)	(0.56)

Table A.4: **Alternative Implementations of AIP**

This table reports several alternative implementations of AIP_10K when calculating the long/short portfolio Carhart (1997) four-factor alpha (in percentage). AIP_10K is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for 10-K filings in the EDGAR system on a set of firm characteristics. In the first row, we calculate AIP_10K using model (9) of equation (1). In the second row, we also include the square term of the four firm characteristics when calculating AIP. In the third row, we include the lagged number of IPs in the expected IP regression. Column (1) reports the results for the equal-weighted portfolio, and Column (2) reports for the value-weighted portfolio. T-statistics are in brackets. The sample runs from January 2003 to December 2014.

	EW	VW
Model (9) of Expected IP Regression	0.672	0.082
	(3.92)	(0.42)
Nonlinear functional form of Expected IP Regression	0.689	0.552
	(4.30)	(2.39)
Control for lagged # of IPs in Expected IP Regression	0.698	0.508
	(5.44)	(2.03)

Table A.5: **Alphas of Portfolios Sorted by Within-Firm Changes of AIP**

This table reports the monthly Carhart (1997) four-factor alphas (in percentage) for decile portfolios sorted by changes in AIP relative to its 12-month moving average (dAIP). In the end of each month, all stocks are sorted into deciles based on their dAIP, and a long-short portfolio is formed by buying the highest decile and shorting the lowest decile portfolio. Portfolio returns are computed over the next month. Panel A reports the results for equally-weighted portfolios and Panel B shows the results for value-weighted portfolios. The sample runs from January 2004 to December 2014.

Panel A: Equal-weighted Decile Portfolio Four-factor Alpha

	dAIP_10K	t-stat	dAIP_funtl	t-stat	dAIP_total	t-stat
Low	-0.45	-2.77	-0.36	-2.19	-0.38	-2.62
2	-0.08	-0.82	-0.03	-0.24	0.00	0.01
3	0.22	1.94	0.02	0.18	0.19	1.42
4	0.21	2.15	0.20	0.99	0.18	1.55
5	0.19	2.04	0.23	2.53	0.21	1.64
6	0.16	0.90	0.27	2.09	0.21	1.24
7	0.22	1.49	0.22	1.77	0.34	2.63
8	0.23	2.14	0.19	1.48	0.28	2.91
9	0.42	3.72	0.23	1.79	0.32	2.67
High	0.43	2.36	0.27	1.81	0.36	2.74
High - Low	**0.88**	4.82	**0.63**	3.27	**0.74**	3.65

Panel B: Value-weighted Decile Portfolio Four-factor Alpha

	dAIP_10K	t-stat	dAIP_funtl	t-stat	dAIP_total	t-stat
Low	-0.24	-1.30	0.05	0.24	-0.10	-0.46
2	-0.20	-1.15	0.00	0.03	-0.18	-1.38
3	0.23	1.52	0.25	1.38	0.18	1.35
4	0.26	1.41	0.13	0.89	0.08	0.56
5	0.39	2.30	0.21	1.69	-0.01	-0.07
6	0.15	1.65	0.04	0.33	0.22	1.37
7	0.14	0.97	0.11	0.84	0.11	0.77
8	-0.14	-0.96	0.18	1.17	0.17	1.05
9	0.19	0.80	0.07	0.35	0.06	0.32
High	0.15	0.87	-0.09	-0.50	0.37	1.94
High - Low	0.39	1.44	-0.14	-0.46	**0.47**	1.73

Table A.6: **Portfolio Sorts Within Industry**

This table reports the Carhart (1997) four-factor alpha of the long/short portfolio (in percentage) sorted on AIP within each industry of Fama-French 12 industry classification. In the end of each month, all stocks within each industry are sorted into quintiles based on their AIP_10K, and a long-short portfolio is formed by buying the highest quintile and shorting the lowest quintile portfolio. AIP_10K is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for 10-K files in the EDGAR database on a set of firm characteristics. The sample runs from January 2003 to December 2014.

Group	Industry	four-factor alpha	t-stat
1	Consumer NonDurables	**0.69**	2.50
2	Consumer Durables	0.82	1.59
3	Manufacturing	**0.66**	2.24
4	Energy	**1.06**	3.31
5	Chemicals	**0.78**	1.81
6	Business Equipment	**0.71**	3.71
7	Telecommunications	**0.94**	2.05
8	Utilities	0.21	0.91
9	Shops	**0.50**	1.99
10	Health	**0.77**	2.24
11	Financials	**0.48**	2.39
12	Other	**0.65**	2.75

Table A.7: **Returns and Alphas of Portfolios Sorted by Raw Number of IPs**

This table reports the monthly excess returns and Carhart (1997) four-factor alphas (in percentage) for decile portfolios sorted by the raw number of IPs searching for SEC filings. At the end of each month, all stocks are sorted into deciles based on their raw numbers of IPs, and a long-short portfolio is formed by buying the highest decile and shorting the lowest decile portfolio. Portfolio returns are computed over the next month. Panel A reports the results for equally weighted excess return and Panel B shows the results Carhart (1997) four-factor alphas. The sample runs from January 2003 to December 2014.

Panel A: Equal-weighted Decile Portfolio Excess Return

	IP_10K	t-stat	IP_funtl	t-stat	IP_total	t-stat
Low	0.73	2.04	0.87	2.62	0.73	2.17
2	0.80	1.87	0.80	1.90	0.92	2.17
3	0.63	1.32	0.91	1.89	1.01	2.19
4	0.95	1.86	1.12	2.28	1.12	2.22
5	1.05	2.01	0.89	1.73	1.12	2.19
6	1.12	2.10	1.17	2.23	1.07	2.08
7	1.12	2.07	1.12	2.11	1.01	1.92
8	1.22	2.25	1.05	1.91	1.14	2.06
9	1.19	2.26	1.04	1.96	0.99	1.84
High	1.10	2.31	1.09	2.20	0.98	1.99
High - Low	0.37	1.58	0.22	0.68	0.26	1.19

Panel B: Equal-weighted Decile Portfolio Four-factor Alpha

	IP_10K	t-stat	IP_funtl	t-stat	IP_total	t-stat
Low	0.04	0.23	0.18	1.18	0.05	0.30
2	-0.12	-0.78	-0.05	-0.39	0.06	0.44
3	-0.26	-1.96	-0.07	-0.54	0.08	0.68
4	-0.08	-0.59	0.05	0.35	0.00	0.00
5	-0.08	-0.70	-0.11	-0.94	0.01	0.08
6	-0.01	-0.12	-0.02	-0.17	-0.09	-0.83
7	0.01	0.15	-0.08	-0.96	-0.09	-0.94
8	0.06	0.77	-0.08	-0.73	-0.11	-1.17
9	0.05	0.49	-0.05	-0.49	-0.13	-1.33
High	0.13	1.49	-0.02	-0.20	-0.05	-0.50
High - Low	0.09	0.47	-0.20	-1.15	-0.09	-0.56

Table A.8: **Two-way Sorts by Firm Size and Abnormal Number of IPs**

This table reports the monthly Carhart (1997) four-factor alphas (in percentages) sorted by stock's market capitalization and the abnormal number of IPs searching 10-K filings (AIP_10K). AIP_10K is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for 10-K filings in the EDGAR system on a set of firm characteristics. In the end of each month, all the stocks are sorted into quintiles based on NYSE size breakpoints. We then independently sort the stocks into quintiles based on their AIP_10K. We also report, for each size quintile, the high-AIP minus low-AIP portfolio alpha. Panel A reports the resuls on an equal-weighted basis and Panel B reports the results on a value-weighted basis. T-statistics are in brackets. The sample runs from January 2003 to December 2014.

Panel A: Equal-weighted four-factor alpha

	Small firms	2	3	4	Large firms
Low AIP	-0.51	-0.14	-0.27	-0.17	-0.19
2	-0.19	-0.17	-0.22	-0.04	-0.23
3	-0.13	0.09	-0.04	0.01	-0.02
4	0.17	0.11	0.10	0.16	0.20
High AIP	0.64	0.22	0.16	0.20	-0.26
High-Low	**1.14**	**0.36**	**0.43**	**0.37**	-0.07
t-stat	(5.38)	(1.72)	(2.01)	(1.68)	(-0.26)

Panel B: Value-weighted four-factor alpha

	Small firms	2	3	4	Large firms
Low AIP	-0.57	-0.20	-0.27	-0.19	-0.20
2	-0.28	-0.17	-0.21	-0.04	-0.19
3	-0.15	-0.04	-0.02	-0.01	-0.02
4	-0.03	0.09	0.11	0.15	0.23
High AIP	0.41	0.02	0.19	0.21	-0.30
High-Low	**0.98**	0.22	**0.46**	**0.40**	-0.10
t-stat	(4.80)	(0.97)	(2.18)	(1.78)	(-0.37)

Table A.9: **Abnormal Number of IPs and Earnings Announcement Returns**

This table reports the results of the Fama and MacBeth (1973) regression of a three-day cumulative abnormal return CAR on the abnormal number of IPs searching for SEC filings through EDGAR system (AIP). AIP_total is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for all type of SEC filings in the EDGAR system on a set of firm characteristics. Similarly, AIP_funtl (AIP_10K) is constructed using the number of unique IPs searching for 10-K, 10-Q, and 8-K (10-K) filings in the EDGAR system. In Columns (1) to (3), abnormal return is calculated as daily stock return minus return on the CRSP value-weighted portfolio return. In Columns (4) to (6), abnormal return is calculated as daily stock return minus the return on the characteristics-matched portfolio following Daniel, Grinblatt, Titman, and Wermers (1997). Size (LnME) is the natural log of a firm's market capitalization at the end of June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short term reversal measure (REV) is the lagged monthly return. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Turnover12 is the monthly turnover ratio averaged over the past 12 months. All t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	Market-adjusted CAR(-1,+1)			DGTW-adjusted CAR(-1,+1)		
	(1)	(2)	(3)	(4)	(5)	(6)
AIP_total	0.0020			0.0019		
	(1.39)			(1.45)		
AIP_fundl		0.0025*			0.0024*	
		(1.90)			(1.93)	
AIP_10K			0.0036***			0.0033***
			(2.74)			(2.93)
Rev	-0.0001	0.0003	0.0002	0.0000	0.0004	0.0004
	(-0.02)	(0.13)	(0.08)	(0.01)	(0.17)	(0.19)
LnME	0.0001	0.0000	0.0001	0.0003	0.0003	0.0003
	(0.17)	(0.05)	(0.16)	(0.54)	(0.46)	(0.52)
LnBM	0.0025**	0.0024**	0.0022***	0.0023**	0.0022**	0.0021**
	(2.56)	(2.61)	(2.71)	(2.55)	(2.61)	(2.67)
MOM	-0.0021	-0.0020	-0.0019	-0.0013	-0.0013	-0.0012
	(-1.54)	(-1.48)	(-1.46)	(-1.25)	(-1.18)	(-1.13)
Turnover12	-0.0188***	-0.0193***	-0.0203***	-0.0208***	-0.0211***	-0.0220***
	(-2.68)	(-2.95)	(-3.65)	(-3.83)	(-4.10)	(-5.12)
IVOL	-0.0395	-0.0420	-0.0402	-0.0219	-0.0244	-0.0228
	(-1.17)	(-1.30)	(-1.11)	(-0.54)	(-0.63)	(-0.53)
IO	0.0153***	0.0157***	0.0158***	0.0147***	0.0150***	0.0151***
	(6.75)	(6.98)	(7.27)	(6.53)	(6.66)	(6.93)
Constant	-0.0041	-0.0037	-0.0049	-0.0051	-0.0048	-0.0058
	(-1.37)	(-1.32)	(-1.36)	(-1.39)	(-1.36)	(-1.36)
Ave.R-sq	0.051	0.051	0.051	0.050	0.050	0.050
N.of Obs.	121929	121929	121929	121530	121530	121530

Table A.10: **Controlling for Firm Events, Change of Breadth of Ownership and Extreme Returns**

This table reports the results of the Fama and MacBeth (1973) regression of monthly stock returns on the abnormal number of IPs searching for EDGAR filings (AIP). AIP is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for all types of files in the EDGAR site on a set of firm characteristics. Columns (1), (4) and (7) show the results for IPs searching for all types of EDGAR filings. Columns (2), (5) and (8) show the results for IPs searching for 10-K, 10-Q, and 8-K files. Columns (3), (6) and (9) show the results for IPs searching for 10-K files. SUE is a firm's standardized unexplained earnings, defined as the realized earnings per share (EPS) minus EPS from four quarters prior, divided by the standard deviation of this difference over the prior eight quarters. EAM is a dummy variable that equals one when a given firm announces quarterly earnings in the month. Upgrade is a dummy equals one when there is an analyst recommendation upgrade in the previous month. Downgrade is a dummy equals one when there is an analyst recommendation downgrade in the previous month. DM is a dummy variable that equals one when there is an ex-dividend event in the previous month. num_8K is the natural log of one plus number of 8-K filings in the previous month. dBreadth is the percentage change of breadth of 13F institutional ownership, following Chen, Hong, and Stein (2002). Following Bali, Cakici, and Whitelaw (2011), the stock's extreme positive return (Maxret) is defined as its maximum daily return in the prior month. Size (LnME) is the natural log of a firm's market capitalization at the end of June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short term reversal measure (REV) is the lagged monthly return. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Turnover12 is the monthly turnover ratio averaged over the past 12 months. All t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	AIP_total	AIP_fundl	AIP_10K	AIP_total	AIP_fundl	AIP_10K	AIP_total	AIP_fundl	AIP_10K
AIP	0.0041**	0.0045***	0.0043***	0.0042**	0.0047***	0.0043***	0.0053***	0.0047***	0.0046***
	(2.45)	(3.09)	(3.81)	(2.49)	(3.10)	(3.94)	(3.38)	(3.14)	(4.20)
REV	-0.0312***	-0.0309***	-0.0312***	-0.0316***	-0.0312***	-0.0315***	-0.0352***	-0.0351***	-0.0358***
	(-4.26)	(-4.23)	(-4.27)	(-4.34)	(-4.29)	(-4.34)	(-4.46)	(-4.48)	(-4.54)
LnME	-0.0018***	-0.0018***	-0.0018***	-0.0018***	-0.0018***	-0.0018***	-0.0018***	-0.0018***	-0.0017***
	(-3.69)	(-3.74)	(-3.72)	(-3.69)	(-3.72)	(-3.72)	(-3.67)	(-3.71)	(-3.73)
LnBM	0.0016	0.0015	0.0015	0.0016	0.0015	0.0015	0.0015	0.0014	0.0014
	(1.50)	(1.44)	(1.46)	(1.52)	(1.46)	(1.47)	(1.48)	(1.43)	(1.41)
MOM	-0.0065	-0.0064	-0.0064	-0.0065	-0.0064	-0.0063	-0.0065	-0.0065	-0.0064
	(-1.15)	(-1.14)	(-1.12)	(-1.14)	(-1.12)	(-1.11)	(-1.16)	(-1.16)	(-1.14)
IVOL	0.0169	0.0131	0.0174	0.0240	0.0209	0.0220	-0.0636	-0.0692	-0.0768
	(0.24)	(0.18)	(0.24)	(0.34)	(0.29)	(0.31)	(-0.69)	(-0.74)	(-0.78)
Turnover12	-0.0087	-0.0082	-0.0084	-0.0091	-0.0086	-0.0089	-0.0085	-0.0079	-0.0080
	(-1.25)	(-1.18)	(-1.19)	(-1.29)	(-1.22)	(-1.24)	(-1.22)	(-1.13)	(-1.14)
IO	0.0118***	0.0113***	0.0110***	0.0120***	0.0115***	0.0112***	0.0120***	0.0114***	0.0111***
	(3.58)	(3.52)	(3.40)	(3.55)	(3.50)	(3.37)	(3.56)	(3.51)	(3.38)
SUE	0.0028***	0.0028***	0.0027***	0.0028***	0.0028***	0.0027***	0.0027***	0.0028***	0.0027***
	(8.48)	(8.52)	(8.57)	(8.57)	(8.62)	(8.64)	(8.49)	(8.53)	(8.54)
EAM	0.0033***	0.0035***	0.0028**	0.0031**	0.0033**	0.0028**	0.0031**	0.0032**	0.0027**
	(2.61)	(2.69)	(2.33)	(2.55)	(2.60)	(2.31)	(2.51)	(2.56)	(2.27)
Upgrade	0.0023***	0.0023***	0.0025***	0.0023***	0.0023***	0.0024***	0.0024***	0.0024***	0.0025***
	(2.76)	(2.76)	(2.95)	(2.79)	(2.77)	(2.94)	(2.89)	(2.90)	(3.03)
Downgrade	-0.0010	-0.0011	-0.0013	-0.0009	-0.0010	-0.0012	-0.0013	-0.0012	-0.0015*
	(-1.00)	(-1.16)	(-1.38)	(-0.90)	(-1.03)	(-1.29)	(-1.54)	(-1.36)	(-1.78)
DM	0.0030***	0.0031***	0.0031***	0.0031***	0.0032***	0.0031***	0.0031***	0.0031***	0.0031***
	(2.78)	(2.77)	(2.75)	(2.95)	(2.96)	(2.86)	(2.87)	(2.89)	(2.83)
num_8K				-0.0010	-0.0012*	-0.0004	-0.0010	-0.0012*	-0.0004
				(-1.55)	(-1.80)	(-0.64)	(-1.51)	(-1.76)	(-0.63)
dBreadth							0.0722	0.0825	0.0836
							(0.94)	(1.06)	(1.11)
Maxret							-0.0308	-0.0317	-0.0346
							(-1.52)	(-1.60)	(-1.53)
Constant	0.0121**	0.0124**	0.0123**	0.0125**	0.0128**	0.0125**	0.0123**	0.0127**	0.0124**
	(2.46)	(2.52)	(2.50)	(2.50)	(2.56)	(2.53)	(2.41)	(2.48)	(2.46)
Ave.R-sq	0.053	0.053	0.053	0.054	0.054	0.053	0.057	0.057	0.057
N.of Obs.	443261	443261	443261	443261	443261	443261	442698	442698	442698

Table A.11: **Controlling for News Coverage and News Sentiment**

This table reports the results of the Fama and MacBeth (1973) regression of monthly stock returns on the abnormal number of IPs searching for SEC filings (AIP). AIP_total is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for all type of SEC filings in the EDGAR system on a set of firm characteristics. Similarly, AIP_funtl (AIP_10K) is constructed using the number of IPs searching for 10-K, 10-Q, and 8-K (10-K) filings in the EDGAR system. News coverage is the natural logarithm of the number of news article covering the company in a given month in the RavenPack database. News sentiment is the event sentiment score from RavenPack, which indicates how firm-specific news events are categorized and rated as having a positive or negative effect on stock prices by experts with extensive experience and backgrounds in linguistics, finance, and economics. Size (LnME) is the natural log of a firm's market capitalization at the end of June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short term reversal measure (REV) is the lagged monthly return. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Turnover12 is the monthly turnover ratio averaged over the past 12 months. All t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
AIP_total	0.0043**			0.0041**		
	(2.33)			(2.40)		
AIP_funtl		0.0040**			0.0044***	
		(2.13)			(2.86)	
AIP_10K			0.0050***			0.0052***
			(3.65)			(3.95)
REV	-0.0250***	-0.0232***	-0.0252***	-0.0270***	-0.0267***	-0.0276***
	(-2.95)	(-2.83)	(-2.96)	(-3.21)	(-3.18)	(-3.24)
LnME	-0.0013***	-0.0013**	-0.0012**	-0.0015***	-0.0016***	-0.0015***
	(-2.62)	(-2.60)	(-2.27)	(-2.67)	(-2.74)	(-2.72)
LnBM	0.0011	0.0012	0.0012	0.0006	0.0005	0.0003
	(1.03)	(1.05)	(1.05)	(0.59)	(0.45)	(0.27)
MOM	-0.0053	-0.0051	-0.0052	-0.0050	-0.0049	-0.0046
	(-0.84)	(-0.81)	(-0.81)	(-0.75)	(-0.74)	(-0.69)
IVOL	0.1334*	0.1171	0.1363*	0.1338*	0.1290*	0.1396*
	(1.66)	(1.52)	(1.68)	(1.73)	(1.69)	(1.74)
Turnover12	-0.0083	-0.0093	-0.0070	-0.0116	-0.0110	-0.0105
	(-0.96)	(-1.01)	(-0.82)	(-1.11)	(-1.08)	(-1.05)
IO	0.0082**	0.0084***	0.0070**	0.0110***	0.0111***	0.0105***
	(2.56)	(2.82)	(2.12)	(3.74)	(3.71)	(3.61)
News Coverage	-0.0004	-0.0005	-0.0005			
	(-0.66)	(-0.71)	(-0.72)			
News Sentiment				0.0161***	0.0161***	0.0171***
				(3.88)	(3.86)	(3.48)
Constant	0.0153***	0.0155***	0.0153***	0.0122**	0.0122**	0.0115**
	(2.88)	(2.92)	(2.91)	(2.26)	(2.27)	(2.10)
Ave.R-sq	0.055	0.055	0.055	0.056	0.055	0.056
N.of Obs.	264816	264816	264816	264816	264816	264816

Table A.12: **Abnormal Number of IPs and Long-horizon Returns**

This table reports the results from the Fama and MacBeth (1973) regression of cumulative returns from month $t + j$ to $t + k$ (Cumret(j,k)) on the abnormal number of IPs searching for 10-K filings in the EDGAR system (AIP_10K) in month t. The dependent variable is next quarter return (skipping the immediate month) in Column (1), the second quarter return in Column (2), the second half-year return in Column (3), and the second year return in Column (4). AIP_10K is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for 10-K filings in the EDGAR system on a set of firm characteristics. Size (LnME) is the natural log of a firm's market capitalization at the end of June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short term reversal measure (REV) is the lagged monthly return. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Turnover12 is the monthly turnover ratio averaged over the past 12 months. All t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	Cumret(2,4)	Cumret(5,7)	Cumret(8,13)	Cumret(14,25)
	(1)	(2)	(3)	(4)
AIP_10K	0.0102***	0.0068**	0.0150	0.0175
	(2.95)	(2.05)	(1.57)	(0.64)
REV	-0.0072	0.0037	0.0033	-0.0451
	(-0.53)	(0.21)	(0.11)	(-0.93)
LnME	-0.0023	-0.0013	-0.0015	-0.0048
	(-1.64)	(-1.03)	(-0.61)	(-1.11)
LnBM	0.0046*	0.0041	0.0118**	0.0197*
	(1.72)	(1.57)	(2.36)	(1.79)
MOM	-0.0193	-0.0117	-0.0300*	-0.0421
	(-1.24)	(-0.88)	(-1.75)	(-1.26)
IVOL	0.0407	-0.0184	0.2652	0.5759
	(0.20)	(-0.10)	(0.73)	(0.84)
Turnover12	-0.0165	-0.0312*	-0.0451	-0.0488
	(-0.92)	(-1.95)	(-1.53)	(-1.08)
IO	0.0116	0.0152**	0.0414**	0.0956**
	(1.63)	(2.18)	(2.42)	(2.47)
Constant	0.0370**	0.0281*	0.0451	0.0947
	(2.41)	(1.72)	(1.53)	(1.51)
Ave.R-sq	0.051	0.044	0.036	0.035
N.of Obs.	469185	456068	425505	360584

Table A.13: **Which Types of SEC Filings?**

This table reports the results of the Fama and MacBeth (1973) regression of monthly stock returns on the abnormal number of IPs searching for SEC filings (AIP). AIP_total is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for all type of SEC filings in the EDGAR system on a set of firm characteristics. Similarly, AIP_funtl (AIP_10K) is constructed using the number of IPs searching for 10-K, 10-Q, and 8-K (10-K) filings in the EDGAR system. Size (LnME) is the natural log of a firm's market capitalization at the end of June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short term reversal measure (REV) is the lagged monthly return. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Turnover12 is the monthly turnover ratio averaged over the past 12 months. All t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Dep.Var = One-month ahead stock returns		
	(1)	(2)
AIP_total	-0.0014	-0.0003
	(-0.63)	(-0.17)
AIP_fundl	0.0022	0.0012
	(1.11)	(0.70)
AIP_10K	0.0049***	0.0043***
	(3.96)	(4.02)
REV		-0.0287***
		(-3.80)
LnME		-0.0014**
		(-2.52)
LnBM		0.0013
		(1.24)
MOM		-0.0048
		(-0.88)
IVOL		-0.0027
		(-0.04)
Turnover12		-0.0088
		(-1.27)
IO		0.0112***
		(3.84)
Constant	0.0122**	0.0120**
	(2.18)	(2.34)
Ave.R-sq	0.005	0.048
N.of Obs.	483667	480793

Table A.14: **Abnormal Number of IPs or Abnormal Number of Searches?**

This table runs horse race Fama and MacBeth (1973) regression of monthly stock returns on AIP and Asearch. Asearch is the residual from a monthly regression of log one plus the total number of EDGAR requests for SEC filings. AIP is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for SEC filings on a set of firm characteristics. Columns (1) and (2) show the results for searching for all types of SEC filings. Columns (3) and (4) show the results for searching activities for 10-K, 10-Q, and 8-K filings. Columns (5) and (6) show the results for searching activities for 10-K filings. Size (LnME) is the natural log of a firm's market capitalization at the end of June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short term reversal measure (REV) is the lagged monthly return. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Turnover12 is the monthly turnover ratio averaged over the past 12 months. All t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	All EDGAR Filings		10-K, 10-Q, 8-K		10-K	
	(1)	(2)	(3)	(4)	(5)	(6)
Asearch	0.0014	-0.0004	0.0020*	-0.0024	0.0033***	-0.0039
	(1.54)	(-0.42)	(1.90)	(-1.49)	(3.93)	(-1.57)
AIP		0.0055**		0.0062***		0.0084***
		(2.45)		(2.83)		(2.90)
REV	-0.0283***	-0.0284***	-0.0283***	-0.0284***	-0.0284***	-0.0289***
	(-3.73)	(-3.76)	(-3.74)	(-3.77)	(-3.75)	(-3.75)
LnME	-0.0014**	-0.0014***	-0.0014**	-0.0014**	-0.0014***	-0.0013***
	(-2.59)	(-2.63)	(-2.61)	(-2.52)	(-2.64)	(-3.11)
LnBM	0.0013	0.0014	0.0014	0.0014	0.0012	0.0015*
	(1.26)	(1.31)	(1.34)	(1.36)	(1.13)	(1.71)
MOM	-0.0049	-0.0048	-0.0048	-0.0049	-0.0048	-0.0049
	(-0.89)	(-0.88)	(-0.87)	(-0.89)	(-0.86)	(-1.15)
IVOL	0.0048	-0.0014	0.0065	-0.0033	0.0039	-0.0021
	(0.07)	(-0.02)	(0.09)	(-0.05)	(0.05)	(-0.03)
Turnover12	-0.0100	-0.0096	-0.0095	-0.0091	-0.0095	-0.0088
	(-1.46)	(-1.39)	(-1.38)	(-1.33)	(-1.37)	(-1.33)
IO	0.0127***	0.0123***	0.0122***	0.0115***	0.0120***	0.0109***
	(4.10)	(4.04)	(4.06)	(3.86)	(4.03)	(3.57)
Constant	0.0115**	0.0120**	0.0116**	0.0119**	0.0117**	0.0120***
	(2.26)	(2.35)	(2.29)	(2.33)	(2.32)	(3.19)
Ave.R-sq	0.046	0.047	0.046	0.048	0.046	0.049
N.of Obs.	480793	480793	480793	480793	480793	480793

Table A.15: **Abnormal Number of IPs, Price Informativeness and Information Asymmetry**

This table reports the results of the Fama and MacBeth (1973) regression. AIP is the residual from a monthly regression of log one plus the total number of unique IP addresses searching for SEC filings on a set of firm characteristics. Columns (1), (4) and (7) show the results for searching for all types of SEC filings. Columns (2), (5) and (8) show the results for searching activities for 10-K, 10-Q, and 8-K filings. Columns (3), (6) and (9) show the results for searching activities for 10-K filings. In Columns (1)-(3), the depdendent variable is stock price synchronicity ($SYNCH$), in Columns (4)-(6) it is bid-ask spread (*Spread*), and in Columns (7)-(9) it is $GPIN$. For each firm-quarter observation, we regress daily returns on the value-weighted market return and the value-weighted two-digit SIC industry return, with a minimum of 50 daily observations.

$$RET_{i,t} = \alpha + \beta_1 MKTRET_t + \beta_2 MKTRET_{t-1} + \beta_3 INDRET_{j,t} + \beta_4 INDRET_{j,t-1} + \epsilon_{i,t}$$

Following the definition in Morck, Yeung, and Yu (2000), we define $SYNCH$ as

$$SYNCH = log(R^2/(1-R^2))$$

where R^2 is the coefficient of determination from the estimation of equation. Negative adjusted R^2 numbers are trimed at 0.0001. *Spread* is the daily percentage bid-ask spread, defined as $Spread = \frac{ClosingAsk_t - ClosingBid_t}{(ClosingAsk_t + ClosingBid_t)/2}$. We average the *Spread* to stock-month level. $GPIN$ is a modified version of PIN measure that captures the probability of informed trading (Duarte, Hu, and Young (2020)). Size (LnME) is the natural log of a firm's market capitalization at the end of June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short term reversal measure (REV) is the lagged monthly return. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Turnover12 is the monthly turnover ratio averaged over the past 12 months. All t-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	Dep.Var = SYNCH			Dep.Var = Spread			Dep.Var = GPIN		
	(1) AIP_total	(2) AIP_fundl	(3) AIP_10K	(4) AIP_total	(5) AIP_fundl	(6) AIP_10K	(7) AIP_total	(8) AIP_fundl	(9) AIP_10K
AIP	-0.4611***	-0.2480***	-0.3261***	0.0434***	0.0745***	0.0903***	-0.0490	0.0109***	0.0196***
	(-3.01)	(-8.39)	(-11.93)	(18.23)	(29.07)	(18.25)	(-0.66)	(2.96)	(4.69)
REV	0.6253***	0.6160***	0.6071***	-0.4549***	-0.4483***	-0.4483***	-0.0486***	-0.0481***	-0.0326*
	(3.07)	(3.02)	(2.98)	(-17.71)	(-17.50)	(-17.54)	(-3.55)	(-3.37)	(-1.74)
LnME	0.7905***	0.7867***	0.7893***	-0.0846***	-0.0854***	-0.0857***	-0.0209***	-0.0200***	-0.0207***
	(36.51)	(36.24)	(36.64)	(-44.63)	(-44.30)	(-44.35)	(-11.98)	(-13.19)	(-13.57)
LnBM	0.1007***	0.0995***	0.1030***	-0.0495***	-0.0509***	-0.0506***	0.0077***	0.0097***	0.0097***
	(5.74)	(5.64)	(5.83)	(-15.35)	(-16.21)	(-16.14)	(9.82)	(8.51)	(5.62)
MOM	0.3730***	0.3788***	0.3689***	-0.1521***	-0.1484***	-0.1491***	-0.0189***	-0.0191***	-0.0205***
	(6.30)	(6.45)	(6.25)	(-10.11)	(-10.06)	(-10.17)	(-2.82)	(-2.99)	(-2.95)
IVOL	-8.0463***	-8.2594***	-8.0971***	15.2094***	15.1552***	15.1380***	4.3360***	4.3474***	4.2948***
	(-5.44)	(-5.59)	(-5.45)	(58.58)	(58.28)	(58.13)	(21.63)	(22.79)	(17.28)
Turnover12	0.9018***	0.8662***	0.8933***	0.3438***	0.3406***	0.3369***	0.1317***	0.1244***	0.1365***
	(6.89)	(6.56)	(6.74)	(17.67)	(17.48)	(17.23)	(7.13)	(7.05)	(5.52)
IO	1.7684***	1.8071***	1.7873***	-0.1022***	-0.0976***	-0.0914***	-0.1784***	-0.1796***	-0.1794***
	(21.68)	(21.27)	(21.00)	(-10.34)	(-9.97)	(-9.37)	(-21.09)	(-18.42)	(-19.60)
Constant	-8.1329***	-8.1199***	-8.1311***	1.1147***	1.1178***	1.1183***	0.5086***	0.5049***	0.5106***
	(-35.93)	(-35.93)	(-35.88)	(45.02)	(44.80)	(44.77)	(26.52)	(31.65)	(31.10)
Ave.R-sq	0.457	0.456	0.456	0.413	0.415	0.416	0.163	0.163	0.165
N.of Obs.	135683	135683	135683	469009	469009	469009	108782	108782	108782