Information Demand and Stock Market Volatility

Nikolaos Vlastakis[*], Raphael N. Markellos[†]

Athens University of Economics and Business, Greece

This Draft: January 2010

Abstract We study intertemporal information demand at the market and firm level using data for the largest 30 stocks traded on the NYSE. Demand is proxied in a novel manner on the basis of weekly internet search volume time series drawn from the recently released Google Trends database. Our paper makes two main contributions. First, we demonstrate that demand for idiosyncratic information has significant impact on individual stock trading volume and the conditional variance of excess stock returns. This effect is robust to the presence of market information and supports the hypothesis that idiosyncratic risk is indeed priced, even in the case of large firms. However, the effect of idiosyncratic information diminishes when we examine expected risk using implied, rather than historical measures of volatility at the firm and market level. This result suggests that, although firm-specific information directly influences stock returns, market-wide information is the main factor investors take into consideration when forming future expectations. Second, using the expected variance risk premium for the S&P 500 index as a metric for time-varying risk attitudes, we confirm empirically for the first time the theoretical proposition that information demand is positively related to risk aversion.

Keywords: Information Demand; Financial Markets; Volatility; Risk Aversion.

JEL Classification Numbers: C32, D83, G12, G14.

[*]Doctoral Candidate, Department of Management Science and Technology, Athens University of Economics and Business, Greece.

[†]Corresponding Author: Associate Professor, Department of Management Science and Technology, Athens University of Economics and Business, Office 915, 47A Evelpidon Str. 113 62, Athens, Greece; Visiting Research Fellow, Centre for Research in International Economics and Finance (CIFER), Loughborough University, UK. E-mail: *rmarkel@aueb.gr* ; Tel. +30 210 8203671; Fax. +30 210 8828078. We thank MSL research seminar participants on October 2009 for their comments on an earlier version of this paper. We particularly thank Sanjay Banerji from Essex Business School, Nikos Korfiatis from Copenhagen University and Apostolos Kourtis from AUEB for valuable feedback. We also thank Efthymia Symitsi and Evanthia Tsalapati for help with data processing. All remaining errors are our responsibility.

1 Introduction

It is often said that information is the most valuable and highly sought asset in financial markets. Unsurprisingly, a voluminous literature has examined over the years the intricacies between announcements, news and market activity. In the present paper, we beg to differ in three main ways. First, rather than looking at the supply side of information, as previous researchers have, we concentrate on the demand for information. Second, we use a novel proxy for intertemporal information demand based on internet search volumes globally. This recognizes the fact that the internet has nowadays revolutionized the production, distribution and consumption of information in the financial industry. Third, our data allows us to test empirically for the first time predictions by theoretical models which link changes in investor risk attitudes to variations in information demand.

Our empirical application focuses on the largest 30 stocks traded on the New York Stock Exchange (NYSE). Proxies of (idiosyncratic) information demand for each stock are built on the basis of measures of the popularity of the company name as a keyword in the most popular internet search engine. Accordingly, information demand for the overall market is proxied using the S&P500 as the search keyword. Our results extend previous empirical findings since we find that both market and idiosyncratic information demand are positively related to individual stock trading volume and excess return conditional variance. More importantly, we find that the expected variance risk premium for the S&P500, as a measure for time-varying risk aversion, is positively related to our proxy of market information demand.

The rest of the paper is structured as follows: the next section reviews the relevant literature and outlines the theoretical and methodological background. Section 3 presents empirical results and provides the relevant discussion and section 4 concludes the paper.

2 Background and theoretical framework

2.1 Information and financial markets

The link between information flow and financial markets is well known to financial economists (see, for example, Fama et al., 1969 and French and Roll, 1986). The widespread hypothesis is that measures of market activity - such as return volatility and trading volume - are directly related to the rate of arrival of information in the market. A relevant strand in the literature has stemmed from the so-called 'Mixture of Distributions Hypothesis' (Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; Andersen, 1996) (MDH henceforth). The MDH provides an explanation to the observed link between volatility and trading volume by imposing a joint dependence of both volume and returns on a latent information process. A direct consequence of the MDH is that observed patterns in market activity, such as volatility persistence are caused by the existence of the same patterns in information flow.

Any attempt to empirically study the effect of information on financial markets requires the use of a proxy for information flow, since it is not directly observable. A variety of measures and proxies have been proposed in a series of empirical applications. Mitchell and Mulherin (1994) derive a metric of information flow by using the number of macroeconomic and firm-specific news announcements released by Dow Jones and Company on the Broadtape and in the Wall Street Journal. They find that the flow of information displays patterns by time of day, by day of week and by month, in accordance to the behavior of asset prices. They also find evidence of a statistically significant relation between information and volume, but a weak relation to volatility. In a related study, Berry and Howe (1994) study the number of news announcements in the Reuters North American Wire. In line with Mitchell and Mulherin (1994), they find seasonal patterns in the arrival of news. They also document a significant difference in the flow of news between trading and non-trading hours, that may be able to account for similar differences in volatility, as presented in French and Roll (1986). Their analysis of the relation between information and market activity (volume and volatility) produced similar results to Mitchell and Mulherin (1994). On the other hand, Ederington and Lee (1993) study the impact of scheduled macroeconomic announcements to the intra-day and daily volatility of interest rate and exchange rate futures and find a strong connection between these announcements and seasonal volatility patterns.

A distinction often made in the literature is between macroeconomic and firm-specific information. Finance theory suggests that firm-specific risk can be eliminated via diversification, in which case investors should only concern themselves with the undiversifiable market risk. Several studies point out that for the majority of investors this hypothesis may not be true, either due to economic constraints inhibiting them from holding a well-diversified portfolio, or due to behavioral biases[1]. If this conjecture is true, then idiosyncratic risk remains an important determinant of asset prices and firm-specific information should influence individual stock returns. Moreover, Campbell et al. (2001) report that firm-level variance has more than doubled between 1962 and 1997, whereas at the same time market and industry variances have remained fairly stable. On the empirical front, Thompson et al. (1987) study the properties of firm-specific news reported in the Wall Street Journal Index for 1983 and report that news coverage varies with respect to firm size and industry, as well as across days of the week and months. They examine stock return levels and variability separately for days with news and days without news across different news categories and find that several firm-specific news categories have a statistically significant impact on stock returns. Bessembinder et al. (1996) examine the relationship between trading volume and information flow for different portfolios of firms based on market capitalization and show that firm-specific information has a positive impact on trading activity for all firms, but that the effect is stronger for small firms. Moreover, they report that market-wide information has a significant impact on larger firms, but a negligible impact on small firms. More recently, Ryan and Taffler (2004) study a sample of the largest 350 firms listed on the London Stock Exchange and find that firm-specific information releases are a highly significant determinant

[1]See, for example, Mayshar (1981), Merton (1987) and Statman (1987)

of individual stock price changes and trading volume activity.

The somewhat weak evidence in favor of the information-volatility link presented in some of the empirical studies may well be a result of the modeling techniques employed in these studies. Several papers (Kalev et al., 2004; Bomfim, 2001, inter alia) suggest the use of GARCH (Engle, 1982; Bollerslev, 1986) models. Kalev et al. (2004) argue that modeling the relationship between information and volatility through a conditional heteroscedasticity process is a great improvement over previously used, unconditional volatility measures, such as absolute daily market returns. They incorporate their information variable (number of news in the Reuters News service) in the variance equation of a GARCH(1,1) model. The results evince a significant relationship between information and conditional variance and a decrease in volatility persistence, which they suggest that, in addition to the strong autocorellation structure of their information variable, are supportive of the MDH.

All of the aforementioned empirical applications have employed measures of information flow that share a common characteristic. Whether the metrics are based on macroeconomic or firm-specific announcements, headlines from newspapers or electronic news services, they all quantify information supply. As such, they also share common limitations. Perhaps the most important is that information supply cannot quantify the impact of new information on investors, its relative importance. Due to this fact, earlier contributions suggest the use of a variety of proxies for information importance. For example, Mitchell and Mulherin (1994) consider measures such as the number of topics covered by an announcement, the size of New York Times headlines, and the occurrence of monthly macroeconomic announcements to proxy for the importance of the news on a particular day, whereas Klibanoff et al. (1998) consider news salience, as proxied by the appearance of a news event in the front page of The New York Times. Ryan and Taffler (2004) follow a different approach. They first identify major market reactions and then focus on the news driving these reactions. Although their approach produces satisfactory results, only focusing on events that produce large reactions means that they exclude a large amount of information, which implies their results could overstate the effect of news on stock returns.

In contrast, we use a measure of information flow that captures information demand. The measure is based on the number of searches in an internet search engine. We selected this measure because of the dominant role of the internet as a source of information. The internet has made information easily accessible, driving down the cost of information acquisition. Notwithstanding, the abundance of information that can be found on the internet is both a blessing and a curse: although almost all information a person may require abides on the internet, obtaining the information is inhibited by this very abundance. This is the main reason that people rely on search engines to locate the information they desire. In fact, using a search engine has become synonymous to accessing the internet. Moreover, several articles have emphasized the growing tendency for investors to turn to the internet for information and brockerage services. Barber and Odean (2001) argue that, as people resort to online brokerage firms, they are deprived of the professional advice they received in traditional firms, but at the same time are unwilling to pay for such services. The reason they provide for this behavior is that people tend to rely more on the internet for information in order to make their investing decisions. In line with this suggestion, Antweiler and Frank (2004) study internet message boards and find that stock messages have a statistically significant effect on stock returns, a clear sign that a considerable amount of investors uses these message boards as a source of information.

As a proxy for information demand, we use data from Google, which is by far the most popular internet search engine, with an estimated market share of over 65% in November 2009[2]. The data are provided through Google Insights for Search, which is a part of the Google Trends Labs, and are publicly available. The Google Insights for Search service provides Search Volume Index (SVI) data for any keyword(s) the user inputs. SVI is derived from the number of searches for the specific keyword(s), divided by the total number of queries at a point in time and scaled to the highest value, for the requested period, so

[2]Google's share of US searches in November 2009 was 65.4%, according to Nielsen, a company that specializes in media information and research.

that the highest value in the sample is 100[3]. The service provides data from 2004 onwards, at weekly frequency, or at daily frequency for periods less than a quarter. Moreover, the user has the ability to compare different queries and filter results according to category or geographical location.

The data provided by Google trends have recently started to attract the attention of researchers. Da et al. (2009a) derive a measure of investor attention using data from Google trends. They approximate investor attention on an asset as the SVI for the ticker of the asset and study its relationship to existing measures of attention, and the hypothesis that SVI captures individual investor attention. They examine a panel of weekly SVI of Russell 3000 stock tickers and its relationship to stock prices. Their results indicate that SVI is able to capture investors attention more efficiently than existing measures of attention, especially in the case of less sophisticated investors. They also provide evidence that increases in SVI lead to temporary increases in stock prices - particularly so for IPOs - and that stronger price momentum is associated with high SVI, in support of the Daniel et al. (1998) explanation of the momentum effect. Following a different approach, Da et al. (2009b) construct a Financial and Economic Attitudes Revealed by Search (FEARS) index by aggregating daily SVI for terms related to household financial and economic concerns, in order to capture investor sentiment. They examine the link between the FEARS index and daily realized volatilities across several asset classes, using data from equity, treasury and commodity exchange-trade funds (ETF). They find that their index is able to predict daily realized volatilities of ETFs and remains significant in the presence of other predictors, such as the CBOE VIX index, volume and turnover, as well as an alternative sentiment measure, in support of the "noise trader" model of De Long et al. (1990). The index also predicts daily fund flows away from equities and into fixed income and metal funds, which is consistent with a "flight to quality" in turbulent times.

[3]For a comprehensive description and application of Google Trends data to forecasting a variety of economic variables, such as automobile and home sales, see Choi and Varian, 2009.

2.2 Information Demand

The determinants of information demand in the context of speculative markets have attracted increasing attention over the past years. In a seminal paper, Grossman and Stiglitz (1980) analyze a noisy rational expectations equilibrium. They show that equilibrium occurs when prices reflect only a portion of the information held by informed investors, what they call an "equilibrium degree of disequilibrium", so that perfect informational efficiency can never exist. This conclusion is based upon the rationale that as the percentage of informed investors increases, prices become more informative, thus the incentives to acquire information are decreasing (information substitutability). This conjecture also implies that the demand for information - the percentage of informed traders - is increasing with the magnitude of noise. Veldkamp (2006) revisits the Grossman and Stiglitz (1980) model, making an important alteration: instead of treating information as exogenous to the market, her model replaces constant information price with an endogenous price set in a market characterized by increasing returns. The model features competitive information suppliers in a complementary market for information. Veldkamp shows that the inclusion of endogenous information in the Grossman and Stiglitz model has an important implication: increasing the number of informed investors increases the returns to information (because the price of information is a decreasing function of the quantity), thus information becomes a strategic complement. Moreover, she suggests that payoff volatility increases information demand, whereas information increases asset prices.

Moscarini and Smith (2002) study the demand for information, concentrating in situations when information demand is very high and its price very small, approximating the conditions prevailing in the internet. They derive an analytical formula for the demand for information and prove that, in the specific setting, information demand is a decreasing function of the informational content of a signal[4]. Informational content is defined as

[4] Moscarini and Smith (2002) show that for an experiment ε with efficiency index $\rho_\varepsilon \in (0,1)$, for almost all p, which is the price of information, demand $n(p)$ is single-valued and decreasing in p and that there exists $\bar{p} \succ 0$ such that for all $p \in (0, \bar{p})$ demand is within 1 of $\frac{\log p + 1/2 \log[(\log p)/\log \rho_E] - \log[c(1-\rho_\varepsilon)]}{\log \rho_\varepsilon}$, and for very small

a measure of how well a signal can help distinguish between different states of the world. When the informational content of a signal is small, in the sense that there is ambiguity with respect to the state of the world, information demand increases and vice versa. Drawing an analogy to the real world, when an event of high significance occurs, it creates ambiguity with respect to its consequences (or, the "state of the world"), so that people demand more information. When they are satisfied with the amount of information they have received (in other words, the effects of the event are known) they stop asking for more information and demand decreases. Therefore, information demand is indicative of the relative importance of new information, because it incorporates the effect of new information on the public.

Another interesting strand in the literature concentrates on the relationship between risk aversion and information demand. The intuitive hypothesis is that information demand is positively related to the degree of risk aversion: information decreases uncertainty, so that risk-averse investors should demand more information than risk-seeking or risk-neutral investors. Notwithstanding, several papers suggest exactly the opposite. Freixas and Kihlstrom (1984) claim that, ex ante, an investor does not know what kind of information he is going to observe ("good" or "bad" news). Because information acquisition is costly, there is a risk entailed in acquiring information. This leads to risk-averse investors being less willing to acquire information than risk-seeking or risk-neutral investors. Willinger (1989) makes the same argument using the expected value of information, whereas Eeckhoudt and Godfroid (2000) conclude, in a similar setting, that increasing risk aversion not always increases the value of information. Verecchia (1980, 1982) shows that information demand is a nondecreasing function of risk tolerance (the reciprocal of risk aversion), as a necessary condition for a "consensus beliefs" efficient market in the first paper and in a rational expectations setting in the second.

The relationship between risk aversion and information demand has not yet been stud-

p : $n(p) \sim \frac{(\log p)}{(\log \rho_\varepsilon)}$. Further, $n(p)$ monotonically rises in ρ_ε, at fixed p. By construction, ρ_ε decreases as the informational content increases, so that the informational content of a signal is represented by $1/\rho_\varepsilon$. So, as the informational content of signals increases, information demand decreases.

ied empirically, mainly due to inherent difficulties of quantifying the two variables. We use our measure of information demand in conjunction with a proxy for time-varying risk aversion recently proposed in the literature and model the impact of varying risk attitudes on information demand.

3 Data and Empirical Analysis

We study information demand and its relationship to market activity on a sample of 30 of the largest stocks traded in the NYSE. Specifically, we selected the constituents (as of June 2009) of the Dow Jones Industrial Average index. Our sample covers the period January 2004 to October 2009 and comprises of weekly closing prices, trading volume and information demand data for the aforementioned stocks. Data on the S&P 500 index are used as a proxy for market return, whereas the CBOE VIX index is used as a measure of market implied volatility.

3.1 Information Demand Data

As stated previously, Google Trends provides SVI for any possible query. With an infinite number of possible queries, it is perhaps understandable that the choice of keywords is very important. In order to avoid any arbitrary definitions on what constitutes a search for information about a specific firm, there are two alternatives: we can either use the company name or the stock ticker. Da et al. (2009a) argue that it is preferable to use the stock ticker, as opposed to the company name. They cite three reasons: first, that people may search for the name of a company for many reasons other than their interest in the company as investors. Second, that there are many different ways to spell the name of a company. The final reason they cite is the fact that Google Trends does not allow alpharithmetic input, which would inhibit the use of names for companies such as 3M (this is no longer the case).

We opted for the use of the company name, for the following reasons. With respect to the first argument of Da et al. (2009a), we agree that the SVI for the company name does include some noise, which derives from searches not associated with information demand, such as people searching for products or support online. Notwithstanding, we expect that such noise should be random and therefore should not influence the variable significantly. Nevertheless, we test the data for seasonal patterns that could influence the behavior of the variable significantly and filter them out. Another reason we preferred the company name is that we derive a measure of the demand for information for a particular company, and not a measure of investor attention for the company stock. When investors search for information about a company not directly related to the stock (but still relevant, such as news about the company) they are more likely to use the company name. Finally, in order to account for the fact that the name of a company can be spelled in a variety of manners, we tried different spellings and selected the one that had the highest SVI globally. Table 1 presents a list of the companies in our sample, the corresponding stock ticker and the search query we used.

In addition to a proxy for firm-specific information demand, we also need a measure of the demand for information that affects the market as a whole. We base the definition of such a measure on the following rationale. When new information about an event that affects the whole of the market becomes available, investors are going to react by demanding information about the particular event, as well as its impact on the market. Because a proxy that captures all the adverse information that affects the market - which ranges from macroeconomic announcements to major political events, natural disasters, even major firm-specific events, such as a big merger or a bankruptcy - is very difficult to define, we preferred a proxy that captures the demand for information about the impact of such an event on the market. The best way to gauge this effect is to examine the market index. Therefore, we use the demand for information about the S&P 500 index as a proxy for market-related information.

Descriptive statistics of the information demand variable can be found in Table 2. The statistics vary significantly across different keywords. The main conclusion that can be drawn from the table is that the information demand variable is not normally distributed, with the exception of 4 cases, as is evident from the Jarque-Berra statistic. For the majority of keywords, information demand exhibits positive skewness and appears to be leptokurtic (with several exceptions), although the departure from normality is somewhat less emphatic than what one expects to see in, for example, stock return data. Furthermore, the existence of positive skewness is in stark contrast to the negative skewness usually associated with stock return data, but is consistent with the behavior of price variability measures, such as absolute returns.

Because the information demand variable lies in the center of this empirical study, it is useful to examine the time series properties of this variable, particularly stationarity, as it is going to be implemented in regression models subsequently. To this end, we run a series of unit root tests on the information demand variable. The results are reported in Table 3. Three different tests are implemented. The first is the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), using MacKinnon (1991, 1996) critical values. The second is the Phillips-Perron (PP) test (Phillips and Perron, 1988) and the third, the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (Kwiatkowski et al., 1992). The KPSS test differs from the other two tests in the null hypothesis: whereas the ADF and PP test the null hypothesis of a unit root in the data, the null hypothesis for the KPSS test is stationarity. For this reason, the KPSS test complements the other tests, especially in case the latter do not provide very clear results. For each test, two different specifications are implemented. In the first specification, the test equation only includes an intercept and in the second, it includes an intercept and a linear trend.

The results reported in Table 3 appear, at first, relatively unclear. When only an intercept is included in the test specification, the ADF and PP tests present mixed results. On the other hand, the KPSS test rejects stationarity at the 1% level for the majority of series. Adding a linear trend to the test specification tilts the scale towards stationarity, for all three tests. Therefore, we conclude that the information demand variable is stationary around a deterministic trend. We remove the trend from the data series, by running ols regressions of the variables on a time trend and extracting the residual series.

As stated previously, the information demand variable may contain noise. Such noise should be random in nature, but it may present seasonal patterns related to similar patterns in business activity, but not related to information demand. We therefore test the information demand variable for seasonal effects. Because our data is in weekly frequency, we test for a month effect. Table 4 shows the results of F-tests for the equality of SVI mean across months. The results indicate that, for the majority of series, there exists a month effect, as the tests reject the null hypothesis of equality of monthly means. In order to remove this effect, we implement a demeaning procedure, whereby we calculate the mean SVI for each week across all years and subsequently subtract the corresponding mean from each weekly observation.

3.2 Information Demand and Trading Volume

In order to examine the relationship between trading volume and information demand we use the number of shares traded within a given time period. Because trading volume data typically have a trend component, we apply a logarithmic transformation and subsequently remove the trend through the process discussed in the previous subsection[5].

The first step in exploring the volume/information demand relationship is to examine correlation. Table 5 presents correlation coefficients for the stocks in the sample. For each stock, two coefficients are calculated: one for the correlation between trading volume and firm-specific information demand and the other for the correlation between trading volume and market-related information demand. The results evince a positive relationship between trading volume and information demand, both for market-related and idiosyncratic information demand.

[5] We confirmed the existence of a deterministic trend in our sample by running the series of unit root tests that were described in the previous subsection, the results are available from the authors.

So as to gain better insight on the exact nature and economic significance of the relationship between trading volume and information demand we next employ regression analysis. We estimate an ordinary least squares (OLS) model of the following form:

$$V_t = \theta + \kappa|r_t| + \gamma\pi_t + \delta\phi_t + \varepsilon_t \tag{1}$$

where V_t is the trading volume, θ is the constant, $|r_t|$ is the absolute stock log return, π_t is firm-specific information demand, ϕ_t is market-related information demand and ε_t are the errors. Newey-West HAC standard errors and covariance are employed in the estimation. We control for absolute stock return, because of the accumulated empirical evidence on its relationship with trading volume (for a review of the relevant evidence, see Karpoff, 1987). Variables not found statistically significant have been omitted in a one-step backwards procedure.

The results of the estimation appear in Table 6. Overall, the table appears to be in agreement with the results of the correlation analysis. For the majority of the stocks in the sample, market-related information demand is a statistically significant regressor, with a positive coefficient. The same is true for a considerable number of stocks (roughly half of the stocks) for the firm-specific variable. The magnitude of the coefficients for the information demand variables reveals that the relationship is also economically significant. Moreover, in line with previous evidence, the coefficient for the absolute stock return is positive and statistically significant in all but two cases. Finally, the adjusted coefficient of determination reveals that the models have reasonably adequate explanatory power.

3.3 Information Demand and Volatility

We begin our analysis of the information demand/volatility relationship by examining correlations between information demand and a simple measure of stock price variability. In lieu of such a measure, we use absolute stock return, following previous contributions, such as Mitchell and Mulherin (1994). The results displayed in Table 7 are supportive of the hypothesis that there is a positive link between information demand and price variability. The evidence is particularly strong in favor of market-related information demand, but is nonetheless also supportive of a significant link between firm-specific information and absolute stock returns.

We next examine the relationship between market implied volatility, as proxied by the CBOE VIX index and market-related information demand. Figure 1 depicts the evolution of VIX index weekly closing prices and market-related information demand (SV for the term "s&p 500") for the period under study. The figure reveals there is a link between the two variables, which is intensified by the advent of the financial crisis. Indeed, during the peak of the crisis (Q2/2008 - Q1/2009) the two variables appear to be interlocked.

We confirm this apparent relationship between the two variables through regression analysis. We model the relationship between implied volatility and market-related information demand through a univariate OLS model with Newey-West HAC standard errors. We also employ data from the recently released VIX term structure, which captures implied volatility from a subset of S&P 500 (SPX) index option expirations[6]. We group the term structure expirations in 7 buckets, that correspond to an average of 16.69 (VIX t1), 50.04 (VIX t2), 84.52 (VIX t3), 146.63 (VIX t4), 234.23 (VIX t5), 331.08 (VIX t6) and 469.52 (VIX t7) calendar days, respectively. The term structure may provide a useful insight, as it represents differences in volatility expectations across different investment horizons. The results are presented in Table 8. All coefficients are positive and significant at the 1% level, whereas the adjusted R^2 coefficient indicates that the models have reasonably good explanatory power. These results confirm the hypothesis that market-related information demand is a significant determinant of market volatility. Moreover, the fact that the effect of the market-related information demand variable becomes smaller as the expirations become longer captures the diminishing effects of current information over longer investment horizons, due to increased

[6]For a description of the VIX term structure data, see Symeonidis et al. (2009).

uncertainty.

The final step in our examination of the information demand/volatility relationship is to model the effect of information demand on individual stock volatility explicitly. In order to obtain a more holistic view of this relationship, we examine both historical and implied volatility at the individual stock level. Implied volatility is forward-looking, contrary to historical volatility, as it represents the expectation for return volatility over a period inferred from the corresponding stock options. Therefore, examining both types of volatility may provide better insight on the nature of the effects of information demand on individual stock volatility.

Historical volatility is modelled through the use of a GARCH (1,1) market model that includes the information demand variables in the conditional variance specification, so that the model takes the following form[7]:

$$\begin{aligned} r_t &= \mu + \lambda \nu_t + \varepsilon_t, \qquad \varepsilon_t | \, \Omega_{t-1} \sim N(0, \sigma_t^2), \\ \sigma_t^2 &= \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \pi_t + \delta \phi_t \end{aligned} \tag{2}$$

where r_t is the stock return at interval t, μ is a constant, ε_t are the serially uncorrelated errors of stock returns with mean zero, Ω_{t-1} denotes the information set, σ_t^2 is the conditional variance of ε_t, ν_t is the market return at interval t, π_t is firm-specific information demand at interval t and ϕ_t is market-related information demand at interval t. The results, presented in Table 9, confirm the hypothesis that information demand directly influences excess return historical volatility at the individual stock level. At least one information demand variable enters the conditional variance specification as a statistically significant regressor for 26 out the 30 stocks in the sample. As expected, market information has a significant impact for most stocks in the sample (a total of 22 stocks). Nevertheless, idiosyncratic information appears to equally impact individual stock volatility for a considerable number of stocks

[7]Engle and Ng (1993) compare various ARCH models using the news impact curve, placing an emphasis on the asymmetry of the volatility response to news. In order to examine a potential similar effect in our data, we estimated an EGARCH model. The model did not improve our results, hence we opted for the use of the simple GARCH model instead.

(half the stocks in the sample). This is also evident by the magnitude of the estimated coefficients, which is comparable for the two information variables. In a number of extreme cases, firm-specific information appears to be the sole driver of stock volatility, outweighing the impact of market information to the point of becoming statistically insignificant.

In order to examine the relationship between information demand and individual stock implied volatility we use weekly data on one-month implied volatility for all stocks calculated from the corresponding call stock options and incorporated into a continuous time series for the whole period under consideration. We estimate the following panel OLS model with fixed cross-sectional effects:

$$IV_{it} = \omega + \psi_i + \gamma\pi_{it} + \delta\phi_t + \varepsilon_{it} \tag{3}$$

Where IV_{it} is the implied volatility of stock i at time t, ω is the constant, ψ_i is the cross-sectional fixed effect, corresponding to stock i, π_{it} is the idiosyncratic information demand for stock i at time t, ϕ_t is market-related information demand at time t and ε_{it} are the errors. Table 10 presents the estimation results. The adjusted R^2 coefficient suggests that a large proportion of the variability in implied volatility can be explained from the variability in information demand. Furthermore, it appears that in the case of implied volatility, idiosyncratic information demand has a considerably smaller impact (significant only at the 10% level), compared to market-related information demand. This fact suggests that, in the process of forming future expectations, investors are more influenced by market-wide information.

The magnitude of idiosyncratic information effects on both trading volume and volatility evident in the results becomes even more important, if the reader considers the stocks included in the sample. These are 30 stocks with the highest market capitalization traded in the NYSE. As such, market-related information is expected to have a strong impact on these stocks, whereas the effects of idiosyncratic information should be relatively reduced, as argued by Bessembinder et al. (1996). Due to the fact that we estimate the models for volume and volatility incorporating both information variables simultaneously, this effect is captured in our results. Nevertheless, idiosyncratic information appears to have a direct impact on trading volume and volatility, even in the presence of market information.

3.4 Information Demand and Risk Aversion

We now shift our attention to the determinants of information demand and, in particular, the link between information demand and risk aversion. In order to empirically study this relationship, we are in need of a measure of risk aversion. Several recent papers (examples include Aït-Sahalia & Lo, 2000; Jackwerth, 2000; Rosenberg & Engle, 2002; Bollerslev et al., 2008a,b) suggest that a measure of time-varying risk aversion may be extracted through the relationship between risk-neutral and subjective variance estimates, the so-called variance (or volatility, depending on the definition) risk premium. Theoretically, this hypothesis is based on the fact that these estimates of variance are derived from the corresponding risk-neutral and subjective probability distributions, which are linked by the coefficient of risk aversion (see also Jackwerth, 2000). Intuitively, the variance risk premium is the compensation demanded by investors for bearing the risk of unforseen changes in volatility, thus it is effectively the closest approximation to the investors' risk appetite.

Invariably, researchers rely on implied variance, inferred from option prices, as a measure of risk-neutral variance, whereas the actual, or subjective variance is captured by realized variance. Bollerslev et al. (2008a) point out the advantages of using "model-free" estimates of implied and realized variance in estimating the variance risk premium. They use monthly data from the VIX index (which is calculated in a model-free manner), using the squared index values as a proxy for implied variance. They estimate monthly "model-free" realized variance (Andersen et al., 2001a,b; Barndorff-Nielsen & Shephard, 2002, inter alia) by summing high-frequency intraday (5-minute sampling) S&P 500 squared returns. In order to compensate for the fact that implied variance is a forecast for future variance, they estimate expected realized variance using one-step ahead forecasts from a reduced form time-series model for realized variance. They estimate the expected variance risk premium as the difference between implied variance and expected realized variance:

$$EVRP_t \equiv IV_t - E_t(RV_{t+1}) \tag{4}$$

We use this measure of the variance risk premium in order to examine the hypothesis that risk aversion significantly affects information demand[8]. Because the risk aversion data are provided in monthly frequency, we convert our information demand data to this frequency, by averaging weekly observations across months. We model the relationship between information demand and risk aversion using an OLS model of the following form:

$$\phi_t = a + b\phi_{t-1} + cEVRP_t + dEVRP_{t-1} + \varepsilon_t \tag{5}$$

Where ϕ_t is market-related information demand at time t, a is the intercept $EVRP_t$ is the expected variance risk premium at time t and ε_t are the residuals. We include lagged values of the information demand variable in order to account for autocorrelation. We also estimate the model without including lagged information demand and compare results.

The results, presented in Table 11, confirm the hypothesis that the demand for information is positively related to risk aversion. All coefficients are statistically significant, even if we account for persistence in information demand. Furthermore, the adjusted coefficient of determination is very high and remains so after we exclude lagged information demand from the specification, which demonstrates that a significant portion of the variability in information demand (34.1%) can be explained by the variability in the expected variance risk premium.

Although this certainly does not come as a surprise, it contradicts with part of the literature reviewed earlier. This does not necessarily mean that the hypotheses stated in these

[8]Data are kindly provided by Hao Zhou in his website.

studies are altogether false. These studies (eg. Freixas & Kihlstrom, 1984 and Willinger, 1989) base their arguments to the risk associated by the purchase of information, which is directly affected by the cost of information. Because the cost of information on the internet is extremely small (when compared to other sources), this may be the reason that their hypotheses are not confirmed in our study.

4 Conclusions

This paper studied the demand for idiosyncratic and market-related information and its relationship to financial markets activity, using data on internet search volume to approximate information demand. Our main results are the following.

We document that idiosyncratic information demand has a positive and statistically significant effect on individual stock trading volume and excess return conditional variance, even after we control for the effects of market-related information demand. Moreover, we find that the effects of firm-specific information are comparable with those of market information and in several cases even stronger.

We also studied the determinants of information demand, and in particular the effect of risk aversion on information demand. To the best of our knowledge, we are the first to empirically study this relationship. Using the expected variance risk premium as a proxy for time-varying risk attitudes, we provide evidence of a positive, statistically significant relationship between risk aversion and information demand.

The results presented in this paper shed light on the relationship between information demand and financial markets activity. Notwithstanding, more research is needed to understand the complex nature of the interdependence between financial markets and information flow in general. We intend to return to this issue in the future.

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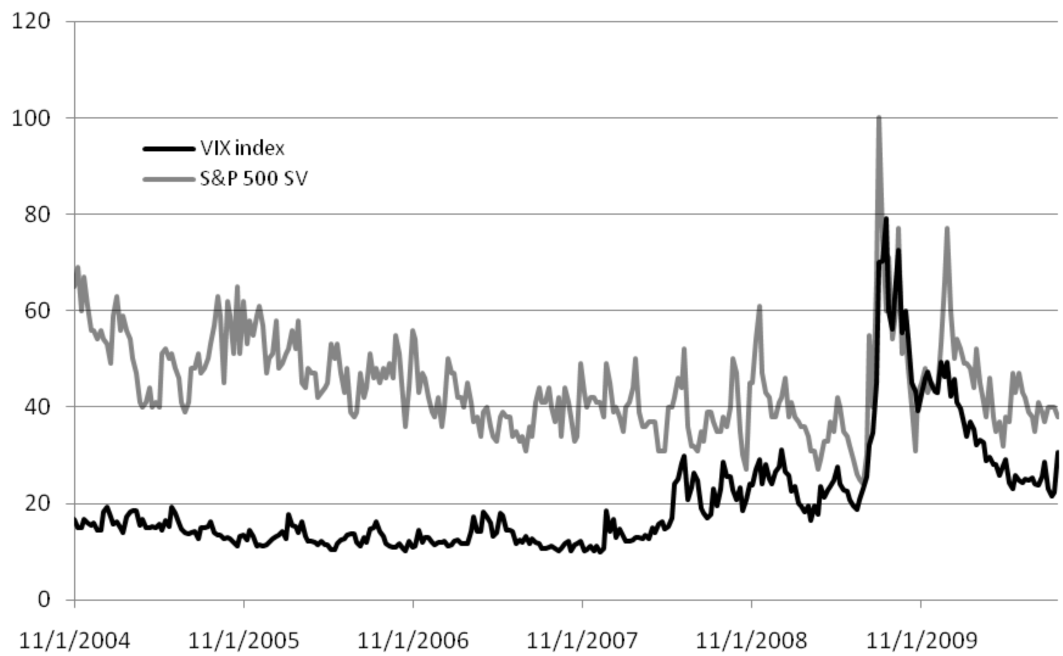

Figure 1: VIX index and market-related information demand

Table 1: **List of Companies in the Sample**

This table presents a list of the companies in our sample. In addition to the company name, the table includes the ticker for the company's stock and the search query used to extract the information demand variable.

Company	Ticker	Search Query
3M Company	MMM	"mmm"
Alcoa Inc	AA	"alcoa"
American Express Co	AXP	"american express"
AT&T Inc	T	"at&t"
Bank of America Corp	BAC	"bank of america"
Boeing	BA	"boeing"
Caterpillar Inc	CAT	"caterpillar"
Chevron Corp	CVX	"chevron"
Cisco Systems Inc	CSCO	"cisco"
Coca Cola Co	KO	"coca cola"
E I du Pont de Nemours and Co	DD	"dupont"
Exxon Mobil Corp	XOM	"exxon mobil"
General Electric Co	GE	"general electric"
Hewlett-Packard Co	HPQ	"hewlett packard"
Home Depot Inc	HD	"home depot"
Intel Corp	INTC	"intel"
International Business Machines Corp	IBM	"ibm"
Johnson and Johnson	JNJ	"johnson and johnson"
JPMorgan Chase and Co	JPM	"jp morgan chase"
Kraft Foods Inc	KFT	"kraft foods"
McDonald's Corporation	MCD	"mcdonald's"
Merck & Co Inc	MRK	"merck"
Microsoft Corp	MSFT	"microsoft"
Pfizer Inc	PFE	"pfizer"
Procter & Gamble Co	PG	"procter gamble"
Travelers Companies Inc	TRV	"travelers companies"
United Technologies Corp	UTX	"united technologies"
Verizon Communications	VZ	"verizon"
Wal-Mart Stores Inc	WMT	"walmart"
Walt Disney Co	DIS	"disney"
S&P 500 Index	.INX	"s&p 500"

Table 2: **Descriptive Statistics of Information Demand**

This table presents descriptive statistics of the SV data. In addition to the standard statistics, the table reports Skewness and Kurtosis coefficients, the Jarque-Berra statistic and the corresponding p-value.

Stock	Mean	Median	Range	Std. Dev.	Skew.	Kurt.	J-B	p-value
MMM	79.5625	79	33	5.7852	0.6166	3.2071	19.8092	0.0001
AA	53.3816	54	75	10.7295	0.1703	3.2995	2.6048	0.2719
T	48.3059	53	82	21.2235	0.0674	1.7895	18.7918	0.0001
AXP	72.3947	71	40	6.1870	1.3447	6.3092	230.3321	0.0000
BAC	61.7171	61.5	70	16.4483	0.0689	2.0763	11.0485	0.0040
BA	39.7829	39	76	9.2864	1.4806	9.7081	681.0554	0.0000
CAT	76.1447	75	49	8.6600	0.2487	2.9682	3.1476	0.2073
CVX	63.3454	63	58	7.1344	0.3939	4.7931	48.5876	0.0000
CSCO	55.1875	56	77	15.1723	0.1619	2.2161	9.1113	0.0105
KO	75.9276	75	49	8.3315	0.4559	3.5308	14.1001	0.0009
DD	71.7533	68	55	14.8407	0.3468	1.7216	26.7937	0.0000
XOM	50.1645	50	68	7.7480	1.7633	10.8069	929.5445	0.0000
GE	61.4540	58	65	17.6792	0.3843	1.7711	26.6110	0.0000
HD	79.7072	80	41	9.1624	0.1065	2.0849	11.1819	0.0037
HPQ	40.0987	35	85	21.7138	0.7473	2.3668	33.3770	0.0000
IBM	56.3290	50	75	21.5674	0.4770	1.8596	27.9996	0.0000
INTC	78.6480	78	36	6.1444	0.2889	3.0057	4.2286	0.1207
JNJ	60.5921	57	61	9.9645	0.6008	2.8600	18.5349	0.0001
JPM	41.6382	41	75	8.1569	2.6369	15.1404	2219.2200	0.0000
KFT	64.2829	63	56	10.3381	0.9216	3.8309	51.7773	0.0000
MCD	52.1842	50	66	10.0421	1.4537	6.3086	245.7282	0.0000
MRK	31.9408	30	88	10.3708	1.1892	7.8219	366.1643	0.0000
MSFT	48.5428	46	67	10.1125	0.7454	3.9030	38.4780	0.0000
PFE	50.6711	48	80	15.4485	0.4716	2.3696	16.3051	0.0003
PG	42.1447	38	83	13.8430	0.8187	3.3817	35.8059	0.0000
TRV	44.4243	43	85	12.7458	0.9865	4.8901	94.5637	0.0000
UTX	39.1382	35.5	83	13.7464	0.9339	3.6483	49.5152	0.0000
VZ	69.0395	69	52	8.9611	-0.0293	3.1068	0.1878	0.9104
DIS	75.0329	74	41	7.1596	0.4905	3.6522	17.5765	0.0002
WMT	36.9309	34	80	12.8945	1.8937	8.2688	533.3324	0.0000
.INX	44.5822	43	76	9.8148	1.1575	6.2628	202.7325	0.0000

Table 3: **Unit Root Tests on Information Demand**

This table presents unit root tests results for the information demand variable. Three types of tests are presented: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). All tests were conducted for two different specifications: the test equation includes a constant in the first and in the second, a constant and linear trend. The null hypothesis for the ADF and PP tests is the existence of a unit root, whereas in the KPSS test, that the series is stationary. A star, dagger and double dagger denote that the null is rejected at the 1%, 5% and 10% level, respectively.

Stock	ADF		PP		KPSS	
	Constant	Constant & Trend	Constant	Constant & Trend	Constant	Constant & Trend
MMM	-5.1511*	-5.7086*	-7.9566*	-8.7392*	0.8977*	0.2061†
AA	-1.3263	-13.1889*	-9.3723*	-13.3212*	1.8850*	0.0302
T	-1.3544	-2.1589	-1.1522	-2.0042	0.8592*	0.4558*
AXP	-4.9429*	-6.7073*	-6.5688*	-7.4032*	1.0247*	0.1251‡
BAC	-1.7242	-5.4749*	-2.1243	-7.9997*	2.0337*	0.0532
BA	-1.6484	-11.4450*	-7.4704*	-12.1431*	1.8563*	0.0959
CAT	-4.1524*	-5.1132*	-5.2907*	-6.6922*	1.2619*	0.1965†
CVX	-3.2903†	-3.4943†	-7.4494*	-8.6777*	0.8855*	0.1855†
CSCO	-1.9061	-11.2761*	-2.7577‡	-11.6378*	2.0798*	0.1017
KO	-5.3210*	-6.2450*	-4.5197*	-5.0853*	1.1281*	0.0522
DD	-1.3085	-7.7692*	-1.6141	-7.9042*	2.0538*	0.3392*
XOM	-8.4928*	-8.5484*	-8.6424*	-8.6983*	0.1797	0.1120
GE	-1.3900	-7.0140*	-1.8010	-6.7689*	2.0708*	0.3992*
HD	-4.5109*	-4.4874*	-4.7602*	-4.7237*	0.0725	0.0729
HPQ	-3.8202*	-3.2538‡	-3.2868†	-2.7042	2.0036*	0.4673*
IBM	-1.4658	-1.5642	-1.2839	-4.2250*	2.0530*	0.4619*
INTC	-4.3117*	-6.0670*	-4.8349*	-5.7813*	0.9710*	0.1127
JNJ	-2.2760	-4.1683*	-3.7668*	-9.0784*	1.8534*	0.3095*
JPM	-8.9442*	-8.9419*	-8.9043*	-8.8961*	0.1531	0.1416‡
KFT	-4.8297*	-4.9213*	-7.7467*	-7.9965*	0.2437	0.0386
MCD	-3.1938†	-4.8433*	-3.3017†	-5.1297*	1.6908*	0.2745*
MRK	-2.2125	-9.9910*	-3.9473*	-9.9668*	2.0272*	0.1736†
MSFT	-2.3597	-6.2983*	-2.6759‡	-8.7747*	1.9951*	0.2508*
PFE	-1.5880	-11.1840*	-3.9768*	-11.1512*	2.0347*	0.3449*
PG	-3.1296†	-6.3733*	-2.7263‡	-6.2540*	1.9754*	0.3012*
TRV	-4.4419*	-4.5152*	-10.3435*	-10.3227*	0.1192	0.0928
UTX	-2.4244	-10.8984*	-4.5379*	-12.3227*	1.9569*	0.3521*
VZ	-3.9734*	-5.8028*	-3.5931*	-5.8297*	1.4916*	0.1752†
DIS	-2.6838‡	-2.8158	-4.3519*	-4.6807*	0.6567†	0.3533*
WMT	-3.8225*	-6.9926*	-4.1568*	-5.4138*	1.4333*	0.0246
.INX	-6.5194*	-6.8056*	-6.1937*	-6.6265*	0.6360†	0.2590*

Table 4: **Test for the Equality of Search Volume Means across Months**

This table presents a hypothesis test for equality of mean for search volume, classified by month. The table reports the F-statistic and the corresponding p-value.

Stock	F-stat.	p-value	Stock	F-stat.	p-value
MMM	1.9786	0.0303	INTC	7.5674	0.0000
AA	2.1341	0.0181	JNJ	3.0089	0.0008
T	0.8459	0.5942	JPM	3.3054	0.0003
AXP	27.4542	0.0000	KFT	23.6840	0.0000
BAC	1.4576	0.1469	MCD	10.1053	0.0000
BA	1.0765	0.3800	MRK	1.1477	0.3239
CAT	8.7555	0.0000	MSFT	1.6400	0.0870
CVX	6.9426	0.0000	PFE	1.2514	0.2526
CSCO	1.4205	0.1626	PG	2.1068	0.0198
KO	14.3688	0.0000	TRV	2.7849	0.0018
DD	0.5105	0.8959	UTX	1.5832	0.1028
XOM	5.5507	0.0000	VZ	10.2355	0.0000
GE	0.4837	0.9129	DIS	8.2340	0.0000
HD	56.3396	0.0000	WMT	22.8193	0.0000
HPQ	0.8760	0.5643			
IBM	0.2191	0.9963	.INX	6.5618	0.0000

Table 5: **Correlation Between Trading Volume and Information Demand**

This table shows correlation coefficients between logarithmic trading volume and information demand for every stock in the sample. It also includes correlation coefficients between individual stock trading volume and market-related information demand. A star, dagger and double dagger denote that the coefficient is significant at the 1%, 5% and 10% level, respectively.

Stock	Firm-specific	Market-related	Stock	Firm-specific	Market-related
MMM	0.0054	0.4015*	INTC	-0.0441	0.2916*
AA	0.1562*	0.4720*	JNJ	0.1241†	0.3114*
T	-0.1198†	0.0507	JPM	0.2281*	0.5359*
AXP	-0.0728	0.4450*	KFT	0.1367†	0.0289
BAC	-0.2782*	0.5782*	MCD	0.0218	0.2115*
BA	0.1194†	0.2702*	MRK	0.4331*	0.2302*
CAT	0.1999*	0.4360*	MSFT	-0.0390	0.2711*
CVX	0.3545*	0.2209*	PFE	0.3676*	0.2748*
CSCO	0.0399	0.2962*	PG	0.1855*	0.3202*
KO	-0.1130†	0.3526*	TRV	0.1864*	0.5007*
DD	0.2262*	0.4117*	UTX	0.3512*	0.4947*
XOM	0.1730*	0.2278*	VZ	0.1799*	0.1869*
GE	0.3440*	0.5659*	DIS	0.0169	0.2016*
HD	0.0087	0.3192*	WMT	-0.0355	0.2132*
HPQ	-0.2420*	0.0329			
IBM	-0.0126	0.2019*	.INX	0.4852*	0.4852*

Table 6: **Volume and Information Demand OLS Estimation Results**

This table presents the results of the estimation of the OLS model for trading volume and information demand. The estimated equation is $V_t = \theta + \kappa|r_t| + \gamma\pi_t + \delta\phi_t + \varepsilon_t$. The dependent variable is stock trading volume. γ and δ are the estimated coefficients for firm-specific information demand and market-related information demand, respectively. κ is the coefficient for stock absolute return, whereas θ is a constant. Variables not found statistically significant have been omitted in a one-step backwards procedure. The last rows of the table present the results of the pooled sample, across all stocks. A star, dagger and double dagger denote the coefficient is significant at the 1%, 5% and 10% level, respectively.

Stock	θ	κ	γ	δ	Adj. R^2
MMM	-0.1502*	6.2591*		0.5517*	0.3050
AA		0.8234‡	0.5869†	1.0749*	0.2596
AXP	-0.0956†	2.6586*		0.8237*	0.2631
T	-0.1253*	4.8926*	-0.1123‡		0.1463
BAC			-2.7479*	2.4455*	0.4244
BA	-0.1210*	3.8373*	0.3616†		0.1573
CAT	-0.1521*	3.9410*		0.7320*	0.3044
CVX	-0.0799*	2.8838*	1.4510*	0.3973*	0.3035
CSCO	-0.1253*	3.9001*	0.4705†	0.4273*	0.2312
KO	-0.0898*	5.0400*		0.4469*	0.2132
DD	-0.1026*	3.5398*		0.4914*	0.2561
XOM	-0.1154*	4.6718*			0.1392
GE	-0.0997†	3.5207*		1.1657*	0.4034
HPQ	-0.1098*	3.4564*	-1.3453*		0.1585
HD	-0.1454*	4.8244*		0.3055†	0.2667
INTC	-0.1221*	5.1970*		0.3431†	0.2330
IBM	-0.1038*	3.1944*		0.2533‡	0.1452
JNJ	-0.1358*	8.0480*		0.3072‡	0.2609
JPM	-0.1002†	2.6323*		1.2142*	0.3614
KFT	-0.1740†	7.7185*			0.0693
MCD	-0.0997*	4.4943*		0.3821†	0.0971
MRK	-0.1685*	5.4229*	1.1140*		0.3636
MSFT	-0.1209*	4.6660*		0.3517†	0.2239
PFE	-0.1224*	4.5997*	0.7811*		0.2651
PG	-0.0909†	5.0668*		0.4770†	0.1621
TRV				1.1639*	0.2507
UTX	-0.0963*	4.0586*	0.4767*	0.6887*	0.3345
VZ	-0.1164*	4.9216*	1.0666*		0.1727
WMT	-0.1128*	5.0580*		0.2487‡	0.1399
DIS	-0.1363*	4.9759*			0.1561
Pooled Sample	-0.0994*	3.4996*	0.0623†	0.4835*	0.1930

Table 7: **Correlation Between Absolute Return and Information Demand**

This table shows correlation coefficients between absolute logarithmic return and information demand for every stock in the sample. It also includes correlation coefficients between individual stock absolute return and market-related information demand. A star, dagger and double dagger denote that the coefficient is significant at the 1%, 5% and 10% level, respectively.

Stock	Firm-specific	Market-related	Stock	Firm-specific	Market-related
MMM	0.0037	0.3398*	INTC	-0.0229	0.2775*
AA	0.1052‡	0.4380*	JNJ	0.1169†	0.3439*
T	0.0871	0.2592*	JPM	0.1922*	0.3820*
AXP	-0.0668	0.4109*	KFT	0.1401†	0.2669*
BAC	-0.0197	0.4093*	MCD	0.0135	0.1334†
BA	-0.0312	0.3732*	MRK	0.3763*	0.2976*
CAT	0.0838	0.3523*	MSFT	-0.0219	0.2337*
CVX	0.0489	0.3594*	PFE	0.2544*	0.2910*
CSCO	-0.1099‡	0.2403*	PG	0.1345†	0.3195*
KO	-0.1215†	0.3603*	TRV	0.1537*	0.4169*
DD	0.1017‡	0.4320*	UTX	0.1857*	0.3518*
XOM	0.1478*	0.2704*	VZ	-0.1084‡	0.2446*
GE	0.2310*	0.3662*	DIS	-0.1843*	0.4043*
HD	-0.0102	0.3796*	WMT	0.0007	0.2364*
HPQ	-0.0182	0.3300*			
IBM	0.0315	0.1893*	.INX	0.4522*	0.4522*

Table 8: **VIX and Market-related Information Demand**

The table presents the results of univariate regressions of market-related information demand on VIX index closing prices. All coefficients are significant at the 1% level.

Index	Intercept	Market-related information demand	Adj. R^2
VIX	20.3603	38.5571	0.2658
VIX t1	19.9398	41.8873	0.2841
VIX t2	20.5587	36.3808	0.2518
VIX t3	20.9949	33.4138	0.2387
VIX t4	21.2850	30.9950	0.2348
VIX t5	21.5085	28.5278	0.2279
VIX t6	21.5014	25.5175	0.2129
VIX t7	21.5056	22.4564	0.1954

Table 9: **GARCH Estimation Results**

This table presents the results of the estimation of the extended GARCH Market Model with firm-specific and market-related information demand. The estimated set of equations is $r_t = \mu + \lambda\nu_t + \varepsilon_t$, for the mean equation and $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\pi_t + \delta\phi_t$, for the variance equation. The dependent variable is stock log return. γ and δ are the estimated coefficients for firm-specific information demand and market-related information demand, respectively. λ is the coefficient for market return, whereas α and β denote the ARCH and GARCH term coefficients, respectively. Variables not found statistically significant have been omitted in a one-step backwards procedure. The last row of the table presents the results of the pooled sample, across all stocks. A star, dagger and double dagger denote the coefficient is significant at the 1%, 5% and 10% level, respectively.

Stock	μ	λ	ω	α	β	γ	δ	Adj. R^2
MMM		0.8598*	0.0002†		0.7066*		0.0003†	0.4957
AA		1.8333*	0.0016*	0.1376‡			0.0028*	0.6080
AXP		1.4236*	0.0007*	0.5455*		0.0024*	0.0022*	0.6022
T		0.8004*	0.0006*	0.1067		0.0003†		0.4328
BAC		0.9296*	0.0000	0.1391*	0.8927*			0.3144
BA		1.1035*	0.0012*		-0.2313	0.0018†	0.0014†	0.4844
CAT		1.5105*	0.0010*	0.1606*		0.0028†		0.5577
CVX		0.9472*	0.0007*	0.0636		0.0014†	0.0008*	0.4979
CSCO		1.0302*	0.0008*	0.2157*		0.0010‡		0.4562
KO		0.5211*	0.0004*	0.1177‡			0.0007*	0.3430
DD		1.1975*	0.0001†	0.1904*	0.6362*		0.0002‡	0.5886
XOM		0.8121*	0.0000	0.1022†	0.8315*			0.4030
GE		1.0479*	0.0006*	0.5426*		0.0017*	0.0008*	0.4379
HPQ		1.1412*	0.0004†		0.6008*	-0.0028*	0.0012*	0.5273
HD		0.9054*	0.0013*	0.1848*	-0.2885*		0.0026*	0.3396
INTC		0.9039*	0.0004*	0.4747*				0.4951
IBM		1.1248*	0.0006†	-0.0419*	0.4766†		0.0007†	0.4281
JNJ		0.4784*	0.0003*	0.0125			0.0006*	0.3488
JPM		1.5370*	0.0008*	0.7237*		0.0006†	0.0019*	0.4859
KFT		0.6152*	0.0006*	-0.0463		0.0016*		0.3240
MCD		0.6025*	0.0001	-0.0096	0.7900†			0.2788
MRK		0.7744*	0.0019*		-0.4292*	0.0048*	0.0017*	0.2151
MSFT		0.8363*	0.0007*	0.3248*			0.0005‡	0.3127
PFE		0.8149*	0.0012*		-0.4766*	0.0014*	0.0017*	0.3319
PG		0.4304*	0.0005*	0.1777*	-0.3463*	0.0011†	0.0008*	0.2771
TRV		0.9143*	0.0004*	0.2889*	0.2760*	0.0004†	0.0013*	0.3519
UTX		0.9209*	0.0006*		-0.3127†	0.0009*	0.0010*	0.5881
VZ		0.8120*	0.0001†		0.7529*		0.0004†	0.4409
WMT		0.5819*	0.0007†		-0.0728		0.0010*	0.2754
DIS		0.9651*	0.0004*	0.1997*	0.3347*		0.0015*	0.5398
Pooled Sample		0.8791*	0.0000*	0.0877*	0.8872*		0.0001*	0.3979

Table 10: **Panel Results: Implied Volatility and Information Demand**

This table presents the results of the panel OLS regression between individual stock implied volatility and information demand. The table has two sections: the first presents the estimated coefficients and the second the estimated cross-sectional effects. ω is the constant, γ is the coefficient for idiosyncratic information demand, δ the coefficient for market-related information demand and ψ_i the cross-sectional fixed effect, corresponding to stock i. p-values (using White diagonal HAC standard errors) appear in parentheses below the estimated coefficients.

ω	γ	δ	Adj. R^2
34.3532	2.4106	54.9978	0.2810
(0.0000)	(0.0802)	(0.0000)	

Cross-sectional Fixed Effects

Stock	ψ_i	Stock	ψ_i
MMM	-5.8057	INTC	4.7443
AA	15.5857	IBM	-4.9395
AXP	9.5635	JNJ	-11.1227
T	-3.3171	JPM	10.8516
BAC	12.4433	KFT	-5.6009
BA	1.5639	MCD	-3.1127
CAT	4.0309	MRK	0.8318
CVX	-1.1836	MSFT	-3.6417
CSCO	4.6189	PFE	-2.0299
KO	-10.9746	PG	-9.9923
DD	-1.7643	TRV	5.2901
XOM	-3.6560	UTX	-4.4557
GE	2.3820	VZ	-4.5744
HPQ	5.1061	WMT	-6.1434
HD	3.2423	DIS	2.0531

Table 11: **Information Demand and Risk Aversion**

This table presents the results of the OLS regression between information demand and time-varying risk aversion (expected variance risk premium). a is the intercept, b the coefficient for lagged information demand, and c and d the coefficients for time-varying risk aversion and its first lag, respectively. Model A includes lagged information demand in the specification, whereas model B does not. p-values (using Newey-West HAC standard errors) appear in parentheses below the estimated coefficients.

Model	a	b	c	d	Adj. R^2
A	-0.0585	0.5906	0.0019	0.0014	0.6381
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	
B	-0.0620		0.0012	0.0024	0.3410
	(0.0282)		(0.0000)	(0.0000)	