Can Information Demand Help to Predict Stock Market Liquidity? Google it!

Mohamed Arouri
CRCGM –University d'Auvergne, France
EDHEC Business School, France
E-Mail: Mohamed.arouri@u-clermont1.fr

Amal Aouadi
CRCGM–University d'Auvergne, France
Email:aouadi_amal@hotmail.com

Philippe Foulquier
EDHEC
Business School,
France
Email: philippe.foulquier @edhec.edu

Frédéric Teulon
IPAG Business School, IPAG–Lab, France
E-Mail: f.teulon@ipag.fr

Abstract

Numerous recent studies indicate that investors' information demand affects stock market return and volatility. In this paper, we contribute to the literature by investigating whether information demand is a significant determinant of liquidity in the French stock market. Our main findings suggest that internet research volume tends to be positively related to market liquidity. In the out-of-sample analysis, we show that introducing information demand variables significantly improves liquidity forecasting.

Keywords: *Information demand, Financial markets, Stock liquidity.*
JEL Classification: C32, D83, G12, G14

1. Introduction

Previous works on information and financial markets were based on the assumption that investors have infinite information processing abilities and that all relevant information available is instantaneously processed and incorporated into stock prices [Fama (1970)]. Drawing on reality, investors have actually scarce cognitive resources. Further, information acquisition costs with respect to tracking, collecting and processing firm news limit the set of information that can be assimilated by investors [Grossman and Stiglitz (1980), Merton (1987) and Barber and Odeon (2008)]. Constrained by limited attention and time, investors retain in their investment choices set the stocks that first grab their attention [Barber and Odeon (2008)]. Consequently, new information cannot be automatically processed by all the market participants.

Before trading, a rational investor paying attention will demand for information. There are several channels through which firms are providing that information. In today's digital age, internet seems to be a highway for information supply. Moreover, thanks mostly to the internet, information technology has been revolutionized and delivers a vast array of data in a timely fashion and at negligible cost. Allowing free access to information, Internet tends to reduce information acquisition costs and increase the number of potential investors processing the information. This aligns investors' information; reducing information asymmetry among investors and increasing, in turn, stock market liquidity [Diamond and Verrecchia (1991)]. Moreover, investors' information demand would play that critical role of enhancing the effectiveness of firm information dissemination into financial markets.

Based on this reasoning, we contribute to the literature by using Google search volume to investigate the role of investors' information demand as a determinant of stock market liquidity. More precisely, we follow Drake et al. (2012) and Vlastakis and Markellos (2012) and use, for the first time, weekly Google search volume (simply referred to as GSV hereafter) for stocks listed in the CAC40 index as a measure of French investors' information demand and study whether GSV helps (i) to explain the formation of stock market liquidity, and (ii) to forecast it.

The 'Google Insights for Search' provides previously unavailable measures of online search behavior. In particular, the application provides the internet users demand for any keyword(s). As in Vlastakis and Markellos (2012), we choose firm name rather than stock ticker for the keyword used in the queries[1]. One might be concerned about the use of firm names. The benefit in query-by-ticker data is that tickers are more specific than names. However, the benefit of unambiguity might come at the cost of precision to the study. In general, it is more likely that French investors are googling the firm name to express their demand for extra news [Drake et al. (2012)].

It is not unrealistic to suggest that French investors are increasingly using internet as a source of information. On the one hand, a search engine is often a first stage of seeking information. In February 2013, Google, the web giant throne on the highest step of the podium and holds a market share of 91,2%[2] (more than five times higher than Voila, Yahoo or Bing). Thereby, Google is, undoubtedly, the unbeatable market leader with 9 net surfers out of 10 using Google in France! On the other hand, in the academic literature, there is strong evidence that investors tend to use the internet for information and brokerage services [Barber and Odeon (2001), Blankespoor et al. (2011) and Rubin and Rubin (2010)]. Finally, searching for firm news on the internet is more likely to be related to an action/intention, as it captures interest better than just looking at advertising.

To the extent that investors trade only after gathering enough information about a stock and their trading causes price pressure that persists over a short period of time, we expect that GSV could lead turnover and even predict stock market liquidity. Following Barber et al. (2009), we also expect the behavior of retail investors to be correlated since they are motivated by the same underlying reasons. This, our paper adds to the growing strand of literature on the impact of information technology on financial markets. Drake et al. (2012) suggest that the act of seeking information proxied by GSV allow investors to partially anticipate the information content of the earnings announcement. Using Google search behavior, Vlastakis and Markellos (2012) investigate the relationship between investor information demand and several measures of stock volatility, after controlling for the market return and information supply. In their seminal paper, Da et al. (2011) find consistent evidence that online search frequency as a proxy for retail attention is related to IPO first-day returns and subsequent return reversal.

[1] The alternative of relying on stock identification tickers instead of firm names turned out to be unproductive as search frequencies tend to be much lower, resulting in many missing values.
[2] Source: AT Internet Search Engine Barometer.

As can be seen, there is ample evidence that information demand affects stock market activity, but the issue of forecasting effectiveness of information demand variables has not yet been well investigated. There is already a growing body of literature on the predictive power of GSV over a number of settings. The major appeal of these studies is that online search behavior contains information that is able to forecast future outcomes. For example, Askitas and Zimmermann (2009) use GSV to forecast unemployment rates. Similarly, Kulkarni et al. (2009) find a strong link between Google searches and expected housing prices. More recently, Vosen and Schmidt (2011) use internet search data to predict private consumption expenditures. Most importantly, online search behavior data have predictive power for future volatility on the stock market [Da et al. (2011) and Dzielinski (2011)]. We exploit this finding and test if the inclusion of Google search data enhances the liquidity forecasting results.

Therefore, another contribution of our paper is to investigate usefulness of GSV as a predictor of stock market activity and especially, stock market liquidity. Consequently, we start by investigating the importance of information demand as a determinant of stock market liquidity. We find that investors' information demand drive effectively movements of stock market liquidity. Building on this evidence, we show that in addition to known factors of liquidity, information demand is even able to refine liquidity forecasting results.

The remainder of this paper is organized as follows. The next section presents the data and reports descriptive statistics. The following section discusses the empirical results and their implications for forecasting outlines. This section also presents the robustness check of the results of the empirical application. The final section concludes.

II. Data and preliminary analysis

1. Google search volume: a proxy of information demand

The search volume data on 'Google insights for search' are aggregated over millions of Google users in all over around the world. In order to control for the increasing use of Internet over time, Google insights system normalizes the data by dividing the total number of Google searches for any keyword by the overall total number of searches during the same time period. Otherwise, repeated queries from a single user over a short period of time are eliminated, so that the level of interest in a particular topic is not artificially inflated. Finally, Google search values range from 0 to 100. The value 0 does not literarily means no search at all, but means that the search volume is too low to provide meaningful statistics while the value 100 represents the highest level of search activity during the sample period. Data from Google insights is available on a daily basis for a period less than 90-day and on a weekly basis beginning in 2004.

As we are only interested on French investors' information demand, we limit the geographical location of the search to "France". Besides, we use the raw search volume index values. While, we have verified that our findings are very similar if we base our tests simply on the rank order of the index values. The latter procedure tends to give less weight to extreme observations.

2. Stock market turnover: a proxy of market liquidity

We follow previous work of stock market liquidity and proxy liquidity by turnover measured by the ratio of trading volume to the number of shares outstanding [Datar et al. (1998), Chordia et al. (2001) and Loughran and Schlutz (2005)]. Amihud and Mendelson (1986) show that turnover is negatively related to illiquidity costs, and Atkins and Dyl (1997) suggest a strong positive relationship between the bid-ask spread and the reciprocal of the turnover ratio.[3]

3. Sample period and basic statistics

Our initial sample consists of the 40 stocks which constitute the CAC 40 index (as of January 2004) and traded in Euronext Paris. Our sample-period goes from January 09, 2004 To June, 22, 2012. The sample period starts in 2004 because Google search data is available only from this year onwards. For each stock in our sample, we use firm name [Vlastakis and Markellos (2012)] rather than stock ticker to extract GSV. The latter tend to be unproductive for the French stocks as search frequencies tend to be much lower, resulting in many missing values. Further, we exclude from our sample firms such as "Thales" and "TF1" to avoid problems associated with the fact that the search queries may have generic meanings. As a result of these restrictions, our final sample consists of 28 firms. Otherwise, notice that data running from June 09, 2004 to March 30, 2012 will be used for the in-sample analysis, while data from April 6, 2012 to June 22, 2012 will be employed in our out-of-sample analysis to shed light on forecasting evaluation and implications of the in-sample results.

Table 1 reports descriptive statistics for GSV while Table 2 the descriptive statistics for turnover. As shown by Table 1, for the majority of stocks, information demand is positively

[3] Note that in the robustness check Part, we make use of alternative measures of stock market liquidity.

skewed with excess kurtosis while normality can be strongly rejected in all but 2 cases with 99% confidence. There is strong variability in information demand across stocks. Specifically, Axa has the highest average GSV in our sample (73,954) while Vinci has the smallest (6,198). Therefore, the search volume series referred to hereafter are logarithmically transformed.

The results in Table 2 indicate that all the stocks turnover series are positively skewed and normality can be rejected with 99% confidence level. Table 2 presents also correlation coefficients between information demand and turnover. The results report that information demand and stock turnover are positively and significantly correlated in most cases (21 out of 28 cases) at the 5% level; while correlation is significant and negative for only 4 stocks at the 5% level. This is consistent with the findings of Vlastakis and Markellos (2012) who report that the GSV of the firm name is positively correlated with trading volume. Furthermore, consistent with investors increasingly using the Internet to acquire information, it is not surprising that the positive trading-search association has become more pronounced over time.

The most important issue for us is to know whether liquidity is forecastable. Autocorrelation in the time series of liquidity measures (as shown by Table 2) suggests that it is actually possible to predict liquidity using publicly available variables. Therefore, liquidity prediction has valuable academic and practical implications both in allowing us to better understand the dynamic of liquidity series, and in helping portfolio managers to conceive less costly trading strategies.

III. Empirical results

We investigate whether information demand proxied by Google Search Volume (GSV) helps to predict liquidity. We begin our analysis with the estimation of multifactor models to identify the determinants of liquidity in the French stock market. Then, we study the sensitivity of liquidity to information demand variables. Finally, we examine whether a model with information demand variables allows getting superior out-of-sample liquidity forecasting results.

1. Determinants of liquidity in the French stock market

We rely on previous works to identify candidate variables to understand liquidity behavior in the French stocks markets. We pay a particular attention to variables that may determine simultaneously the levels of liquidity of the firm and investor information demand. Results for several multifactor model estimations lead us to retain the following variables[4]:

- Absolute returns: several works show that absolute returns significantly affect stock market liquidity. Indeed, returns may influence future trading behavior, which may, in turn, affect liquidity [Karpoff (1987) and Chordia et al. (2005)].
- Firm size: previous work show that liquidity is increasing with firm size [Loughran and Schultz (2005)]. We proxy size by number of employees and market value. Firm size is a proxy of information asymmetry [Chae et al. (2005)]. According to market microstructure theory, information asymmetry costs lower market liquidity. As we commonly suppose that smaller firms exhibit more information asymmetry than larger firms, the latter would be probably more liquid.
- Information supply: in efficient markets, stock prices react instantaneously to information supply [Fama (1965)]. We proxy information supply by the number of analysts covering the firm. There are several reasons to expect that firms covered by more analysts attract more attention. First, news from analysts pushes investors to search more information on firms. Second, investors may be less aware about firms weakly covered by analysts.
- Risk: several works establish that market liquidity is related to risk [Stoll (1978) and Spiegel and Wang (2005)]. We proxy risk that standard deviations of returns in the week. Since investors tend to diversify the risk through trading, we expect a positive relationship between risk and liquidity.
- Trading costs: trading costs affect negatively market liquidity. Intuitively, investors would prefer stocks with lower trading costs. We follow Bartov et al. (2000) and Loughran and Schultz (2005) and use the inverse of the stock price as a proxy for trading costs.

Basic statistics of these variables are reported in Table 3. As we focus on CAC40 firms, we find that firms in our sample have relatively large market values, high number of employees, low stock return volatilities, and high analyst following. Unsurprisingly, the mean weekly market value of our stocks ranges between 54,800 and 84,400 million Euros. On average, the weekly standard deviation varies from 0,0129 to 0,0229, confirming that stock

[4] Details of these model estimations are not reported here to save space but available upon request from authors.

return volatility is low for large capitalizations. Further comments on Table 3 are reported in section 4.

Finally, we estimate the following model that we call Model 1:

$$Turnover_{it} = \alpha + \beta_1 Turnover_{i,t-1} + \beta_2 Ln(Number\_of\_Analysts)_{i,t-1} + \beta_3 Ln(Number\_of\_Employees)_{i,t-1} + \beta_4 Ln(Market\_Value)_{i,t-1} + \beta_5 Inverse\_of\_Stock\_Price_{i,t-1} + \beta_6 Absolute\_return_{i,t-1} + \beta_7 Std\_Dev_{i,t-1} + \varepsilon_{it} \quad (1)$$

Results reported in Table 4 reveal interesting facts. First, signs of coefficients are mostly as expected. The coefficient of the one-lag turnover is significantly positive, confirming finding in Table 2. When it is significant, the coefficient on number of analysts is positive. Thus, turnover seems to augment with the number of analysts covering the firm. Investors are more likely to trade on stocks that are covered by more analysts. Alternately, analysts may cover more heavily traded stocks. The coefficients on number of employees and market value are significantly positive in most cases: turnover increases with the size of the firm. Both institutional and individual investors hold more stocks issued by large firms rather than those by small firms. Thus it is not surprising that stocks of large firms turn over more rapidly than other stocks.

We use the inverse of the stock price as a proxy for trading costs. Hence, we expect that stocks with high trading costs are not traded as much as others: turnover decreases with the stock price inverse. Our results show than when it is significant, the coefficient of inverse of stock price is negative except for Vivendi. The coefficients of absolute returns and standard deviations are positive and highly significant in almost all cases. This is consistent with the idea that higher turnover reveals higher disagreement among active traders and is associated with greater price variability and thus higher risk.

Second, the average R^2 is 0.64. Thus, on average the variables we consider explain sufficiently liquidity formation in the French stock market: they explain 64% of liquidity variations. However, the R^2 varies considerably across firms. The highest R^2 is obtained for Total (0.89) followed by Arcelor (0.84) and the lowest one is observed for Sanofi (0.45) followed by Bouygues (0.47).

2. Effects of information demand variables on liquidity

Descriptive statistics reported in Table 2 show that liquidity is positively linked to investor information demand measured by Google search volume. This suggests that higher level of investor information demand measured by internet search frequency leads to higher liquidity. However, firms differ on several dimensions such as market capitalization, analysts' coverage, trading costs and risks are reported in Table 3. Does investor information demand affects liquidity or is the positive link between liquidity and information demand simply explained by dissimilarities in the characteristics of firms that affects both liquidity and information demand?

To answer this question, we augment Model 1 by two information demand variables: firm-specific information demand (Lgsv) and market information demand (Lgsvm). As defined previously, proxies of firm-specific information demand for each stock are derived on the basis of GSV for the company name. Accordingly, market information demand is proxied using GSV of the keyword "CAC 40". This approach recognizes the fact that little attention is devoted in the literature on measuring the separate impact of specific and market-related information demand on individual stock activity. Moreover, since an attention-constrained investor tend to process more market information than firm-specific information [Peng and Xiong(2006)], we choose to control for the importance of market information demand. Recently, Vlastakis and Markellos (2012) find that when one excludes market information demand from the regression analysis, firm-specific information demand becomes more statistically significant.

Formally, we estimate the following model that we call Model 2:

$$\begin{aligned} Turnover_{it} &= \alpha + \beta_1 Turnover_{i,t-1} + \beta_2 Ln(Number\_of\_Analysts)_{i,t-1} + \beta_3 Ln(Number\_of\_Employees)_{i,t-1} \\ &+ \beta_4 Ln(Market\_Value)_{i,t-1} + \beta_5 Inverse\_of\_Stock\_\mathrm{Pr}ice_{i,t-1} + \beta_6 Absolute\_return_{i,t-1} + \beta_7 Std\_Dev_{i,t-1} \\ &+ \lambda_1 Ln(GSV)_{i,t-1} + \lambda_2 Ln(GSV)_{CAC40,t-1} + \varepsilon_{it} \end{aligned} \tag{2}$$

Results are summarized in Table 5. In 23 out of 28 cases, at least one of the information variables is significant. Firm-specific information demand is significant in 22 cases, whereas market information demand is significant in 12 cases. The estimated coefficients show that the two information variables have effects of comparable magnitude. Overall, we conclude than firms that are more searched on internet are more liquid since the effect of information demand variables on stock market liquidity is positive in most cases.

As previously discussed, information often reach only a subset of investors, which results in information asymmetry among investors, and therefore lower stock market liquidity. Particularly, with the help of information demand on Internet (resulting in information acquisition), information can reach a broader set of investors, thereby alleviating information asymmetry among investors and, in turn, enhancing liquidity, such that stocks with higher information demand become relatively more liquid than stocks of less information demand.

According to market microstructure theory, we believe that the positive relationship between liquidity and information demand is most likely due to a reduction in asymmetric information costs. This confirms previous contributions which show that the kind of public interest captured by Google search activity represents the degree to which a respective asset is traded by less-sophisticated investors [Da et al. (2011), Bank et al. (2011) and Vlastakis and Markellos (2012)]. This finding suggests mainly that firms can reduce information asymmetry by more broadly disclosing their positive news via the internet. Information demand, therefore, may play that critical role of enhancing the effectiveness of firm information supply, and more precisely with respect to information asymmetry.

Second, compared to Model (1) the adjusted R^2 in Model (2) has increased in all cases suggesting that information demand variables contribute also to better understand liquidity variations in the French stock market.

3. Out-of-sample forecasts of sector stock market liquidity

Among the many issues involving portfolio investment and management, forecasting stock liquidity is one of the most intriguing topics that attract great interests from investors and researchers. Our analysis shows that information demand variables significantly affect stock market liquidity in most cases. Moreover, as we have pointed out above, Model 2 provides better fit to our data than Model 1 in most cases. However, this does not guarantee that model with information demand variables will perform better in actual forecasting of stock liquidity.

The aim of forecasting evaluation is to minimize the expected loss, *i.e.* the difference between the predicted and actual liquidity. There is, up to date, a wide range of standard statistical loss functions that can be used to evaluate such a deviation in forecasting tasks. In this paper, we retain the most commonly used loss functions, namely Root Mean Squared

Error (RMSE) and Mean of Absolute Percent Error (MAPE), that are robust to possible noise in the liquidity measure. They are defined as:

$$RMSE_i = \sqrt{h^{-1} \sum_{t=T+1}^{T+h} (l_{it} - \hat{l}_{it})^2} \tag{3}$$

$$MAPE_i = h^{-1} \sum_{t=T+1}^{T+h} \left| \frac{l_{it} - \hat{l}_{it}}{l_{it}} \right| \tag{4}$$

where t denotes time period of the forecast sample, $t = T+1, T+2, \ldots, T+h$. l_{it} and $\hat{l}_{it}$ stand for the actual and forecasted liquidity respectively.

We evaluate the forecasting performance of Model 1 and Model 2 out-of-sample for three horizons: h=4, h=8 and h=12 weeks. Results are summarized in Table 6. Model 2 shows better forecasting results than Model 1 in most cases and for almost all horizons. We thus conclude that augmenting the Model 1 with information demand variables leads to better forecasting of sector stock liquidity in most cases.

Exploiting the fact that Google search volume and stock turnover are highly correlated, we show that changes in the level of investors' information demand drive significantly stock market liquidity. In particular, liquidity increases following a rise in information demand. Building on this finding, we also present new evidence regarding on Google search behavior forecasting liquidity for French firms. Indeed, augmenting our model with Google search data leads to more precise out-of-sample forecasts. Interestingly, search queries constitute a valuable source of information for future liquidity. From a practical standpoint, it would then appear inappropriate to trade on days immediately following a decrease in information demand. Similarly, portfolio managers would be well advised to avoid trading on days when the information available is on one side of the market.

4. Robustness checks

To check whether our results are sensitive to liquidity measure, we replicate our analyses by considering alternative liquidity measures. More precisely, we consider the following liquidity measures as the dependent variables to replace turnover in Model 1 and Model 2.

- The Amihud(2002) illiquidity ratio: [Acharya and Pedersen (2005), Goyenko et al. (2009) and Xiong et al. (2013)]:

$$Illiq_{it} = \frac{|r_{it}|}{TV_{it}} \tag{5}$$

As equation (5) shows, the Amihud(2002) illiquidity ratio is calculated by dividing the absolute return $|r_{it}|$ of stock i on period t and the traded volume in Euros TV_{it}. As indicator of illiquidity, a high estimate indicates low liquidity (high price impact of trades).

- The relative bid-ask spread: [Amihud and Mendelson (1986), Eleswarapu (1997) and Hameed et al. (2010)]

$$\mathrm{Re}\,lative\_Spread_{it} = \frac{Ask_{it} - Bid_{it}}{\frac{ask_{it} + Bid_{it}}{2}} \tag{6}$$

We also employ the relative bid-ask spread to account for transaction costs. Equation (6) shows that Relative_Spread is calculated by dividing the quoted spread (the difference between the best ask and bid quotes) by the midpoint price (the average of the best ask and bid quotes) of stock i at the end of trading period.

- The Roll spread estimator : [Huang and Stoll (1996) and Schultz (2000)]:

$$Roll_{it} = \begin{cases} 2\sqrt{-\operatorname{cov}(\Delta P_t, \Delta P_{t-1})} & if\ \operatorname{cov}(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & if\ \operatorname{cov}(\Delta P_t, \Delta P_{t-1}) > 0 \end{cases} \tag{7}$$

The Roll (1984) estimate provides an alternative approximation of bid-ask spreads. Basically estimated from the negative serial covariance of successive price changes, it is mainly considered as a measure of return reversal. A higher Roll (1984) estimate means a more negative serial correlation of daily returns which can be interpreted as being more illiquid.

- The Amivest Ratio : [Cooper et al. (1985), Amihud et al. (1997) and Hasbrouck (2009)]:

$$AMIVEST_{it} \; \frac{TV_{it}}{\left| r_{it} \right|} \qquad (8)$$

As shown by Equation (8), the Amivest liquidity ratio is defined as the ratio of trading volume TV_{it} of stock i in period to the corresponding absolute return $\left| r_{it} \right|$. A high Amivest ratio indicates that investors can trade a large number of shares without changes in price. Hence, an increase (decrease) in the Amivest measure shows an increase (decrease) in market depth. It is a volume-based measure that assesses the trading volume associated with a unit change in the stock price. A higher ratio implies greater market liquidity.

Descriptive statistics for these alternative liquidity measures are reported in Table 3. As discussed earlier, large firms tend to be more liquid. That is why; as expected, stocks in our sample have, on average, low Amihud illiquidity ratio and relative spread and high liquidity ratio and ROLL estimates.

Overall, our findings, not reported here to save space but available upon request, confirm the main result of our analysis based on turnover: investor information demand measured by Google search volume is positively related to liquidity and helps to predict it in most cases. This confirms that our findings are not specific to any particular measures of liquidity.

IV. Conclusion

Using Google search volume as a proxy of investors' information demand, we contribute to this literature by providing new evidence that information demand drives effectively stock market liquidity. Indeed, exploiting the fact that most previous studies focus only on stock market volatility and returns, we choose to explore the information demand effect on stock market liquidity. Furthermore, while previous academic researches on GSV focuses mostly on US stock market; we are, to the best of our knowledge, the first to use French data. Finally, since it is doubtful that only one measure can cover all aspects of liquidity, we assess the robustness of our results by the use of various measures of liquidity.

In sum, our results indicate that after controlling for known determinants of stock liquidity, there is a positive, robust, and economically significant relation between several measures of stock liquidity and information demand variables. Most importantly, we find that liquidity is highly forecastable not only by classical liquidity predictors, but also by investors' information demand variables. Indeed, augmenting our model by Google search volume data provides more precise out-of-sample forecasts of liquidity. As can be seen, inclusion of online search variables influences materially the results, overscoring the importance of controlling for investors' information demand. These findings show that liquidity cannot be solely explained by known factors such as – risk, firm size and trading costs - but also substantiate the importance of including online investor search behavior in forecasting important outcomes. These include, among others, unemployment rate, housing prices, automobile sales, stock trading volume, stock market return and stock volatility.

According to the assumption that what people are searching for leaves a track about "what we collectively think" and probably "what might happen in the future" [Rangaswamy et al. (2009)], the usefulness of measures of internet search behavior is undoubtedly going to increase. As we go with giant strides into the digital age, more research efforts should be done on the use of Google search data.

References

Acharya, V.V. and L.H. Pedersen. “Asset pricing with liquidity risk.” *Journal of Financial Economics*, 77 (2005), pp. 375-410.

Allen, B. “Information as an economic commodity.” *American Economic Review*, 80 (1990), pp. 268-273.

Amihud, Y. and H. Mendelson. “Asset pricing and the bid–ask spread.” *Journal of Financial Economics*, 17 (1986), pp. 223-249.

Amihud, Y., H. Mendelson, and B. Lauterbach. “Market microstructure and securities values: evidence fromthe Tel Aviv exchange.” *Journal of Financial Economics*, 45 (1997), pp. 365-390.

Amihud, Y. “Illiquidity and Stock Returns: Cross-Section and Time-Series Effects.” *Journal of Financial Markets*, 5 (2002), pp. 31-56.

Askitas, N. and K.F. Zimmermann. “Google Econometrics and Unemployment Forecasting.” *Applied Economics Quarterly*, 55 (2009), pp. 107-120.

Atkins, A.B. and E.A. Dyl. “Transactions costs and holding periods for common stocks” *Journal of Finance*, 52 (1997), pp. 309-325.

Bank, M., M. Larch, and G. Peter. “Google Search Volume and its Influence on Liquidity and Returns of German Stocks.” *Financial Markets and Portfolio Management*, 25 (2011), pp. 239-264.

Barber, B.M. and T. Odean. “The internet and the investor.” *Journal of Economic Perspectives*, 15 (2001), pp. 41-54.

Barber, B.M., T. Odean, and N. Zhu. “Do retail trades move markets? ” *Review of Financial Studies*, 21 (2009), pp. 151-186.

Bartov, E., I. Krinskyand and S., Radhakrishnan. “Investor sophistication and patterns in stock returns after earnings announcements.” *Accounting Review*, 75 (2000), pp. 43-63.

Blankespoor, E., G.S. Miller, and H.D. White. “Firm dissemination, direct-access information technology and information asymmetry.” Working Paper, University of Michigan, 2011.

Chordia, T., A. Subrahmanyam, and V.R. Anshuman. “Trading Activity and Expected Stock Returns.” *Journal of Financial Economics*, 59 (2001), pp. 3-32.

Chordia, T., A. Sarkar, and A. Subrahmanyam. “An Empirical Analysis of Stock and Bond Market Liquidity.” *Review of Financial Studies*, 18 (2005), pp. 85-129.

Cooper, S.K., J.C. Groth, and E.W. Avera. “Liquidity, exchange listing and common stock performance.” *Journal of Financial Markets*, 1 (1985), pp. 203-219.

Datar, V., N. Naik, and R. Radcliffe. “Liquidity and asset returns: An alternative test.” *Journal of Financial Markets*, 1 (1998), pp. 203-219.

Diamond, D., and R. Verrecchia. “Disclosure, liquidity, and the cost of capital.” *Journal of Finance*, 46 (1991), pp. 1325-1359.

Da, Z., J. Engelberg, and P. Gao. “In Search of Attention.” *Journal of Finance*, 46 (2011), pp. 1461-1499.

Drake, M.S., D.T. Roulstone, and J.R. Thornock. “Investor Information Demand: Evidence from Google Searches around Earnings Announcements.” *Journal of Accounting Research*, 50 (2012), pp. 1001-1040.

Dzielinski, M. “Measuring economic uncertainty and its impact on the stock market.” *Finance Research Letters*, 9 (2012), pp. 167-175.

Eleswarapu, V.R. “Cost of Transacting and Expected Returns in the Nasdaq Market.” *Journal of Finance*, 52 (1997), pp. 2113-2127.

Fama, E. “The behavior of stock market prices.” *Journal of Business*, 38 (1965), pp. 34-105.

Fama, E. “Efficient Capital Markets: A Review of Theory and Empirical Work.” *Journal of Finance*, 25 (1970), pp. 383-417.

Goyenko, R.C. Holden, and C. Trzcinka. “Do liquidity measures measure liquidity?” *Journal of Financial Economics*, 92 (2009), pp. 153–181.

Grossman, S.J. and J.E. Stiglitz. “On the Impossibility of Informationally Efficient Markets.” *American Economic Review*, 70 (1980), pp. 393-408.

Hameed, A., W. Kang, and S. Viswanathan. “Stock market declines and liquidity.” *Journal of Finance*, 65 (2010), pp. 257–294.

Hasbrouck, J. “Trading costs and returns for US equities: estimating effective costs from daily data.” *Journal of Finance*, 64 (2009), pp. 1445-1477.

Huang, R. and H. Stoll. “Dealer versus auction markets: a paired comparison of execution costs on NASDAQ and the NYSE.” *Journal of Financial Economics*, 41 (1996), pp. 313-357.

Karpoff, J.M. “The Relation Between Price Changes and Trading Volume: A Survey.” *Journal of Financial and Quantitative Analysis*, 22 (1987), pp. 109-126.

Kihlstrom, R. “A general theory of demand for information about product quality.” *Journal of Economic Theory*, 8 (1974), pp. 413-439.

Kulkarni, R.K. Haynes, R., Stough, and J.H.P. Paelinck. "Forecasting housing prices with Google econometrics." mimeo, School of Public Policy, George Mason University, Fairfax, VA 22030, 2009.

Lintner , J. "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets." *Review of Economics and Statistics*, 47 (1965), pp. 13-37.

Loughran, T. and P. Schultz. "Liquidity: Urban versus rural firms." *Journal of Financial Economics*, 78 (2005), pp. 341-374.

Merton, R. "A Simple Model of Capital Market Equilibrium with Incomplete Information." *Journal of Finance*, 42 (1987), pp. 483-510.

Peng, L. and W. Xiong. "Investor attention, overconfidence and category learning." *Journal of Financial Economics*, 80 (2006), pp. 563-602.

Rangaswamy, A., C.L. Giles, and S. Seres. "A Strategic Perspective on Search Engines: Thought Candies for Practitioners and Researchers." *Journal of Interactive Marketing*, 23 (2009), pp. 49-60.

Roll, R. "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market." *Journal of Finance*, 39 (1984), pp. 1127-39.

Rubin, A. and R. Rubin. "Informed investors and the internet." *Journal of Business Finance and Accounting*, 37 (2010), pp. 841-865.

Schultz, P. "Regulatory and legal pressures and the costs of Nasdaq trading." *Review of Financial Studies*, 13 (2000), pp. 917-958.

Sharpe, W.F. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *Journal of Finance*, 19 (1964), pp. 425-442.

Spiegel, M. and X. Wang. "Cross-sectional variation in stock returns: Liquidity and idiosyncratic risk." Working Paper, Yale University, 2005.

Stoll, H. "The Pricing of Security Dealer Services: An Empirical Study of NASDAQ Stocks." *Journal of Finance*, 33 (1978), pp. 1153-1172.

Vlastakis, N. and R.N. Markellos. "Information Demand and Stock Market Volatility." *Journal of Banking and Finance*, 36 (2012), pp. 1808-1821.

Vosen, S. and T. Schmidt. "Forecasting private consumption: survey-based indicators vs. Google trends." *Journal of Forecasting*, 30 (2011), pp. 565-578.

Xiong, X.J., R. Sullivan, and P. Wang. "Liquidity-Driven Dynamic Asset Allocation." *Journal of Portfolio Management*, 39 (2013), pp. 102-111.

Appendix A. Variable definitions

Variable	Description
Dependant variables	
Turnover	The trading volume divided by shares outstanding
Relative spread	The quoted spread (the difference between the best ask and bid quotes) divided by the midpoint price (the average of the best ask and bid quotes)
The Roll estimate	The negative serial covariance of successive price changes
The Amihud (2002) ILLIQ ratio	The absolute return divided by the value of traded volume
The Amivest ratio	The ratio of trading volume in Euros divided by the corresponding absolute return
Independent variables	
GSV	The Google search frequency of firm name as provided by Google Insights for search
GSV_{CAC40}	The Google search volume of the term "CAC40" as provided by Google Insights for search
Absolute_return	The absolute value of the stock returns
Number_of_Analysts	The number of analysts covering the stock
Number_of_Employees	The number of employees of the firm
Std_Dev	The standard deviations of stock returns
Inverse_Of_Stock _Price	The inverse of the stock price
Market_value	The market capitalization

Table 1. Descriptive statistics of Google Search Volume

This table reports the descriptive statistics of the original information demand data (GSV). GSV is the firm name search intensity defined as the weekly search volume index of a firm name on Google, scaled from 0 to 100 by Google Insights for search. The sample spans from January 2004 to June 2012. In addition to the central tendency characteristics (Mean and Median), this table reports the kurtosis and the skewness. This table reports also the standard deviation (dispersion characteristics), the coefficient of variation (CV) and the Jarque–Berra (J–B) normality test statistic.

*,**,*** denote 10%, 5% and 1% significance levels.

Stock	Mean	Median	St.Dev	CV	Skew	Kurt.	J-B
Accor	43,3589	40	14,9365	0.3448	0,8139	3,1109	40,07***
Axa	73,9548	74	6,8479	0.0925	0,1989	3,1170	143,42***
Air Liquide	36,7652	33	12,4620	0.3389	1,5934	6,2081	3,39
Arcelor	15,1467	14	8,8667	0.5853	3,3686	25,3191	367,19***
Bnp Paribas	38,8532	38	15,6388	0.4025	1,0644	4,4970	77,32***
Bouygues	44,2708	42	9,7337	0.2198	1,0666	5,5091	90,84***
Cap Gemini	22,3115	16	17,8874	0.8017	1,7121	6,2650	153,86***
Carrefour	63,2347	61	11,0266	0.1743	0,6705	3,4319	31,81***
Crédit Agricole	64,3972	67	13,0746	0.2030	-0,57921	2,5968	22,07***
Danone	33,2054	27	19,0002	0.5722	1,1781	1,1781	75,65***
Dexia	15,3860	14	7,0004	0.4549	8,2089	89,0125	670,36***
Eads	37,4763	31	16,3717	0.4368	1,0588	3,5529	64,12***
France Telecom	32,2347	26	24,1480	0.7491	0,6517	2,1488	70,47***
Lagardère	13,1286	11	8,7875	0.6693	4,9021	41,9290	485,05***
L’oréal	27,4424	22	18,1123	0.6600	0,9967	3,8601	62,88***
LVMH	35,5349	33	12,8964	0.3629	1,1285	4,5981	84,10***
Michelin	62,0654	60	12,7661	0.2056	0,6662	3,3263	30,43***
Pernod Ricard	23,5553	20	13,1578	0.5585	1,5021	7,6871	150,74***
Peugeot	62,8465	61	9,0052	0.1432	0,8285	3,6971	47,05***
PPR	31,4379	27	13,6110	0.4329	1,60987	6,5334	148,34***
Renault	55,4921	54	9,5813	0.1726	0,7588	3,6742	41,31***
Saint Gobain	41,1535	39	12,9640	0.3150	1,0544	4,5849	77,70***
Sanofi	21,6298	20	8,4790	0.3920	2,7711	21,6114	317,35***
Schneider	46,5237	43	14,8258	0.3186	0,5453	2,8807	20,20***
Société Générale	49,7449	52	14,4687	0.2908	0,1855	3,3176	4,50
STMIcroelectronics	21,3476	17	16,0484	0.7517	1,8315	6,9248	170,59***
Total	55,1083	52	11,0926	0.2012	0,7746	3,3281	38,61***
Vinci	6,1986	5	5,5336	0.8927	12,3465	195,6525	840,43***
Vivendi	22,60948	16	15,44113	0.6829	1,988646	7,550328	189,22***
CAC 40	11,03612	9	8,753205	0.7931	6,104132	54,80927	558,49***

Table 2. Descriptive statistics of Turnover

This table reports descriptive statistics of the stock turnover over the period 2004-2012. Turnover is defined as the trading volume divided by shares outstanding for each week. In addition to the mean and the median controlling for central tendency, skewness and kurtosis indicate the shape of the distribution. While, the standard deviation reports the dispersion characteristics. The Jarque–Berra (J–B) is the normality test statistic and Box-Pierce Q statistic [Q (1) and Q (6)] assess auto-correlation test among stock turnover values. Finally, the last column provides correlation coefficients between stock turnover and stock-specific information demand, p_values are presented in parentheses under these coefficients.

*, **, *** denote significance at the10%, 5% and 1% level, respectively.

	Mean	Median	Std.Dev	Skew	Kurt.	J-B	Q(1)	Q(6)	corr with
Accor	0,0283	0,0264	0,0102	0,9583	4,3102	65,91***	110,81***	253,62***	0.1139** (0.0164)
Axa	0,0240	0,0218	0,0097	2,1582	12,0353	234,59***	162,48***	408,47***	0.2473*** (0.000)
Air Liquide	0,0346	0,0297	0,0189	1,1525	4,7869	88,70***	274,05***	1237,9***	0.5857*** (0.000)
Arcelor	0,0356	0,0320	0,0303	0,5466	2,7517	21,28***	363***	1863,3***	-0.5244*** (0.000)
Bnp Paribas	0,0258	0,0229	0,0115	1,7437	7,9623	173,21***	165,34***	479,33***	0.1504*** (0.001)
Bouygues	0,0216	0,0205	0,0076	1,5075	7,8277	152,46***	108,92***	230,9***	0.0441 (0.354)
Cap Gemini	0,0509	0,0454	0,0228	1,4675	6,3884	134,89***	140,15***	461,31***	0.4537*** (0.000)
Carrefour	0,0241	0,0218	0,0099	1,8709	8,8827	191,16***	156,95***	357,6***	-0.0000 (0.999)
Crédit Agricole	0,0178	0,0146	0,0098	1,8785	7,3608	178,65***	241,13***	747,92***	0.0932** (0.049)
Danone	0,0356	0,0295	0,0269	3,4946	24,313	372,87***	228,6***	867,73***	0.6453*** (0.000)
Dexia	0,0125	0,0093	0,0097	2,4986	11,6583	258,14***	224,86***	795,65***	0.4548*** (0.000)
Eads	0,0178	0,0150	0,0106	3,9289	37,0217	423,56***	147,15***	531,96***	0.1393*** (0.003)

France Télécom	0,0208	0,0190	0,0083	1,7846	7,6387	173,65***	87,239***	247,95***	0.1481*** (0.001)
Lafarge	0,0322	0,0291	0,0135	1,4101	5,8227	123,63***	183,67***	558***	0.2225*** (0.000)
Lagardère	0,0229	0,0207	0,0094	1,4435	6,0477	129,06***	121,51***	254,46***	0.0288 (0.545)
L'oréal	0,0098	0,0092	0,0036	1,7075	8,7163	176,55***	128,11***	374,79***	0.1403*** (0.003)
LVMH	0,0139	0,0125	0,005	1,8732	9,0443	192,59***	164,69***	434,25***	0.1558*** (0.001)
Michelin	0,0371	0,0326	0,0165	1,2937	4,7914	100,70***	176,56***	547,87***	0.2375*** (0.000)
Pernod Ricard	0,0370	0,0310	0,0278	2,1978	11,5059	234,61***	212,95***	875,96***	0.1530*** (0.001)
Peugeot	0,0473	0,0432	0,0229	1,2430	5,7381	108,50***	240,07***	876,67***	-0.3818*** (0.000)
PPR	0,0229	0,0201	0,0113	1,6801	7,8192	166,72***	226,26***	899,57***	0.0882* (0.063)
Renault	0,0344	0,03161	0,0158	1,3494	5,8204	118,48***	235,54***	894,54***	-0.2757*** (0.000)
Saint Gobain	0,0291	0,0257	0,0126	2,056	9,4996	210,57***	181,09***	502,12***	0.1439*** (0.000)
Sanofi	0,0165	0,0150	0,0075	3,8502	30,242	407,59***	98,564***	183,91***	0.3186*** (0.000)
Schneider	0,0239	0,0220	0,0096	1,7429	8,825	180,32***	159,12***	511,88***	-0.1442*** (0.002)
Société Générale	0,0358	0,0296	0,0207	2,6763	15,083	288,05***	206,55***	662,5***	0.1783*** (0.000)
STMIcroelectronics	0,0301	0,0282	0,0098	0,8255	4,1822	53,38***	106,58***	247,88***	0.0304 (0.522)
Total	0,0370	0,0194	0,0333	1,2783	3,3952	80,88***	364,96***	1925,1***	0.7174*** (0.000)
Vinci	0,0273	0,0239	0,0131	2,7153	15,1069	290,93***	145,13***	331,6***	0.2604*** (0.000)
Vivendi	0,0270	0,0252	0,0094	1,6373	7,8875	163,80***	137,46***	277,3***	0.3331*** (0.000)

Table 3. Descriptive statistics for alternative liquidity measures and control variables

This table reports average statistics of alternative liquidity measures (the Amihud ILLIQ ratio, the relative spread, the ROLL estimate and the Amivest ratio) and control variables. The sample runs from 2004 to 2012. All variables are defined in the appendix.

	Nb.Obs	Amihud	Relative Spread	Amivest	Roll	Return	Std.Dev	Market_Value (in1M€)	Nb_of_ Analysts	Nb_of_ Employees
Accor	443	0,0004	8,78e-03	6.84e+09	0,3598	0,0012	0,0183	6150,000	19,0067	129121,2
Axa	443	0,0001	6,44e-03	3.19e+10	0,2621	0,0008	0,0221	39300,000	32,0361	93739,37
Air Liquide	443	0,0001	7,053e-03	2.03e+10	0,5565	0,0020	0,0133	14300,000	27,2799	41790,74
Arcelor	443	0,0005	6,020e-03	1.99e+10	0,4586	0,0039	0,0273	18700,000	23,9729	17157,31
Bnp Paribas	443	0,0001	6,343e-03	4.84e+10	0,7398	0,0008	0,0212	55100,000	31,7381	154837
Bouygues	443	0,0003	8,419e-03	1.11e+10	0,4961	0,0008	0,0177	12400,000	18,7652	132383,2
Cap Gemini	443	0,0003	7,962e-03	9.39e+09	0,5222	0,0008	0,0208	5010,000	23,9209	87439,78
Carrefour	443	0,0001	5,088e-03	2.58e+10	0,3413	-0,0013	0,0154	22800,000	34,4469	456410,5
Danone	443	0,0001	6,351e-03	3.07e+10	0,4327	0,0015	0,0129	20500,000	34,1625	89345,03
Eads	443	0,0003	6,30e-03	9.53e+09	0,2908	0,0022	0,0204	16800,000	28,8239	116939,4
France Telecom	443	0,0001	6,112e-03	4.66e+10	0,1773	-0,0012	0,0133	48300,000	35,4447	181981,9
Lafarge	443	0,0002	7,061e-03	1.73e+10	0,2290	0,0010	0,0189	12800,000	24,4605	76230,6
Lagardère	443	0,0007	1,171e-02	6.48e+09	0,4654	-0,0007	0,0162	54,800	16,9819	36140,02

L'oréal	443	0,0001	7,040e-03	2.14e+10	0,7675	0,0012	0,0133	45500,000	29,8848	62504,19
LVMH	443	0,0001	7,158e-03	2.26e+10	0,9049	0,00236	0,0158	39300,000	27,7607	74586,47
Michelin	443	0,0003	9,055e-03	1.08e+10	0,7626	0,0021	0,0211	8100,000	19,4537	113315,6
Pernod Ricard	443	0,0002	9,228e-03	1.48e+10	0,6389	0,0028	0,0143	10400,000	25,0045	16719,24
Peugeot	443	0,0003	8,051e-03	1.11e+10	0,3735	-0,0018	0,0211	7520,000	28,4514	206621,4
PPR	443	0,0002	8,422e-03	1.20e+10	1,0069	0,0021	0,0164	11900,000	21,1805	72870,2
Renault	443	0,0002	8,068e-03	1.61e+10	0,7116	0,0005	0,0223	16400,000	28,5620	129813
Saint Gobain	443	0,0001	6,314e-03	2.10e+10	0,5612	0,0009	0,0201	393,000	24,8171	194390,4
Sanofi	443	0,0001	6,047e-03	5.52e+10	0,5795	0,0006	0,0136	74400,000	31,8171	102119,2
Schneider	443	0,0001	6,047e-03	5.52e+10	0,5523	0,0022	0,0189	865,000	23,7629	114222
Société Générale	443	0,0001	7,058e-03	3.82e+10	0,7848	-0,0003	0,0229	33100,000	27,0496	136544,9
STMIcroelectronics	443	0,0004	5,911e-03	1.05e+10	0,1289	-0,0024	0,0202	9180,000	29,9661	51095,87
Total	443	0,0000	9,033e-03	1.12e+11	0,4515	0,0005	0,0135	84400,000	35,6275	99505,17
Vinci	443	0,0001	7,446e-03	1.93e+10	0,4605	0,0027	0,0168	14800,000	21,4153	157703,7
Vivendi	443	0,0001	5,548e-03	3.31e+10	0,2260	0,0001	0,0145	25700,000	27,4650	45526,97

Table 4. Determinants of Liquidity

This table reports the coefficients values from weekly regressions of the turnover on traditional known determinants of stock liquidity. Turnover of stock *i* in week *w* is given by the trading volume divided by shares outstanding for each week. The independent variables are as follows: the one-lag turnover, natural logarithm of number of analysts covering the stock, natural logarithm of number of employees, natural logarithm of market value, the inverse of stock price as a proxy of trading costs, the absolute return and finally the standard deviation of returns to control for risk. The sample-period is 2004-2012. The regression is as follows:

$$Turnover_{it} = \alpha + \beta_1 Turnover_{i,t-1} + \beta_2 \; Ln(Number\_of\_Analysts)_{i,t-1} + \beta_3 Ln(Number\_of\_Employees)_{i,t-1} + \beta_4 Ln\,(Market\_Value)_{i,t-1}$$
$$+ \beta_5 \; Inverse\_of\_Stock\_\mathrm{Pr}ice_{i,t-1} + \beta_6 Absolute\_return_{i,t-1} + \beta_7 Std\_Dev_{i,t-1} + \varepsilon_{it}$$

The AdjR² values assess if the independent variables that are added to the regression enhance the overall explanatory power of the regression. Robust standard errors are presented in parentheses under the coefficient estimates. Ln L is the log-likelihood function value.

*, **, *** denote significance at the10%, 5% and 1% level, respectively.

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	**n**	**AdjR²**	**Ln L**
Accor	-0.245* (0.14)	0.321*** (0.038)	0.021*** (0.006)	0.006*** (0.001)	0.011* (0.006)		0.062*** (0.013)	0.386*** (0.038)	428	0.474	1493.04
Axa		0.359*** (0.036)				-0.096* (0.051)	0.037*** (0.008)	0.264*** (0.024)	428	0.572	1553.51
Air Liquide	0.739*** (0.134)	0.344*** (0.041)	0.015** (0.007)		0.029*** (0.003)	-2.332*** (0.437)	0.105*** (0.026)	0.518*** (0.073)	428	0.728	1371.37
Arcelor		0.767*** (0.028)	0.004*** (0.001)					0.155*** (0.037)	428	0.838	1281.17
Bnp Paribas		0.326*** (0.034)	0.024*** (0.006)	0.011*** (0.002)			0.052*** (0.009)	0.391*** (0.029)	428	0.639	1526.2
Bouygues		0.293*** (0.039)			0.007* (0.004)		0.034*** (0.009)	0.308*** (0.029)	428	0.471	1614.38
Cap Gemini	-0.470** (0.241)	0.364*** (0.034)	0.016** (0.007)	0.036*** (0.004)	0.036*** (0.011)	-0.663* (0.377)	0.160*** (0.022)	0.812*** (0.070)	428	0.586	1200.61
Carrefour		0.448*** (0.034)		0.016** (0.007)	0.015*** (0.006)		0.096*** (0.012)	0.410*** (0.042)	428	0.582	1550.56
Danone		0.329*** (0.038)	0.061* (0.032)	0.022*** (0.008)	0.026*** (0.003)	-1.143*** (0.240)	0.198*** (0.040)	0.882*** (0.111)	428	0.689	1191.69
Eads		0.505*** (0.035)					0.116*** (0.010)	-0.048*** (0.009)	428	0.491	1482.8

France Telecom	-0.574*** (0.210)	0.267*** (0.035)			0.020*** (0.008)		0.125*** (0.014)	0.374*** (0.045)	428	0.523	1600.25
Lafarge	0.394*** (0.114)	0.401*** (0.036)			0.010*** (0.002)	-0.896*** (0.108)	0.096*** (0.013)	0.394*** (0.043)	428	0.619	1440.98
Lagardère		0.371*** (0.035)		0.046* (0.021)			0.075*** (0.012)	0.353*** (0.038)	428	0.514	1537.87
L'oréal	-0.211** (0.100)	0.267*** (0.035)	0.005*** (0.001)	0.003** (0.001)	0.010*** (0.003)	-0.577** (0.237)	0.039*** (0.005)	0.219*** (0.015)	428	0.607	1989.32
LVMH	0.195** (0.082)	0.380*** (0.038)	0.005*** (0.001)	0.004*** (0.002)			0.034*** (0.008)	0.225*** (0.023)	428	0.563	1790.19
Michelin		0.412*** (0.037)	0.010** (0.005)	0.019** (0.009)	-0.009* (0.005)	-0.746** (0.313)	0.126*** (0.016)	0.441*** (0.053)	428	0.593	1339.52
Pernod Ricard	0.861*** (0.071)	0.305*** (0.040)			0.028*** (0.003)	-2.327*** (0.347)	0.127*** (0.034)	0.719*** (0.107)	428	0.669	1168.22
Peugeot		0.444*** (0.038)	0.024*** (0.008)				0.127*** (0.018)	0.430*** (0.058)	428	0.679	1265.53
PPR	-0.471*** (0.115)	0.339*** (0.037)		0.024*** (0.002)	0.009** (0.004)		0.067*** (0.010)	0.367 *** (0.037)	428	0.705	1570.06
Renault	1.332*** (0.318)	0.444 *** (0.034)		0.130*** (0.031)	0.008** (0.003)		0.089*** (0.011)	0.400*** (0.037)	428	0.705	1426.87
Saint Gobain		0.507*** (0.037)			0.014*** (0.002)	-0.494*** (0.105)	0.056*** (0.011)	0.338*** (0.042)	428	0.539	1422.42
Sanofi	0.400*** (0.074)	0.334*** (0.038)		0.017*** (0.006)	0.007*** (0.001)	-0.763*** (0.158)	0.047*** (0.013)	0.357*** (0.039)	428	0.452	1609.9
Schneider		0.367*** (0.038)	0.382*** (0.076)				1.212*** (0.250)	7.386*** (0.726)	428	0.568	238.554
Société Générale		0.446*** (0.034)				-0.302** (0.144)	0.085*** (0.014)	0.490*** (0.046)	428	0.634	1272.16
STMIcroelectronics	-0.464** (0.193)	0.372*** (0.034)		0.049*** (0.014)		-0.107*** (0.027)	0.101*** (0.011)	0.431*** (0.038)	428	0.520	1527.64
Total	0.683*** (0.218)	0.345*** (0.041)	0.025* (0.014)		0.031*** (0.002)	-1.757*** (0.260)	0.061** 026)	0.315*** 067)	428	0.887	1317.51
Vinci	0.648** (0.269)	0.485*** (0.040)			0.037*** (0.007)	-0.972*** (0.388)	0.225*** (0.052)	0.392*** (0.134)	428	0.713	910.938
Vivendi		0.376*** (0.038)		0.020*** (0.004)	0.015** (0.006)	0.316* (0.171)	0.076*** (0.016)	0.353*** (0.047)	428	0.489	1529.31

Table 5. Role of information demand

This table assesses the role of information demand as a determinant of stock market liquidity. The latter is proxied by the stock turnover, obtained by dividing, for every trading week over the period 2004-2012, the total number of firm shares traded that week by the total number of shares outstandings. While, stock-specific and market information demand are proxied by Google search volume of the firm name and Google search volume of the term “CAC40”, respectively. The control variables are as follows: the one-lag turnover, natural logarithm of number of analysts covering the stock, natural logarithm of number of employees, natural logarithms of market value, the inverse of stock price as a proxy of trading costs, the absolute return and finally the standard deviation of returns to control for risk. Then, we estimate for each stock the following time-series regression:

$$Turnover_{it} = \alpha + \beta_1\, Turnover_{i,t-1} + \beta_2\, Ln(Number\_of\_Analysts)_{i,t-1} + \beta_3 Ln(Number\_of\_Employees)_{i,t-1} + \beta_4 Ln\,(Market\_Value)_{i,t-1}$$
$$+ \beta_5\, Inverse\_of\_Stock\_\mathrm{Pr}ice_{i,t-1} + \beta_6 Absolute\_return_{i,t-1} + \beta_7 Std\_Dev_{i,t-1} + \lambda_1 Ln(GSV)_{i,t-1} + \lambda_2 Ln(GSV)_{CAC40,t-1} + \varepsilon_{it}$$

The AdjR² values assess if the independent variables that are added to the regression enhance the overall explanatory power of the regression. Robust standard errors are presented in parentheses under the coefficient estimates. Ln L is the log-likelihood function value.

*, **, *** denote significance at the10%, 5% and 1% level, respectively.

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	λ_1	λ_2	n	AdjR²	Ln L
Accor	-0.264*	0.282***	0.018***				0.058***	0.377***	0.009***		428	0.492	1501.33
	(0.137)	(0.040)	(0.006)				(0.013)	(0.042)	(0.002)				
Axa		0.371***					0.037***	0.281***	0.011***	-0.002*	428	0.578	1557.95
		(0.036)					(0.008)	(0.028)	(0.004)	(0.001)			
Air Liquide	0.619***	0.315***	0.016**		0.031***	-2.675***	0.088 ***	0.417 ***	0.009***	0.003**	428	0.738	1380.65
	(0.148)	(0.041)	(0.007)		0.003)	(0.444)	(0.026)	(0.078)	(0.002)	(0.001)			
Arcelor		0.729***	0.003***					0.142***	-0.004***	0.004***	428	0.840	1285.08
		(0.031)	(0.001)					(0.045)	(0.001)	(0.002)			
Bnp Paribas	0.229**	0.284***	0.026***	0.019***			0.053***	0.337***	0.003**	0.004***	428	0.649	1533.54
	(0.102)	(0.035)	(0.005)	(0.003)			(0.009)	(0.032)	(0.001)	(0.001)			
Bouygues		0.271***					0.033***	0.283***			428	0.472	1615.6
		(0.042)					(0.009)	(0.034)					
Cap Gemini	-0.791***	0.353***	0.016**		0.031***	-0.648**	0.163***	0.870***	0.010***	-0.007***	428	0.617	1218.09
	(0.240)	(0.034)	(0.007)		(0.011)	(0.364)	(0.021)	(0.073)	(0.002)	(0.002)			
Carrefour		0.436***		0.019**	0.016***		0.097***	0.387***	-0.003**		428	0.584	1552.94
		(0.035)		(0.008)	(0.006)		(0.012)	(0.045)	(0.002)				
Danone		0.338***	0.001*	0.022***	0.022***	-0.982***	0.197***	0.937***	0.006**		428	0.693	1195.17
		(0.038)	(0.039)	(0.008)	(0.003)	(0.246)	(0.039)	(0.125)	(0.003)				

Eads		0.483*** (0.035)					0.108*** (0.010)	-0.050*** (0.009)	0.006*** (0.001)	0.002** (0.001)	428	0.512	1492.86
France Telecom		0.232*** (0.037)		0.028** (0.013)	0.020*** (0.0079)	-0.235* (0.132)	0.115*** (0.013)	0.359*** (0.048)	0.005*** (0.001)	0.002*** (0.001)	428	0.542	1610.07
Lafarge	0.309*** (0.111)	0.360*** (0.036)	0.013*** (0.005)	-0.016*** (0.006)	-0.004** (0.002)	-0.545*** (0.138)	0.096*** (0.013)	0.382*** (0.045)	0.010*** (0.001)		428	0.645	1456.69
Lagardère		0.366*** (0.038)					0.074*** (0.012)	0.334*** (0.043)			428	0.514	1538.01
L'Oréal	-0.213** (0.099)	0.238*** (0.036)	0.005*** (0.001)	0.007*** (0.002)	0.012*** (0.003)	0.601*** (0.235)	0.039*** (0.005)	0.207*** (0.017)	0.001** (0.000)	0.001*** (0.000)	428	0.615	1994.87
LVMH	0.328*** (0.080)	0.310*** (0.038)	0.006*** (0.001)		0.013*** (0.003)	-0.742*** (0.244)	0.029*** (0.007)	0.201*** (0.024)	0.004*** (0.001)	0.001*** (0.001)	428	0.603	1811.72
Michelin		0.410*** (0.038)	0.011** (0.005)				0.127*** (0.017)	0.470*** (0.058)			428	0.594	1341.34
Pernod Ricard	0.674*** (0.081)	0.320*** (0.039)			0.023*** (0.003)	-1.876*** (0.355)	0.148*** (0.033)	0.945*** (0.121)	0.002** (0.001)	-0.012*** (0.003)	428	0.682	1178.29
Peugeot	-0.508** (0.245)	0.433*** (0.038)	0.042 *** (0.010)	0.051*** (0.019)			0.125*** (0.019)	0.442*** (0.061)	0.020*** (0.006)		428	0.684	1270.17
PPR	-0.437*** (0.115)	0.319*** (0.038)		0.023*** (0.002)	0.007** (0.004)		0.063*** (0.010)	0.336*** (0.040)	0.002*** (0.001)	0.002** (0.001)	428	0.710	1574.92
Renault	1.605*** (0.333)	0.436*** (0.035)		0.157*** (0.033)	0.009** (0.003)		0.085*** (0.011)	0.379*** (0.041)	0.008** (0.003)		428	0.709	1430.39
Saint Gobain		0.477*** (0.052)			0.019*** (0.006)	-0.356*** (0.093)	0.053*** (0.011)	0.314*** (0.045)	0.010*** (0.001)		428	0.572	1438.42
Sanofi		0.345*** (0.039)			-0.004** (0.001)	-0.408** (0.199)	0.046 *** (0.013)	0.361*** (0.042)	0.003*** (0.001)		428	0.462	1614.61
Schneider		0.350*** (0.037)	0.697*** (0.095)	0.188** (0.090)			1.258*** (0.245)	7.329*** (0.798)	0.147*** (0.026)		428	0.596	253.981
Société Générale		0.379*** (0.035)		0.014*** (0.005)		-0.524*** (0.145)	0.081*** (0.014)	0.502 *** (0.051)	0.013*** (0.002)		428	0.659	1288.48
STMIcroelectronics	-0.425** (0.194)	0.353*** (0.036)		0.046*** (0.014)		-0.118*** (0.028)	0.101*** (0.011)	0.410*** (0.040)			428	0.521	1529.29
Total	0.699*** (0.232)	0.342*** (0.041)			0.031*** (0.002)	-1.769*** (0.267)	0.058** (0.026)	0.282*** (0.084)			428	0.888	1318.21
Vinci		0.483*** (0.040)			0.033*** (0.008)		0.253*** (0.052)	0.691*** (0.165)		-0.018*** (0.005)	428	0.719	916.225
Vivendi	-0.542*** (0.168)	0.350*** (0.038)			0.024*** (0.007)	-0.378** (0.167)	0.071*** (0.015)	0.359*** (0.052)	0.005*** (0.001)		428	0.524	1545.48

Table 6. Forecasting evaluation results

This table presents the out-of-sample liquidity forecasting results of Model 1 and Model 2 for three horizons: h=4, h=8 and h=12 weeks. Liquidity is measured by stock turnover - the total number of firm shares traded by week divided by the total number of shares outstandings. Stock-specific and market information demand are proxied by Google search volume of firm name and Google search volume of the term "CAC40", respectively.
Root Mean Squared Error (RMSE) and Mean of Absolute Percent Error (MAPE) are defined as:

$$RMSE_i = \sqrt{h^{-1}\sum_{t=T+1}^{T+h}(l_{it}-\hat{l}_{it})^2}$$

$$MAPE_i = h^{-1}\sum_{t=T+1}^{T+h}\left|\frac{l_{it}-\hat{l}_{it}}{l_{it}}\right|$$

Where, t denotes time period of the forecast sample, $t = T+1, T+2, \ldots, T+h$. l_{it} and $\hat{l}_{it}$ stand for the actual and forecasted returns respectively.

		Model 1			***Model 2***		
		H=4	**H**=8	**H**=12	**H**=4	**H**=8	**H**=12
Accor	*RMSE*	**0.0033**	0.0076	0.0090	0.0057	**0.0055**	**0.0075**
	MAPE	**8.0415**	24.840	29.894	13.260	**17.135**	**20.361**
Axa	*RMSE*	0.005	**0.005**	0.008	**0.004**	0.006	**0.007**
	MAPE	20.678	18.712	25.017	**16.675**	**18.357**	**24.996**
Air Liquide	*RMSE*	**0.0013**	0.0040	0.0042	0.0021	**0.0035**	**0.0036**
	MAPE	**7.9318**	16.772	**17.866**	11.896	**15.676**	18.002
Arcelor	*RMSE*	0.0069	0.0105	0.0100	**0.0064**	**0.0090**	**0.0085**
	MAPE	9.0713	11.322	10.847	**8.774**	**10.108**	**10.325**
Bnp Paribas	*RMSE*	0.0080	0.0097	0.0120	**0.0064**	**0.0085**	**0.0111**
	MAPE	20.240	24.311	29.053	**17.008**	**21.066**	**26.317**
Bouygues	*RMSE*	**0.0021**	**0.0037**	0.0033	0.0023	0.0039	**0.0032**
	MAPE	**10.249**	10.898	**9.829**	11.123	**10.043**	10.190
Cap Gemini	*RMSE*	0.0109	0.0098	0.0094	**0.0059**	**0.0069**	**0.0091**
	MAPE	27.906	26.972	22.519	**13.902**	**18.116**	**19.601**
Carrefour	*RMSE*	**0.003**	**0.0032**	0.0073	**0.003**	0.0036	**0.0070**
	MAPE	**9.718**	**12.807**	21.479	10.256	13.993	**20.709**
Danone	*RMSE*	**0.0032**	0.0035	0.0047	0.0038	**0.0033**	**0.0042**
	MAPE	19.723	17.393	21.786	**16.126**	**13.424**	**17.361**
Eads	*RMSE*	0.0020	0.0059	0.0067	**0.0016**	**0.0050**	**0.0049**
	MAPE	14.210	49.600	53.559	**12.404**	**41.344**	**39.526**

France Telecom	*RMSE*	0.0042	0.0042	0.0068	**0.0038**	**0.0036**	**0.0060**
	MAPE	23.711	**18.982**	23.347	**16.539**	19.362	**22.243**
Lafarge	*RMSE*	0.0054	0.0072	0.0079	**0.0025**	**0.0053**	**0.0062**
	MAPE	15.814	20.122	23.647	**7.2590**	**14.211**	**18.117**
Lagardère	*RMSE*	**0.6062**	0.5458	**0.4818**	0.6177	**0.5404**	0.4842
	MAPE	**19.361**	**20.245**	19.712	19.844	20.253	**19.671**
L’Oréal	*RMSE*	0.0018	0.0027	**0.0024**	**0.0017**	**0.0026**	0.0025
	MAPE	16.699	**23.189**	24.067	**15.745**	**23.631**	**23.689**
LVMH	*RMSE*	0.0042	**0.0030**	0.0028	**0.0039**	0.0032	**0.0027**
	MAPE	16.989	15.292	16.333	**15.016**	**14.882**	**15.614**
Michelin	*RMSE*	**0.0040**	0.0103	**0.0088**	0.0041	**0.0097**	0.0089
	MAPE	15.186	33.193	**27.894**	**14.987**	**31.450**	27.980
Pernod Ricard	*RMSE*	0.0046	0.0074	0.0067	**0.0029**	**0.0065**	**0.0060**
	MAPE	28.546	55.699	45.432	**19.107**	**49.873**	**42.452**
Peugeot	*RMSE*	0.0202	0.0161	**0.0202**	**0.0201**	**0.0156**	0.0205
	MAPE	**23.649**	19.541	19.019	23.743	**18.007**	**18.416**
PPR	*RMSE*	0.0059	0.0091	0.0077	**0.0044**	**0.0075**	**0.0062**
	MAPE	17.250	26.701	24.870	**14.829**	**20.956**	**17.355**
Renault	*RMSE*	0.0041	0.0047	0.0057	**0.0038**	**0.0043**	**0.0056**
	MAPE	13.029	13.314	15.229	**12.146**	**12.416**	**14.627**
Saint Gobain	*RMSE*	0.4271	0.3942	0.4968	**0.3653**	**0.3376**	**0.4316**
	MAPE	21.894	23.485	24.370	**18.710**	**20.105**	**20.890**
Sanofi	*RMSE*	0.0015	0.0043	**0.0040**	**0.0014**	**0.0042**	**0.0040**
	MAPE	10.881	15.583	**16.625**	**10.273**	**15.363**	16.404
Schneider	*RMSE*	0.1204	0.1482	0.1427	**0.0862**	**0.1247**	**0.1239**
	MAPE	23.216	27.564	25.681	**16.210**	**22.391**	**21.304**
Société Générale	*RMSE*	0.0335	0.0360	0.0386	**0.0226**	**0.0256**	**0.0275**
	MAPE	51.226	56.514	64.421	**31.267**	**38.228**	**44.471**
STMIcroelectronics	*RMSE*	1.1519	1.6509	**1.8962**	**1.2520**	**1.5585**	2.1303
	MAPE	**35.267**	**40.273**	49.822	38.312	45.522	**46.114**
Total	*RMSE*	0.0082	**0.0062**	**0.0060**	**0.0081**	0.0063	**0.0060**
	MAPE	23.439	23.511	**25.739**	**21.130**	**23.424**	26.799
Vinci	*RMSE*	0.0051	**0.0066**	**0.0070**	**0.0111**	0.0137	0.0126
	MAPE	**26.515**	**29.370**	**25.726**	39.460	50.218	47.439
Vivendi	*RMSE*	0.0044	0.0040	0.0042	**0.0038**	**0.0033**	**0.0032**
	MAPE	12.836	11.288	13.528	**11.263**	**8.9027**	**9.7570**