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Information demand and stock market liquidity: International evidence

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ABSTRACT

The aim of this paper is to investigate whether information demand is a significant determinant of stock liquidity. For a large sample of 209 firms from 7 countries over the 2004–2014 period, we show that information demand, as proxied by daily search volume in Google, is positively associated with stock market liquidity. Most importantly, this relationship is found to be shaped by the firm's overall visibility and information asymmetry levels. We test the robustness of our results by employing different estimation methods and alternative proxies. Thus, it may be that investors and managers who are concerned with stock liquidity should consider investor information demand in addition to specific investment fundamentals.

1. Introduction

According to recent research, factors such as information asymmetry and idiosyncratic risk are likely to be relevant for determining trading activity levels. Particularly, several research studies on stock markets have investigated the issue of liquidity under information asymmetry (Admati and Pfleiderer, 1988; Easley et al., 1996; Kyle, 1985; Li and Wu, 2006). Actually, illiquidity is primarily caused by asymmetric information (Akerlof, 1970; Bagehot, 1971).

To reduce the cost arising from information asymmetry, investors naturally demand more information before making financial decisions (Drake et al., 2012; Peng and Xiong, 2006; Vlastakis and Markellos, 2012). Thus, information demand increases with information asymmetry from the perspective of investor rationality. In response to such information demand, firms attempt to improve the quality of information disclosure in the hope of reducing information asymmetry, and in turn improving trading activity.

The present paper proposes investor demand for information as a determinant of stock liquidity. In particular, relying on international data, we provide original evidence that information demand, as proxied by Google research volume (*GSV)*, tends to be positively associated with liquidity. Apart from this basic relationship, we rely on previous theories and empirical findings (Brandt and Kavajecz, 2004; Green, 2006; Grullon et al., 2004) and suggest more specific mechanisms for how the link between information demand and stock liquidity might work. First, we control for firm visibility proxied by advertising expenditures, firm size and stock performance. Interestingly, we find that information demand reduces information asymmetry, but only for low-visibility firms, while the relationship becomes weaker for high-visibility firms. Then, we split our sample with respect to information asymmetry levels, as proxied by quoted spread, stock volatility and analysts' forecasts dispersion. We find that information demand and stock liquidity are positively related only for high information asymmetry firms.

Overall, our empirical findings suggest that investors demand more information via the Internet when trading in the security is more difficult, which would be reflected in more liquid stocks. In addition, as suggested by Drake et al. (2015), it may be that investors focus on their search where the benefits from acquiring information are the highest (i.e., where information asymmetry is the highest, as proxied by high bid-ask spreads and idiosyncratic volatility). Finally, to control for endogeneity issues, and to explore attributors of substantial increase in stock liquidity, we employed alternative estimation methods and continue to find a significant positive association between the liquidity and information demand.

There is a vast empirical literature which had tried to explore the contribution of information retrieved from the internet in the context of developed markets. The importance of information demand in explaining stock market activity is first suggested in Drake et al. (2012) and

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Vlastakis and Markellos (2012). Information demand proxies were derived from Google Trends, a free application which provides Google search volume of search queries in a timely fashion. For instance, Drake et al. (2012) attempt to explain investor information demand around earnings announcements and find that abnormal *GSV* increases around two weeks before the earnings announcement, peaks significantly at the announcement, and sometimes remains high after the announcement. Further, when investors search for more information before the announcement, stock prices and volume are significantly affected as compared to the actual announcement date. Drake et al. (2012) suggest that the act of seeking information proxied by *GSV* allows investors to partially anticipate the information content of the earnings announcement.

Using Google search volume, Vlastakis and Markellos (2012) investigate the relation between investor information demand and several measures of stock volatility, after controlling for the market return and information supply. Similarly, Zhang et al. (2013) employ the number of information appeared in Baidu News as the proxy for information flow and find that this Internet-based information proxy can reduce the volatility persistence of the SME price index. 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. Taken together, these studies suggest an important role for information demand levels as proxied by Google search volume. However, the issue of whether information demand matters for stock liquidity has not yet been investigated, especially with high-frequency data and apart from the US stock market.

So far, theoretical models (Glosten and Milgrom, 1985; Kyle, 1985) predict that information asymmetry among market participants increase the adverse selection risk for liquidity providers. In response, liquidity providers demand a higher compensation and widen the quoted spread, thereby lowering liquidity and increasing the cost of capital. However, this literature was mainly 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).

Investors actually have scarce cognitive resources. Thus, information acquisition costs with respect to tracking, collecting and processing firm news limit the set of information that can be assimilated by them (Barber and Odean, 2008; Merton, 1987). Constrained by limited attention and time, investors often retain in their investment choices set the stocks that first garner their attention (Barber and Odean, 2008). Consequently, new information cannot be automatically impeded into stock prices. It is not unrealistic to suggest that investors are increasingly using the internet as a source of information. Further, Google is, undoubtedly, the unbeatable market leader with 9 net surfers of 10 using Google in all over the world.[1] In addition, there is strong academic evidence that investors tend to use the internet for information and brokerage services (Barber and Odean, 2001; Blankespoor et al., 2013; Rubin and Rubin, 2010). Searching for firm news on the internet is also more likely to capture interest. Furthermore, there is ample evidence that Google search volume is a predictor for a number of social, economic and financial outcomes and especially stock market activity. For instance, *GSV* appear to be a significant predictor of cancer-related trends (Cooper et al., 2005), flu outbreaks (Dukic et al., 2012), automobile sales (Choi and Varian, 2012), jobless claims (Choi and Varian, 2009), inflation Guzman (2011) and IPO returns (Da et al., 2011).

Our paper differs from other papers such as Drake et al. (2012) and Vlastakis and Markellos (2012) that examine information demand and stock market activity as we provide unique international evidence that information demand reflects reduced information asymmetry which in turn improves stock market liquidity. As previously mentioned, the relevance of information demand was only suggested for stock volatility and earning announcements with a focus on the US stock market (Drake et al., 2012; Vlastakis and Markellos, 2012). While, our contribution is to show that daily information demand as proxied by *GSV* has a significant impact on liquidity levels in different financial markets.

Based on the analysis of S&P 500 stocks, Ding and Hou (2015) suggest that Google search volume as a measure of investor attention improves the shareholder base and stock liquidity. Our paper differs from Ding and Hou (2015) as we do not only focus on the US stock market and provide new international evidence that Google search volume do enhance stock liquidity, but under some conditions such as firm visibility and information asymmetry levels.

This paper further complements and links prior literature in two ways. First, to the best of our knowledge, we are the first to bring new international evidence that daily information demand as proxied by *GSV* improves stock liquidity. This suggests that Internet search activity may partially resolve information asymmetry problems. Furthermore, prior studies investigate the explanatory power of Google data on price dynamics and volatility clustering without exploring the underlying mechanisms (Bank et al., 2011; Drake et al., 2012; Vlastakis and Markellos, 2012). In this study, we attempt to identify underlying mechanisms, i.e., information asymmetry and firm visibility, to explain the stock liquidity reaction to investor information demand (Zhang et al., 2016).

The remainder of this paper proceeds as follows. The next section describes the data, sample construction and methodology. Section 3 reports our empirical results and discusses theoretical and practical implications. In Section 4, we address some methodological concerns by employing a battery of validity check tests. Section 5 sets forth concluding remarks.

2. Variables, sample and descriptive statistics

2.1. Measuring information demand

The question of whether information demand matters for stock liquidity has been difficult to test due primarily to the absence of a valid proxy of information demand. Da et al. (2011) introduce Google search volume of ticker symbols as provided by Google Trends as a proxy of investor attention. They also provide consistent evidence that, in an average week, *GSV* is positively associated with market capitalization, abnormal returns of *IPO*s, turnover, and media attention. *GSV* could also proxy for information demand as in Drake et al. (2012) and Vlastakis and Markellos (2012). Google Trends is a free tool provided by Google which covers the query records from January 2004 to present. In particular, for any given term, this application can report the search volume index, which quantitatively measures how often this term is searched via Google by internet users.

In this study, Google Trends provides the raw inputs for information demand proxy. In particular, to identify investor demand for firm-specific information (*SID* hereafter), we use the stock ticker as the search criterion submitted to Google Trends.[2] One of the shortcomings of this application is that Google data with a daily frequency are available only for 90 days, whereas weekly data are available for an extended period.[3] To create daily data for periods longer than 90 days, we have developed an R code to automatically download daily data for all stocks under

[1] Source: AT Internet Search Engine Barometer.

[2] Using search volume for the company name to identify a stock is potentially problematic since people may be searching the company name for reasons unrelated to investing. Conversely, searching for a stock using its ticker is more precise and relates to people acquiring financial information about the company. The use of tickers instead of firm names increases the likelihood that the user is an investor, rather than an individual searching Google for other company information, such as products.

[3] Some other minor concerns with Google data are: (1) the search volume does not include searches from other major search engines such as Bing and Yahoo!; and (2) the data do not include searches using other major search mechanisms, such as Google Finance.

Table 1
Description of variables.

Variable	Definition	Variable description
Dependent variables		
ILLIQ	The Amihud (2002) *ILLIQ* ratio	The natural logarithm of (the absolute return divided by the value of traded volume)
Quoted spread	Illiquidity ratio	The natural logarithm of (the difference between the best ask and bid quotes)
Turnover	Liquidity ratio	The natural logarithm of (the trading volume divided by shares outstanding)
TPI	Turnover price impact	The natural logarithm of (the absolute return divided by the stock turnover)
Independent variables		
SID	Firm-specific information demand	The natural logarithm (1 + Google Search Volume (*GSV*) of the stock ticker for a given firm on day t)
MID	Market-related information demand	The natural logarithm (1 + Google Search Volume (*GSV*) of the stock market main index for a given country on day t)
AbSID	Abnormal firm-specific information demand	The average value of raw Google Search Volume (*GSV*) of the stock ticker for a given firm on day t minus the average *GSV* for the same weekday over the past 10 weeks, scaled by the average *GSV* for the same weekday over the past 10 weeks.
AbMID	Abnormal market-related information demand	The average value of raw Google Search Volume (*GSV*) of the main stock index for a given country on day t minus the average *GSV* for the same weekday over the past 10 weeks, scaled by the average *GSV* for the same weekday over the past 10 weeks.
Absolute_return	Stock returns	The absolute value of the stock returns
Number_of_Analysts	Information supply	Natural logarithm (number of analysts covering the stock+1)
Number_of_Employees	Firm size	Natural logarithm (number of employees of the firm+1)
Volatility	Risk	The standard deviations of stock returns
Inverse _Price	Trading costs	1/share price
Market_value	Firm size	Natural logarithm (market capitalization)
Advertising expenditures	Firm vibility	Natural logarithm (Advertising expenses)

analysis during the 2004–2014 period.

Daily data are finer than weekly *GSV* data used in previous studies (Da et al., 2011; Vlastakis and Markellos, 2012), which allows us to more directly isolate investors demand for information in tighter frequency. The same procedure is followed to proxy market-related information demand (*MID* hereafter) which is calculated on the basis of *GSV* of the stock market main index.

2.2. Measuring liquidity

The literature has not provided a clear indication to practitioners as to which measure of liquidity does a better job at measuring stock liquidity. Thus, a wide range of measures are used to evaluate liquidity. While the market microstructure literature has proposed various liquidity measures, we follow Goyenko et al. (2009) and Xiong et al. (2013) and use the Amihud (2002) illiquidity ratio, calculated as the ratio of absolute return of stock i on day t to trading volume (Acharya and Pedersen, 2005; Goyenko et al., 2009; Hasbrouck, 2009). A high estimate indicates low liquidity (high price impact of trades). Next, due to the non-normality of illiquidity series, the natural logarithm of this measure (denoted as *ILLIQ*) is used in all regression estimations. In the robustness part, we employ alternative measures of stock liquidity to test the sensitivity of the results. Financial data is retrieved from Thomson Reuters Datastream, Worldscope and I/B/E/S databases.

2.3. Control variables

We rely on previous works to identify candidate variables to understand stock liquidity (Benston and Hagerman, 1974; Demsetz, 1968; Tinic, 1972). In particular, we focus on variables that may simultaneously determine the levels of liquidity as well as investor information demand. All variables under analysis are described in Table 1.

The results from 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. Further, since investors are likely to be attracted to firms that are doing well (Chordia et al., 2005; Karpoff, 1987), we control for stock returns.
- Firm size: previous work show that liquidity is increasing with firm size (Loughran and Schultz, 2005). We proxy size by the market value. Firm size is a proxy of information asymmetry (Chae, 2005). According to market microstructure theory, information asymmetry costs lower market liquidity. Because we commonly suppose that smaller firms exhibit more information asymmetry than larger firms, the latter would probably be 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 seek 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 (Spiegel and Wang, 2005; Stoll, 1978). We use the standard deviations of returns to account for differences in total risk across our sample
- Trading costs: trading costs affect negatively market liquidity. Intuitively, investors would prefer stocks with lower trading costs. As in Bartov et al. (2000) and Loughran and Schultz (2005), we use the inverse of the stock price as a proxy for trading costs.
- Advertising expenditures: Information about firms can be disseminated through several channels, including company-controlled channels, such as advertising and corporate webpages, and non-corporate sources, such as media outlets rating agencies. Advertising expenses provide insights into the firm's information environment (Nelson, 1974), firm visibility (Grullon et al., 2004) and consumer awareness (Servaes and Tamayo, 2013). We use advertising as a proxy for firm visibility as in Grullon et al. (2004). Note that since the data for such expenditure are often missing, we follow the literature by setting unavailable data to zero (Barnett and Salomon, 2012; Fee et al., 2009; Hale and Santos, 2009; Masulis and Reza, 2014; Servaes and Tamayo, 2013).
- Country, year and sector effects: It is well known that stock liquidity changes over time. Further, since we use an international dataset, liquidity may be altered by changing financial market regulations and securities laws. Thus, we control for year, sector and country effects.

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

Table 2
Descriptive statistics.

Variable	Mean	Std. Dev.	Minimum	Maximum	VIF	Obs.
ILLIQ	−21.921	2.4280	−34.556	−17.071	–	598,899
SID	0.0014	0.1319	−0.4201	0.6698	1.15	799,262
MID	0.0038	0.0238	−0.0523	0.0741	1.21	804,750
ABS_RETURN	0.0136	0.0151	0.0000	0.0852	1.29	804,442
VOLATILITY	0.3039	0.1750	0.1135	1.1254	2.00	803,956
ANALYSTS	2.7798	0.5075	1.0986	3.6635	1.52	796,746
EMPLOYEES	9.7048	1.4026	5.4930	12.8650	1.57	797,356
MARKET_VAL	23.1867	1.0606	20.8947	26.1620	2.06	707,542
ADVERTISING	14.1118	1.3382	10.5772	17.1523	1.18	741,674
TRADE_COSTS	0.0346	0.0264	0.0047	0.1647	1.42	804,448

This table reports the descriptive statistics of liquidity, information demand and a set of control variables. Information demand is proxied by daily Google search volume calculated on the basis of Google Trends data. In addition to the mean and median controlling for the distribution's central tendency, this table reports the minimum, maximum, standard deviation of the variables and variance inflation factors (VIFs). To reduce the potential impact of outliers, all variables are winsorized at the 1 and 99% level. All variables are defined in Table 1. The sample spans from 2004 to 2014.

2.4. Sample and preliminary analysis

Our sample consists of 290 stocks from 7 countries (United Kingdom, United States, China, Netherlands, Ireland, United Arab Emirates and Germany) and the period spans from January 12, 2004 to August 29, 2014. Table 2 provides summary statistics of all variables under analysis. On average, the mean *ILLIQ* ratio for the sample is −21.921 and median *ILLIQ* is 2.428. An average firm has market capitalization of 23.186 billion and an absolute return of 0.013.

Table 3 reports correlation coefficients between all variables under analysis. Results show that *SID* and *ILLIQ* are significantly and negatively correlated. Likewise, the correlation between *MID* and *ILLIQ* is negative and highly significant. It may be that greater investor demand allows for a reduction of information asymmetry, which in turn positively relates to stock liquidity. In addition, as prior literature has suggested, illiquidity is highly correlated to firm attributes.

3. Regression analysis

The aim of this paper is to revisit the determinants of stock market liquidity, in an international setting, by introducing the role of investor information demand. Most importantly, we attempt to identify the mechanisms which may shape this relationship. Relying of a panel of 209 firms from 7 countries over the 2004–2014 period, we first identify basic determinants of stock liquidity. Then, we add information demand proxies as main explanatory variables. Finally, we attempt to explain the sensitivity of liquidity to greater information demand.

3.1. Determinants of stock market liquidity

In this subsection, relying on international data, we first estimate a multifactor model to identify basic determinants of liquidity. Formally, we estimate the following model, which we call Model (1):

$$\begin{aligned} ILLIQ_{i,t} = {} & \alpha + \beta_1 Absolute\_return_{i,t-1} + \beta_2 Std\_Dev_{i,t-1} + \beta_3 Ln(Number\_of\_Analysts)_{i,t-1} \\ & + \beta_4 Ln\ \ (Market\_Value)_{i,t-1} + \beta_5 Advertising_{i,t-1} + \beta_6\ Inverse\_of\_Stock\_Price_{i,t-1} + \\ & + YEAR_{effects} + SECTOR_{effects} + COUNTRY_{effects} + \varepsilon_{it-1} \end{aligned} \tag{1}$$

Therefore, given the correlation between some variables, we tested for multicollinearity. *VIF*s are usually considered reliable indicators of multicollinearity. However, in fixed effects models, it is more complicated to calculate VIFs. Indeed, by construction fixed effects are expected to be inflated (Baum, 2006). Thus, to obtain reliable indicators of multicollinearity, we re-estimate a transformed model using the OLS method, which removes the fixed effects from the estimation but still produces the same estimated coefficients as in the fixed effects model (Gormley and Matsa, 2014). As usually performed, the transformed model is achieved by subtracting from each explanatory variable its average. We then perform an *OLS* estimation procedure using these transformed variables (Wooldridge, 2003). Following this method, *VIF*s do not exceed 3 for all the variables under analysis, confirming the absence of significant multicollinearity.

Preliminary analysis supports the relevance of information demand as a determinant of liquidity in financial markets. However, does investor information demand influence stock liquidity or is this correlation simply reflects dissimilarities in the firms' characteristics that affect both liquidity and information demand? We rely on regression analysis to response this question.

where *i* indexes firm and *t* indexes time.

All variables are described in Table 1. As can be seen, we have lagged all explanatory variables to account for a possibly endogenous interdependence. We also correct for both autocorrelation and heteroskedasticity given the high serial correlation of stock liquidity.

Empirical results, reported in the first column of Table 4, are as expected. For instance, the coefficient of the number of analysts is negative and significant at the 1% level. Thus, the number of analysts who cover the firm appears to improve the firm's information environment and in turn, stock liquidity. Further, analysts may cover more heavily traded stocks (Bhushan, 1989). The coefficients on the market value as well as on advertising are also significantly negative supporting that liquidity increases with the firm overall visibility in line with Grullon et al. (2004). Further, it is well known that 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 are more heavily traded. Overall, coefficients estimates are as expected supporting results of prior studies.

Table 3
Correlation matrix.

	ILLIQ	*SID*	*MID*	ABS_RETURN	VOLATILITY	ANALYSTS	EMPLOYEES	MARKET_VAL	VISIBILITY	TRADE_COSTS
ILLIQ	1									
SID	−0.101***	1								
MID	−0.074***	0.349***	1							
ABS_RETURN	0.313***	0.006***	−0.053***	1						
VOLATILITY	0.143***	0.006***	−0.085***	0.4415***	1					
ANALYSTS	−0.321***	0.010***	0.220***	−0.0332***	−0.064***	1				
MARKET_VAL	−0.507***	0.146***	0.157***	−0.1270***	−0.267***	0.506***	0.553***	1		
VISIBILITY	−0.357***	0.110***	0.090***	−0.0719***	−0.145***	0.304***	0.562***	0.6740***	1	
TRADE_COSTS	0.116***	−0.140***	−0.171***	0.1732***	0.345***	−0.124***	−0.125***	−0.3562***	−0.1176***	1

This table reports pairwise correlations between variables under analysis. All variables are defined in Table 1. ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively.

Table 4
Determinants of stock liquidity: The role of information demand.

Model	**Model 1**	**Model 2**	**Model 3**
Dependent variable	***ILLIQ***	***ILLIQ***	***ILLIQ***
$SID_{t\text{-}1}$			−0.021***
			(0.002)
$MID_{t\text{-}1}$		0.429*	0.420*
		(0.242)	(0.250)
$\text{Absolute\_Return}_{t\text{-}1}$	−3.046***	−3.054***	−2.906***
	(0.652)	(0.648)	(0.665)
$\text{Volatility}_{t\text{-}1}$	0.890***	0.877***	1.003***
	(0.071)	(0.071)	(0.072)
$\text{Analysts}_{t\text{-}1}$	−0.296***	−0.297***	−0.383***
	(0.010)	(0.010)	(0.010)
$\text{Market\_Value}_{t\text{-}1}$	−1.112***	−1.112***	−1.120***
	(0.004)	(0.004)	(0.004)
$\text{Advertising}_{t\text{-}1}$	−0.148***	−0.148***	−0.145***
	(0.002)	(0.002)	(0.002)
$\text{Trading\_Costs}_{t\text{-}1}$	−5.826***	−5.815***	−6.893***
	(0.168)	(0.167)	(0.190)
$\text{Constant}_{t\text{-}1}$	5.857***	4.224***	5.711***
	(0.109)	(0.933)	(0.966)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes
R-squared (percentage)	27.15	27.16	27.20
Number of observations	364,788	364,788	364,788

This table depicts results of fixed-effects time series regression for stock liquidity as measured by Amihud (2002) illiquidity ratio (*ILLIQ*), on information demand variables, namely SID and MID proxying for firm-specific information demand and market related information demand, respectively. Unreported industry controls are based on the GICS classification. All regressors are lagged to account for a possibly endogenous interdependence between information demand and stock liquidity and winsorized at the 1 and 99% level to mitigate the effect of outliers. The variables are defined in Table 1. Robust standard errors, corrected for autocorrelation and heteroscedasticity, are in parentheses. Our sample spans from 2004 to 2014. ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively.

3.2. Liquidity in financial markets: does information demand matter?

The aim of this paper is to investigate whether information demand is a determinant of stock market liquidity, while controlling for basic attributes of liquidity. It may be that Internet search provides useful information about investor firm-specific information demand. If Internet information demand has an impact on how stock markets react to news, we expect it to influence stock liquidity.

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

$$ILLIQ_{i,t} = \alpha + \beta_1 SID_{i,t-1} + \beta_2 MID_{i,t-1} + \beta_3 Absolute\_return_{i,t-1} + \beta_4 Std\_Dev_{i,t-1} + \beta_5 Ln(Number\_of\_Analysts)_{i,t-1} + \beta_6 Ln\ (Market\_Value)_{i,t-1} + \beta_7 Advertising_{i,t-1} + \beta_8\ Inverse\_of\_Stock\_Price_{i,t-1} + YEAR_{effects} + SECTOR_{effects} + COUNTRY_{effects} + \varepsilon_{it-1} \quad (2)$$

The main explanatory variable, *SID* captures firm-specific information demand. As previously mentioned, we further control for market-related information demand. As previously defined, proxy of *SID* for each stock is derived on the basis of *GSV* of the stock ticker. Whereas, MID is proxied by the *GSV* of the main market stock index. This approach recognizes the fact that minimal effort is devoted in the literature on measuring the separate impact of specific and market-related information demand on individual stock market activity. Furthermore, as suggested by Peng and Xiong (2006), an attention-constrained investor tends to process more market information than firm-specific information, we choose to control for the importance of MID. Otherwise, Vlastakis and Markellos (2012) find that, excluding market information demand from the regression specification, *SID* becomes more statistically significant.

The liquidity measure, Amihud (2002) *ILLIQ*, is measured for firm *i* over day *t*. Since both *SID* and *ILLIQ* are in logarithm form, the regression coefficient estimate on *SID* gives us the elasticity of liquidity to information demand. The vector of control variables is the same as in Model 1. We also control for year, country and industry characteristics that obviously differ across firms, to absorb the time effect and to account for intertemporal variation that may affect the relation between information demand and stock liquidity. Liquidity (our dependent variable) is more likely to be autocorrelated over time. Thus, standard errors are corrected for autocorrelation and heteroscedasticity (Driscoll and Kraay, 1998) and clustered by firm, to avoid inflated *t*-statistics (Anderson et al., 2004; Lamont and Polk, 2001; Petersen, 2009; Sapienza, 2004).

Results from the multivariate analysis, as reported in column (2) and (3) of Table 4, reveal interesting facts. Most importantly, it appears that greater *SID*, as measured by abnormal Google search volume of stock ticker, is positively and significantly associated with stock liquidity, while controlling for MID. In addition, although the estimated coefficient on MID is found to have larger magnitude effect, it appears to be not statistically significant. Otherwise, the coefficient estimates of control variables remain as expected in most cases.

These results are also economically significant. For instance, an interpretation of the coefficients on advertising expenditures from columns (1) to (3) of Table 4 suggests that a change of one standard deviation in advertising expenditures would increase the stock liquidity 14.5%, independently of any changes in firm size, profitability, or risk.

Thus, one may primarily conclude that stocks which are searched more on the internet are those which are more traded in financial markets. Furthermore, Shleifer and Summers (1990) claim that judgment biases of investors related to information processing tend to be highly correlated. For instance, subjects in psychological experiments incline to make the same mistake: i.e. they do not make random mistakes. This suggests that information demand reduces in a direct way information asymmetry and generates more noise trading or increases the proportion of irrational market participants, or in an indirect manner indicates the higher overconfidence level of market makers.

In the next section, we attempt to explore the underlying mechanisms which may explain how the relation between information demand and stock liquidity might work.

3.3. Possible mechanisms

Rather than merely suggesting that information gathering as proxied by *GSV* induces higher stock liquidity, we explore possible mechanisms for how it becomes possible. To do so, we first use an interaction term between firm visibility and *GSV*. Then, we examine if changes in hypothesized mechanisms are more significant for firms with a higher information asymmetry than for firms with less information asymmetry. It is of course challenging to provide definitive proof of underlying mechanism(s) through which *SID* reduces liquidity, thus our tests are only suggestive.

3.3.1. The role of firm visibility

A key motivation for exploring the mechanisms which may explain information implications for stock liquidity comes from the firm visibility literature. For instance, Bushee et al. (2010) find that press coverage improves the firm's information environment, which reduces firm-level information asymmetry. Similarly, Soltes (2009) investigates how variation in business press coverage affects stock market activity and finds that greater press coverage is associated with lower spreads, increased turnover, and lower idiosyncratic volatility. Otherwise, Blankespoor et al. (2013) investigate managers' use of Twitter as a tool for voluntary disclosure. They find that firms with more "tweets" during news events have lower bid-ask spreads and greater depth.

Based on this literature, we explore in this subsection the role of firm visibility in the relationship between investor information demand and stock liquidity. Firm visibility is proxied by advertising expenditures, firm size and stock return (Grullon et al., 2004). The impact these firm assets can have on aggregate stock-level liquidity is, to some extent, obvious. It is likely to boost visibility, thereby potentially stimulating both trading activity and liquidity. Second, higher visibility could translate into a feeling of familiarity (Jacobs and Hillert, 2016) which may induce both higher trading activity (Huberman, 2001) and liquidity (Grullon et al., 2004).

Formally, we report results from fixed-effects estimations of the following model, which we call Model (3)[5]:

Table 5
Information demand and stock liquidity: Possible mechanisms.

Model	Model 1	Model 2	Model 3
Dependent variable	***ILLIQ***	***ILLIQ***	***ILLIQ***
Visibility proxy	**Fim size**	**Low information asymmetry**	**High information asymmetry**
SID_{t-1}*$Visibility_{t-1}$	0.013*** (0.001)	–	–
SID_{t-1}	−0.282*** (0.027)	0.0389*** (0.002)	−0.0185*** (0.002)
MID_{t-1}	0.427* (0.242)	−0.106 (0.266)	0.726*** (0.266)
$Absolute\_Return_{t-1}$	−3.049*** (0.648)	−3.613*** (1.078)	−3.020*** (0.662)
$Volatility_{t-1}$	0.879*** (0.071)	2.007*** (0.186)	0.723*** (0.081)
$Analysts_{t-1}$	−0.293*** (0.010)	−0.289*** (0.012)	−0.296*** (0.014)
$Market\_Value_{t-1}$	−1.146*** (0.005)	−1.061*** (0.005)	−1.185*** (0.007)
$Visibility_{t-1}$	−0.149*** (0.002)	−0.098*** (0.003)	−0.185*** (0.003)
$Trading\_Costs_{t-1}$	−5.867*** (0.168)	−7.479*** (0.327)	−4.496*** (0.185)
$Constant_{t-1}$	5.027*** (0.934)	4.137*** (1.029)	5.241*** (1.039)
Industry fixed effects	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
R-squared (percentage)	30.90	28.10	34.70
Number of observations	364,788	186,233	178,555

investors and, in turn, improves liquidity, but only for low visible firms. One could suppose that high-visibility firms experience lower information asymmetry costs and uncertainty. In contrast, firms, particularly those that are smaller and less well known, often struggle with gaining recognition from investors. As shown theoretically by Merton (1987), this lack of recognition can have implications for stock dynamics. For instance, firms with limited visibility often have higher costs of capital and lower values. Empirical evidence supporting this theory suggests that a firm that successfully increases its investor recognition should achieve a related increase in liquidity. Thus, in the next section, we attempt to explore the role of information asymmetry levels on the relationship between information demand and stock liquidity.

This table reports fixed-effects estimation results of regressing stock liquidity as measured by Amihud (2002) illiquidity ratio (*ILLIQ*), on information demand variables, namely *SID* and *MID* proxying for firm-specific information demand and market related information demand, respectively. In particular, this table reports results on how changes in firm visibility and information asymmetry affect the sensitivity of stock liquidity to greater investor information demand. Information demand is proxied by daily Google search volume. Firm visibility is measured by advertising expenditures; while information asymmetry is proxied by stock volatility. All regressors are lagged to account for a possibly endogenous interdependence between information demand and

$$ILLIQ_{i,t} = \alpha + \beta_1 SID_{i,t-1} + \beta_2 MID_{i,t-1} + \beta_3 SID_{i,t-1} * Visibility_{t-1} + \beta_4 Absolute\_return_{i,t-1}$$

$$+\beta_5 Std\_Dev_{i,t-1} + \beta_6 Ln(Number\_of\_Analysts)_{i,t-1} + \beta_7 Ln\ ((Market\_Value)_{i,t-1} + \beta_8 Advertising_{i,t-1} + \beta_9\ Inverse\_of\_Stock\_Price_{i,t-1} + YEAR_{effects} + SECTOR_{effects} + COUNTRY_{effects} + \varepsilon_{it-1} \quad (3)$$

Surprisingly, the results from Table 5 show different facts as compared to the previous a priori expectation, in which the stock liquidity is positively influenced by firm visibility. In particular, it appears that the impact of information demand on stock liquidity becomes weaker for high-visibility firms. Accordingly, we suggest that information demand on the internet alleviates information asymmetry among

[5] For sake of brevity, note that we have reported only results for one measure of firm visibility. Unreported results are available upon request from the authors.

stock liquidity and winsorized at the 1 and 99% level to mitigate the effect of outliers. All variables are defined in Table 1. Standard errors, adjusted for autocorrelation and heteroscedasticity, are given in parentheses ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively.

3.3.2. The role of information asymmetry

We aim to investigate the relevance of information demand as a determinant of stock liquidity, while controlling for well-known determinants of liquidity. As previously discussed, information often achieves only a subset of investors, which results in information asymmetry among investors and therefore, lowers stock market activity.

Higher information asymmetry is costly as it increases the adverse selection risk for market participants and lowers liquidity. Since the relation between information demand and stock liquidity appears to be conditional on firm visibility, we hereby control for the relevance of information asymmetry levels for how this relationship might work. We proxy information asymmetry by financial analysts' forecast errors of earnings (Green, 2006; Krishnaswami and Subramaniam, 1999), quoted spread and stock volatility (Krishnaswami and Subramaniam, 1999).[6] For instance, the literature has suggested that greater analyst forecast dispersion leads to higher information asymmetry (Brandt and Kavajecz, 2004). Earnings forecast dispersion can arise from either heterogeneous private information or different interpretations of public information by analysts.

As reported in the last columns of Table 5, we find that information demand improves stock liquidity only for high information asymmetry firms. In contrast, this relationship disappears for less information asymmetry firms. Results strongly suggest the prediction that the relation between information demand and liquidity may be nonlinear, which depends on information asymmetry, search frictions and firm's overall visibility. If investors differ in their ability to process firm specific information, then Google search volume of stocks with poor information environment can result in better informed investors and thereby reduce the information asymmetry in financial markets (Diamond and Verrecchia, 1991; Kim and Verrecchia, 1994).

One interpretation of this finding is that investors focus on their search where the benefits from acquiring information are the highest (i.e., where information asymmetry is the highest, as proxied by high bid-ask spreads and idiosyncratic volatility). Furthermore, as in Drake et al. (2015), it may be that investors feel a greater need to gather information when stock price changes suggest that things are not going well, but apply less scrutiny to firms with strong performance.

4. Robustness

Instead of rethinking the direct relation between information demand and stock liquidity, our focus is further directed towards a deeper understanding of how the relationship might work. We particularly provided evidence that information demand improves stock liquidity, but only for less-visibility stocks and when information asymmetry is more pronounced. In this section, we aim to verify the robustness of our results to a set of control tests such as endogeneity issue and alternative proxies.

4.1. Abnormal Google search volume

As in Drake et al. (2012), instead of using Google search volume as a proxy of information demand, we calculate abnormal search volume for firm i on day t as the raw *GSV* of stock ticker as provided by Google Trends, minus the average raw *GSV* for the same day of the week k over the prior 10 weeks, scaled by the average raw *GSV* for the same day of the week k over the prior 10 weeks. This allows us to control for the normal level of search volume of a particular stock. Moreover, capturing deviations from a benchmark allows us to increase the power of the statistical tests and reduces noise and imprecision of the data. We further use the natural logarithm of 1 + *SID* to normalize the distribution.

In unreported results,[7] the effect of *SID* remain the same providing additional evidence that empirical results are not sensitive to the use of alternative measures of information demand.

Table 6
Alternative measures of liquidity.

Model	Model 1	Model 2	Model 3
Dependent variable	**Quoted spread**	**Turnover**	**TPI**
$SID_{t-1}*Visibility_{t-1}$	0.018***	−0.000***	0.006***
	(0.001)	(0.000)	(0.002)
SID_{t-1}	−0.233***	0.001***	−0.088***
	(0.011)	(0.000)	(0.029)
MID_{t-1}	−0.400***	−0.007***	−0.657**
	(0.128)	(0.001)	(0.317)
$Absolute\_Return_{t-1}$	1.671***	0.111***	7.057***
	(0.324)	(0.005)	(0.799)
$Volatility_{t-1}$	0.676***	0.018***	−0.347***
	(0.027)	(0.001)	(0.088)
$Analysts_{t-1}$	−0.223***	0.003***	0.364***
	(0.007)	(0.000)	(0.015)
$Market\_Value_{t-1}$	−0.022***	−0.002***	−0.264***
	(0.002)	(0.000)	(0.007)
$Visibility_{t-1}$	−0.056***	0.000	0.013**
	(0.002)	(0.000)	(0.006)
$Trading\_Costs_{t-1}$	−12.183***	0.008***	−4.290***
	(0.272)	(0.001)	(0.248)
$Constant_{t-1}$	6.026***	0.055***	8.951***
	(0.608)	(0.004)	(1.230)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes
R-squared (percentage)	35.00	35.00	9.00
Number of observations	180,114	508,509	494,059

Instead of the Amihud (2002) *ILLIQ* ratio, we employ alternative measures of stock liquidity, which are respectively, the quoted spread which reflects the difference between the best ask and bid prices, turnover as proxied by the ratio of trading volume to the number of shares outstanding and the turnover price impact (TPI) estimated from the Amihud (2002) illiquidity ratio, where trading volume in the denominator is replaced by turnover. All regressors are lagged to account for a possibly endogenous interdependence between information demand and stock liquidity and winsorized at the 1 and 99% level to mitigate the effect of outliers. All variables are defined in Table 1. Standard errors, adjusted for autocorrelation and heteroscedasticity, are in parentheses ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively.

4.2. Alternative measures of liquidity

Table 6 reports the regression results estimating Model (3) with the dependent variable replaced. In columns (1), (2) and (3) of Table 6, we particularly replace the dependent variable (*ILLIQ*) with the quoted spread, stock turnover and the TPI ratio, respectively. Quoted spread is defined as the difference between the best ask and bid quotes. We also proxy liquidity by turnover measured by the ratio of trading volume to the number of shares outstanding (Chordia et al., 2001; Datar et al., 1998; Fang et al., 2014; Loughran and Schultz, 2005). Amihud and Mendelson (1986) show that turnover is negatively related to illiquidity costs, and Atkins and Dyl (1997) suggest a strong positive relation between the bid-ask spread and the reciprocal of the turnover ratio. Finally, liquidity is proxied by turnover price impact (*TPI*), estimated from the Amihud (2002) illiquidity ratio, where trading volume in the denominator is replaced by turnover.

Empirical results remain the same. In particular, information demand is positively and significantly associated with stock liquidity at the 1% level. This relation becomes weaker for high visibility firms and tends to be exacerbated in high information asymmetry environments. While

[6] For sake of brevity, we have reported estimation results of only one measure of information asymmetry. Unreported results are available upon request from the authors.

[7] Results are available upon request.

Table 7
Robustness to endogeneity.

Model	Model 1	Model2	Model 3
Estimation method	**OLS**	**2SLS**	**2SLS**
Dependent variable	***ILLIQ***	***ILLIQ***	***ILLIQ***
Firm-fixed effects	**Included**	**Not included**	**Included**
$SID_{t-1}*Visibility_{t-1}$	0.004***	0.004***	0.007***
	(0.001)	(0.001)	(0.001)
SID_{t-1}	−0.047***	−0.048***	−0.107***
	(0.015)	(0.017)	(0.021)
MID_{t-1}	−0.377	−0.620***	−0.290***
	(0.374)	(0.093)	(0.014)
$Absolute\_Return_{t-1}$	−3.384***	−3.931***	−3.292***
	(0.443)	(0.154)	(0.189)
$Volatility_{t-1}$	0.618***	0.622***	0.518***
	(0.059)	(0.020)	(0.020)
$Analysts_{t-1}$	−0.019**	−0.011	−0.010
	(0.010)	(0.010)	(0.012)
$Market\_Value_{t-1}$	−0.489***	−0.492***	−0.517***
	(0.010)	(0.009)	(0.010)
$Visibility_{t-1}$	−0.003	−0.001	−0.065***
	(0.005)	(0.006)	(0.007)
$Trading\_Costs_{t-1}$	0.765***	0.829***	1.141***
	(0.207)	(0.197)	(0.237)
$Constant_{t-1}$	−10.238***	−12.160***	−9.160***
	(0.253)	(1.781)	(1.712)
Firm-fixed effects	Yes	No	Yes
Year-fixed effects	Yes	Yes	Yes
Country-fixed effects	No	Yes	No
Industry-fixed effects	No	Yes	No
R-squared (percentage)	8.24	8.28	7.40
Number of obs.	372,227	272,662	186,819

This table reports results from regressing stock liquidity on information demand variables and a set of controls over the period of 2004–2014. In this study, we explore the relationship between stock illiquidity *(ILLIQ),* firm specific information demand (*SID*) and the interaction between firm visibility and investor information demand as measured by Google search volume of stock ticker, while controlling for endogeneity concerns. The first model investigates the inclusion of firm-fixed effects. The second and third models are estimated in two stages. The first-stage regression involves regressing of the endogenous variable namely, *SID* on all independent variables, fixed effects, and the instruments (lead and lagged values of *SID*). While, the second-stage regression results use the predicted values of *SID* from the first-stage regressions. Only Model 1 and Model 3 include firm-fixed effects. All regressors are lagged to account for a possibly endogenous interdependence between information demand and stock liquidity and winsorized at the 1 and 99% level to mitigate the effect of outliers. All variables are defined in Table 1. Standard errors, adjusted for autocorrelation and heteroscedasticity, are in parentheses ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively.

liquidity is certainly multidimensional, we find strong evidence for most standard measures of liquidity, thereby confirming that our findings are not specific to any particular proxy.

4.3. Endogeneity issue

Endogeneity concerns arise because some unobservable firm characteristics may simultaneously affect both stock liquidity and information demand. Furthermore, using an international dataset, the relation between stock liquidity and information demand may be not uniform across different country, corporate or industry related settings. These reasons may explain the lack of consensus on the effects of information demand on stock liquidity in the empirical financial literature.

Endogeneity issue was partially resolved by using lagged explanatory variables. In this subsection, we attempt to tackle endogeneity issues by first accounting for firm fixed effects to control for omitted firm characteristics that are constant over time (Wooldridge, 2003). As can be evidenced by column (1) of Table 7, the results are similar to those obtained without controlling for firm fixed effects.

Otherwise, OLS regression analysis implicitly assumes that information demand is an exogenous variable. In order to account for the potentially reciprocal dependence between liquidity and information demand, we implement a two-stage instrumental variable (IV) approach (El Ghoul et al., 2016; Reeb et al., 2012), while controlling for both heteroscedasticity and autocorrelation. Further, we follow the common approach and use lead and lag values of information demand as instruments.

In unreported results, the analysis from the first stage regression shows that the instruments (lead and lag values of *SID*) are significantly related to the raw values of *SID*. We then retain the predicted values of firm specific information demand and use them in the regressions examining the effect of *SID* on liquidity. As reported in the right-hand panel of Table 7, results from the second-stage regressions strongly support OLS regression analysis and confirm that endogeneity is not a concern in our study, regardless the inclusion of firm fixed effects.

5. Conclusion

In this study, we observe a large period of daily data which range from January 2004 to August 2014 and relate to 209 firms from 7 countries (United Kingdom, United States, China, Netherlands, Ireland, United Arab Emirates and Germany). Confirming the earlier results on the usefulness of Google search data for explaining several economic outcomes, we provide new international evidence that daily *GSV* of the stock ticker (Drake et al., 2012) is a significant determinant of stock market liquidity.

The main contributions of this paper are ii) to document the positive effect of daily information demand, as proxied by *GSV* on stock liquidity, and ii) to offer evidence that the firm's overall visibility with investors and information asymmetry have important consequences for this relationship. In a way, this paper both extends and links the existing empirical findings in the prior literature (Drake et al., 2012, 2015; Grullon et al., 2004; Peng and Xiong, 2006). Furthermore, in a broad setting, most previous studies focus only on the relationship between information demand and stock volatility and returns in the US stock market in a low frequency period; we hereby investigate the impact of daily investor information demand on stock liquidity in an international setting. We also add to existing literature by proposing some mechanisms that may shape the relation between information demand and stock liquidity. Overall, we suggest that information demand variables contribute to better understanding the liquidity variations in financial markets.

One may conclude that liquidity cannot be solely explained by known factors such as risk, firm size and trading costs, but we substantiate the importance of including online search behavior in explaining important financial outcomes. According to the assumption that what people are searching for leaves a track regarding “what we collectively think”, the usefulness of the information retrieval from digital platforms will undoubtedly increase. As we move with giant strides into the digital age, more research in this area is highly warranted.

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