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IS THERE ASYMMETRIC INFORMATION ABOUT SYSTEMATIC FACTORS? EVIDENCE FROM COMMONALITY IN LIQUIDITY

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ABSTRACT

This paper provides an empirical investigation of the hypothesis that there exists information asymmetry about systematic factors. Using a sample of 112 exchange traded funds (ETF) we provide evidence in support of this hypothesis. Furthermore, through the analysis of the the adverse selection component of the bid-ask spreads (lambdas) of these ETFs and all common stocks trading on the NYSE and the NASDAQ from January 1999 to December 2003, we provide strong evidence of commonality in the adverse selection component of liquidity. We use the estimated lambda of Standard and Poor's Depository Receipts (SPDRs) as a measure of information asymmetry about the U.S. equity market and find that these are (i) positively correlated with the lambdas of other exchange traded funds (ii) related to the lambdas on individual equity securities and (iii) they can be explained by measures of uncertainty about the aggregate market.

JEL: D82, G19

KEYWORDS: Liquidity, Information Asymmetry, Commonality

INTRODUCTION

The market microstructure literature posits inventory risk and asymmetric information risk as the two drivers of liquidity. Chordia, Roll, and Subrahmanyam (2000) document commonality in liquidity. They use commonality to reveal the existence of asymmetric information effects on liquidity, but provide no evidence that asymmetric information has common components. We examine the liquidity of exchange traded funds (ETFs) and provide evidence that the asymmetric information portion of liquidity has common determinants. More specifically, we show that there is asymmetric information about systematic factors. Typically, the microstructure literature assumes that informed traders are privy to firm specific information such as a pending merger or product development. This idiosyncratic information would be diversified away in a large portfolio and knowledge about any one firm in the portfolio would not prove very useful in predicting the return on the portfolio (Hughes, Liu and Liu, 2007). Subrahmanyam (1991), Gorton and Pennacchi (1993) present models where the bundling of claims on individual assets into composite claims reduces informed traders' informational advantage.

As portfolios get large, the impact of asset specific information gets arbitrarily small and the adverse selection component of liquidity (lambda) will have to come through asymmetric information about common factors. Whether there is asymmetric information about systematic components of asset returns has not been determined. Subrahmanyam (1991) entertains the possibility and includes factor informed traders in his model. Aboody et al. (2005); Francis et. al. 2005; and Easley, Hvidkjaer, and O'Hara (2002) present models that allows for a common component in private information. Chordia, Roll, and Subrahmanyam (2002) consider asymmetric information for the aggregate market unlikely and adopt the inventory paradigm to explain the relation between order imbalances and market wide returns.

Knowing whether there is a common component to adverse selection is important for the following reasons. First, there is disagreement about its existence. Second, Gorton and Pennacchi (1993) show that the microstructure impact of idiosyncratic private information cannot be diversified away. Easley, Hvidkjaer, and O'Hara (2002), and Easley and O'Hara (2004) show that cumulative idiosyncratic information asymmetry affects asset returns. Asymmetric information about systematic factors is non- diversifiable and depending on its magnitude, also affects expected returns. Third, most textbooks on investing include sections on "Top Down" strategies and tactical asset allocation. Such approaches to investing rely on investors being able to avoid (select) asset categories or industries that will do relatively poorly (well). Absent information asymmetry about systematic factors, the value of these approaches is questionable. We use trading data on Standard and Poor's Depository Receipts (SPDRs), other ETFs, and, equities traded on the NYSE and NASDAQ to provide evidence on commonality in the adverse selection component of liquidity. Our evidence is consistent with investors facing asymmetric information costs even when trading well diversified baskets of securities. The magnitude of these costs is inversely related to the degree of diversification. The SPDR is the most diversified of the ETFs we employ so we use its lambda as a measure of asymmetric information about market wide information. We relate the lambdas on the other ETFs to the SPDR lambda and find that the SPDR lambda explains considerable time series variation in the lambdas of other ETFs. Further, we find that the SPDR lambda explains time series variation in the lambdas of individual equities. Finally, we present evidence that SPDR lambdas are reliably related to measures of aggregate market uncertainty. The remainder of the paper continues as follows. In Section 2 we present a brief literature review and our empirical predictions. Section 3 discusses our data and our estimation technique. In Section 4 we present our results. We conclude in Section 5.

LITERATURE REVIEW AND EMPIRICAL PREDICTIONS

Information asymmetry among investors has been widely studied in the field of financial economics. However, there still remains considerable lack of consensus as to the nature of the risk posed by it. On the theoretical front, models such as Easley, Hvidkjaer, and O'Hara (2002), Easley and O'Hara (2004), Garleanu and Pedersen (2004)) argue that information risk is not diversifiable. Therefore, information asymmetry risk must be priced, because uninformed investors need to be compensated for the risk of systematically losing out to better informed investors. However, a competing line of reasoning, represented by Hughes, Liu and Liu (2007) and Lambert, Leuz and Verrecchia (2007) argue that information risk is either fully diversifiable when the economy is large enough or has been captured by existing risk measures. Lambert Leuz and Verrecchia (2012) takes the latter line of argument further by presenting a rational expectations model with perfect competion where informational differences across investors affect asset returns not through information asymmetry per se, but through the difference in their precisions. On the empirical front, using the probability of informed trading (PIN) measure, Easley, Hvidkjaer, and O'Hara (2002) provide evidence consistent with information asymmetry affecting asset returns. However, the findings of Duarte and Young (2009) casts serious doubts on the credibility of the PIN measure. They find that PIN is priced because it captures illiquidity rather than information asymmetry. Similarly, Akay, Cyree, Griffiths and Winters (2012) in their study of PIN have suggested that in the T-bill markets, PIN could be picking up the activities of discretionary liquidity traders.

This paper contributes to the above debate by providing some new empirical evidence which could potentially further our understanding of the information risk in the financial market. We build this paper arround the notion that information asymmetry arrises not only from the knowledge of firm-specific information, but also from a superior ability to process information (Kim and Verrechia, 1997). This information could be firm-specific, or sector-specific, or market-wide (Chordia, et al. 2000; Gilson, et al. 2001). It could even be something unconnected to the firm, such as the trading environment (Easley et. al., 1998). The paper is structured into two parts. First part attempts to demonstrate the existence of systematic information asymmetry, and the second part explores its relationship with firm level information asymmetry. The first part of this paper exploits the insights from Subrahmanyam (1991) and Gorton and

Pennacchi (1993) to identify market-wide, sector and firm level information asymmetry. These studies argue that the bundling of claims on individual assets into composite claims or baskets of securities reduces the informational advantage of the informed traders'. This would suggest that the greater the level of diversification, the lower the adverse selection cost of trading that asset in the market. We thus make predictions about levels of information asymmetries and their correlation structure across a set of broadbased, sector, and international ETFs (exchange traded funds) and a set of U.S. traded common stocks.

The general idea is that SPDRs and other Broad-based ETFs should reflect primarily market wide uncertainty and therefore have low, but positive levels of asymmetric information. The level of a Broad-based ETF's information asymmetry should be related to its level of diversification. We expect a positive correlation between the lambdas of Broad-based ETFs. Sector ETFs should have market wide asymmetry, and also asymmetry related to the industry component of their returns which by construction is a component of portfolio returns. This suggests Sector ETFs should have higher lambdas than Broad-based ETFs. Since Sector ETF lambdas will have a market component, we predict a positive correlation between SPDR and Sector lambdas. Based on the informational arguments for home bias, we expect high levels of asymmetric information about International ETFs Brennan and Cao (1997). However, we do not expect that the asymmetric information about domestic systematic factors that would drive the lambdas on SPDRs to be related to the lambdas on International ETFs. While we expect that International ETF lambdas will be greater than SPDR lambdas, we expect that the lambdas will be uncorrelated.

Individual equities that trade on U.S. exchanges should have three components to their information environment. First is market-wide information, second is information about the industry, and finally there is the idiosyncratic information. Based on this decomposition, we expect the lambdas on individual equities to be greater than that on SPDRs because of the two addition sources of asymmetry. We also expect that lambdas on individual equities are positively correlated with SPDR lambdas through the common component of information about systematic factors.We are not the first researchers to investigate the impact of order flow on the pricing of composite or basket securities. Neal and Wheatley (1998) examine lambdas for a sample of closed-end funds and a sample of matched individual equities. They argue that closed-end funds are transparent relative to operating companies and that therefore there should be less asymmetric information about closed end funds. Using a sample of 17 closed-end funds and 17 matched control firms they report estimates of lambda that are large and significant in both samples. Neal and Wheatley interpret their evidence as suggesting that adverse selection might arise from factors other than a firm's liquidation value.

Our study differs from Neal and Wheatley in the following ways. First the ETFs we examine are more diversified than the closed end funds they examine. The positive lambdas Neal and Wheatley observe could have come through the variability of the idiosyncratic information of the securities in the basket. Second, there is greater trading activity in our sample of ETFs. Low variation in liquidity trading would result in high estimates of lambda. Third, we employ 112 ETFs as compared to 17 closed-end funds. Fourth, ETFs have very low discounts as copared to the closed end fund discounts. Discounts are a potential source of information asymmetry. Pontiff (1997) reports that the average closed-end fund's monthly return volatility exceeds that of its underlying assets by 64%. This suggests that closed-end funds are less transparent than Neal and Wheatley assume. Finally, examining the lambdas through the lens of Subrahmanyam (1991), we attempt to explain any positive ETF lambdas observed.

DATA AND METHODOLOGY

Data

We employ SPDRs, other Broad Based ETFs, International ETFs, and Sector ETFs in this study. Our sample covers the period from January 1999 to December 2003. We start in 1999 because although SPDRs began trading on the AMEX in February 1993, Sector ETFs did not begin trading until December 1998. The exponential increase in high frequency trading as well as the increased prevalance of alternate trading venues such as dark pools post 2003 could potentially confound our time series results. Therefore, we choose to stop the analysis end of 2003. We begin with a total of 146 ETFs (SPDRs, 63 other Broad-Based, 47 sector and 34 International) before applying screens to the data. Our first screen requires the ETF to have data available on NYSE Trade-and-Quote database (TAQ) and the Center for Research in Security Prices (CRSP) database. Additionally, sample ETFs must have a price of at least $5.00 and must have traded at least 24 month (two years) to be included into our sample. The final ETF sample consists of SPDRs, 41 other Broad-Based, 37 Sector and 34 International ETFs.

Table 1 presents detailed descriptive statistics for the sample. The sample size increases from 29 ETFs in 1999 to 112 ETFs in 2003. Panel A presents information on the capitalization of the ETFs. In 1999 the typical Broad-based ETF contains $5 billion and the total Broad-based class has a capitalization of approximately $32 billion. The SPDR market capitalization in 1999 is $3.6 billion. Sector ETFs contained $2.7 billion with the average Sector ETF having $192 million in assets. While there were more International ETFs at this time, the typical International ETF is smaller ($78 million) as is the International class ($1.3 billion). There is tremendous growth in Broadbased ETFs between 1999 and 2000. The capitalization of Broad-based and International ETFs increase to $17.67 billion. The growth is through an increase in smaller ETFs as can be seen in approximate halving of the average ETF size. Broad-based ETFs were hit quite hard by the breaking of the tech-stock bubble. Sector and International ETFs better weathered the market downturn. Over the sample period the total capitalization in all three classes increases and in 2003 the combined capitalization the sample ETFs is $96.5 billion. On December 31, 2003 the SPDR market capitalization is $44 billion.

Table 1: Some Descriptive Statistics For the Set of 112 ETFs Included in This Study

	Broad Based		Sector		International	
	Mean	Sum	Mean	Sum	Mean	Sum
Panel A: Market Capitalization (in $Mill)						
1999	5,308	31,849	192	2,717	78	1,328
2000	2,653	49,520	139	2,831	89	1,749
2001	964	29,066	116	3,412	78	1,814
2002	1,705	60,805	151	5,366	187	4,865
2003	2,040	80,061	250	8,818	277	7,660
Panel B: trading volume (in millions of shares traded)						
1999	4,563	27,380	304	4,302	166	2,830
2000	1,737	32,721	313	6,356	141	2,786
2001	1,680	50,833	277	8,229	139	3,216
2002	3,395	121,088	484	17,254	335	8,723
2003	3,614	142,156	492	17,333	675	18,684

This table presents sample descriptive statistic. Panel A presents the average and total market capitalization (in millions USD) of Broadbased, Sector and International ETF's, from 1999 through 2003 (our sample period). Panel B presents the corresponding average and total trading volume (in millions of shares traded).

Panel B presents information on the trading volume of the ETFs. Broad-based ETF total trading volume in 2003 is 5 times higher than the trading volume in 1999. For Sector and International ETFs the increases are 4 times and 6.6 times respectively. In 2003 the typical Broad-based ETF has a trading volume of 3.6 billion shares, which is about one-half of Microsoft's 2003 trading volume and twice that of General Motors' 2003 trading volume. The trading volume of SPDRS in 2003 is 10.36 billon shares. We also employ two samples of common stocks traded on the NYSE and NASDAQ. We use the first sample to perform our tests on the levels of ETF and common stock lambdas. In this sample common stocks are matched to ETFs each month based on the average share price, trading volume, and the standard deviation of daily returns. We use daily data from the CRSP database for this matching procedure. For each ETF we select the common stock with characteristics that minimize the following equation.

$$Score_{j,k} = \left(\frac{P_{stock,i,k} - P_{ETF,j,k}}{P_{stock,i,k} + P_{ETF,j,k}} \right)^2 + \left(\frac{V_{stock,i,k} - V_{ETF,j,k}}{V_{stock,i,k} + V_{ETF,j,k}} \right)^2 + \left(\frac{\sigma_{stock,i,k} - \sigma_{ETF,j,k}}{\sigma_{stock,i,k} + \sigma_{ETF,j,k}} \right)^2 \qquad (1)$$

Where P is the price of the stock or ETF, V is the trading volume of the stock or ETF, and σ is standard deviation of returns for the stock or ETF. This matching is designed to reduce disparity in the inventory and order processing components of trading costs. Table 2 presents information on the matches. In all three ETF categories the price matches are quite close with the largest average deviation being $2.94 for the Broad-based ETFs. The broad-based matching firms are closer in terms of trading volume than either the Sector or International matching equities. Finally, we note that the matching process yields substantial differences in the standard deviation of returns. This is to be expected, as the returns on portfolios are lower than those on individual equities. Because of the imperfections in our matching, we control for differences in these characteristics in our cross-sectional examination of levels of lambda.

The second sample is used to examine the correlation between SPDR lambdas and the lambdas of common equities. We do not use the control sample described above because the matching firm can change from month to month. We start with all NYSE and NASDAQ stocks and apply the following screens. We include only common stocks with at least 24 months of data available in both the CRSP and the TAQ databases over the sample period. To avoid undue influence from extreme observations, we exclude all stocks with an average monthly price less than $5 and greater than $500. This yields 2649 NYSE firms and 4470 NASDAQ firms, giving us a total of 7119 stocks.

Table 2: Matching Sample Descriptive Statistics

Cat	ETF Price	ETF Trading Vol	σ_{ETF}	Stk_Prc	Stock Trading Vol	σ_{stock}
Broad based	79.60	25,611,673	0.0133	76.65	20,670,124	0.0325
Sector	43.07	1,926,838	0.0161	42.91	16,556,207	0.0326
International	21.19	1,792,150	0.0170	20.98	10,585,622	0.0323

Equation (1) is used for matching ETFs in various categories (broadbased, Sector, and International) with a set of common stocks trading on the same exchange. This table presents the average price, trading volume, and standard deviation for the set of ETFs and corresponding set of matched stocks.

Intraday, transaction level, trade and quote data for all ETFs and stocks are retrieved from the NYSE TAQ database, while the monthly closing price, return volatility and trading volume are obtained from the CRSP. To avoid the influence of any possible recording errors in TAQ, we exclude all quotes with a raw spread greater than $6.5 and with a percentage spread greater than 10%. The TAQ database does not eliminate auto-quotes (passive quotes by secondary market dealers). This can cause quoted spreads to be artificially inflated. Since there is no reliable way to filter out auto-quotes in TAQ, only BBO (best bid or offer)-eligible primary market (NYSE) quotes are used. Quotes established before the opening of the market or after the close are discarded. Negative bid-ask spread quotations, negative transaction prices, and negative quoted depths are discarded. Trades with non-standard settlement conditions are excluded. The first trade of each day is discarded to avoid the effects of the opening procedure. Following Lee and Ready (1991), any quote less than five seconds prior to the trade is ignored and the first one at least five seconds prior to the trade is retained.

Measuring Lambda

We estimate the level of adverse selection component of bid-ask spreads using the advocated by Lin, Sanger, and Booth (1995) (Hereafter referred to as LSB). We have also run our analysis using the adverse selection cost component as proposed by, Glosten and Harris (1988) and Neal and Wheatley (1998). Our results are robust to the methodology selected. For the sake of brevity, we report only the results corresponding to Lin, Sanger, and Booth (1995) estimation. This method is based on the approaches in Stoll

(1989) and Huang and Stoll (1997). LSB use a regression approach to estimate the proportion of the effective spread that can be attributed to information asymmetry. The main idea is that the quote revision reflects the adverse selection component of the spread, while the change in the transaction price reflects order processing costs and bid-ask bounce.

In the LSB model, information revealed by the trade at time t is reflected in quote revisions, $B_t = B_{t-1} + \lambda S_{t-1}$ and $A_t = A_{t-1} + \lambda S_{t-1}$, where B_{t-1} and A_{t-1} are the prevailing bid and ask prices at time t, and λ can be interpreted as the proportion of the effective spread due to adverse selection. $S_{t-1} = P_{t-1} - Q_{t-1}$ is one-half of the effective spread. Here, P_t is the transaction price and Q_{t-1} is the quote midpoint at time t. The revision in the quote mid point is expressed as:

$$\begin{aligned} \Delta Q_t &= \lambda S_{t-1} + \varepsilon_t \\ S_t &= \theta S_{t-1} + \eta_t \end{aligned} \tag{2}$$

where, $\Delta Q_t = Q_t - Q_{t-1}$ and $Q_t = (B_t + A_t)/2$. θ represents the order processing cost component of the spread and (1-λ–θ) represents the inventory cost component of the bid-ask spread.

RESULTS

Table 3 presents descriptive statistics for lambda (scaled by price) for the sample ETFs and their matched common equities. The average adverse selection cost of trading a Broad-based ETF is 0.36¢ per share. For Sector and International ETFs the corresponding numbers are 0.65¢ and 1.74¢ per share. A similar pattern is found in the median estimates. The higher lambda in the Sector ETFs is consistent with the idea that diversification reduces the adverse selection component of transactions costs, and suggests that some of the asymmetric information could be about industry factors. International ETFs' higher lambdas are consistent with the information explanations of home bias.

We also see that the lambdas of the matched common equities are higher than lambdas of the ETFs. For the equities matched to Broad-based ETFs, estimated adverse selection costs are 0.68¢ per share. The equities matched to Sector and International ETFs have estimated adverse selection costs of 1.23¢ and 3.04¢ per share. These differences are both economically and statistically significant. It is also interesting to compare the average lambda of the common equities matched to the Broad-based and Sector ETFs to that of the International ETFs. The adverse selection cost of trading an international portfolio is twice as large as that of trading a high priced and heavily traded domestic equity and approximately the same as trading a medium priced share with relatively high trading volume. Examination of the differences in lambda in each calendar year shows that the estimated differences are stable over the sample period. Panel B of the table shows that estimated differences are stable over the sample period.

Table 3: Distribution of the Adverse Selection Cost Component of the Spread

	ETF		Stock		Mean Difference
	Mean	Median	Mean	Median	
Broad based	0.0036***	0.003	0.0068***	0.0061	-0.0031***
Sector	0.0065***	0.005	0.0138***	0.0123	-0.0073***
International	0.0174***	0.0134	0.0359***	0.0304	-0.0185***

*This table presents the mean and median adverse selection costs (estimated using equation (2)) scaled by price for the set of ETFs and the corresponding set of matched stocks. ***, **, and * indicate significance at the 1, 5 and 10 percent levels respectively. The last column tests for the difference in mean between ETFs and the set of matched stocks.*

Transaction costs are affected by prices, trading volume, and volatility. Our matching process attempted to control for these characteristics, but as shown in Table 2 ETFs and their matched equities still differ along these dimensions. We utilize a multivariate regression to test for differences in the levels of adverse selection costs of trading controlling for differences in, trading volume, and volatility. We estimate the following regression

$$\lambda/P = \alpha + \beta_0 \times P + \beta_1 \times \sigma + \beta_2 \times \ln(vol) + \beta_3 \times D_{cat} + \varepsilon \quad (3)$$

The dependent variable is the adverse selection cost component of the spread (λ) (scaled by share price). The independent variables are share price (P), Share volatility (σ), natural logarithm of the trading volume, and dummy variable (D_{cat}) that takes the value 0 for the base case category and the value 1 for the comparison category. Table 4 presents estimates of β_3 (the coefficient on D_{cat}) and their corresponding t-statistics. The table columns present the base cases while the rows represent the comparison group. The conclusions for Table 3 robust to controlling for stock price, trading volume and volatility. Sector ETFs adverse selection cost of trading, on average exceeds the adverse selection cost of trading in broad based ETF by 0.11¢. Interestingly, comparison of Broad-based and Sector ETFs to International ETFs show them to have similar differences in the adverse selection component of trading of approximately 1¢.

Table 4 also sheds more light on the relative levels of asymmetric information about international portfolios and domestic equities. After controlling for differences in stock price, trading volume and volatility, the average International ETF's lambda is 0.68¢ greater than the lambda of the common equities matched to Broad-based ETFs, is insignificantly different from the lambdas of equities matched to Sector ETFs, and is 1.76¢ less than the lambda of their own matched equities. These results indicate that there is more asymmetric information about systematic factors in foreign countries than there is about idiosyncratic factors for some domestic equities.

Table 4: Comparing the Adverse Selection Cost of Trading

	Broad Based	(1)	(2)	(3)	(4)
Sector ETF (1)	0.0011***				
	(4.21)				
International ETF (2)	0.0105***	0.0110***			
	(6.259)	(11.492)			
Broad Based (Matched Stocks) (3)	0.0028***	0.0023***	-0.0068***		
	(15.804)	(3.026)	(-3.572)		
Sector (Matched Stocks) (4)	0.0069***	0.0082***	0.0011	0.0033***	
	(7.365)	(9.862)	(0.753)	(3.705)	
International (Matched Stocks) (5)	0.0302***	0.0289***	0.0176***	0.0258***	0.0176***
	(7.697)	(9.721)	(7.511)	(6.83)	(7.445)

*The numbers presented in this table are the D_{CAT} coefficients β_3 from equation (3): $\lambda/P=\alpha+\beta_0\times P+\beta_1\times\sigma+\beta_2\times\ln(vol)+\beta_3\times D_{cat}+\varepsilon$. The table columns present the base cases while the rows represent the comparison group. Eg: Controlling for stock price, trading volume and volatility, sector ETFs adverse selection cost of trading, on average exceeds the adverse selection cost of trading in broad based ETF by $0.0011 or 0.11 cents. The numbers in the parenthesis present the t-statistics. ***, **, and * indicate significance at the 1, 5 and 10 percent levels respectively.*

Having established patterns in levels of lambdas consistent with diversification of idiosyncratic asymmetric information, we now look at the correlation structure of the lambda estimates. Table 5 presents results from estimating the following regression for non-SPDR Broad-based, Sector, and International ETFs.

$$\left(\lambda_{ETF}/P_{ETF}\right) = \alpha + \beta_0\left(\lambda_{SPY}/P_{SPY}\right) + \beta_1 \ln(vol_{ETF}) + \beta_2 \ln(P_{ETF}) + \varepsilon \quad (4)$$

We are interested in the coefficient estimates of β_0 and the R^2 of the regressions. The first column presents the results using the monthly average lambda of Broad-based ETFs in each month as the dependent variable. The estimate of β_0 is positive and significant. After controlling for price and volume differences between SPDRs and other Broad-based ETFs, the SPDR lambda explains variation in the adverse selection component of other market tracking ETFs. This is consistent with there being a common component in adverse selection risk. The adjusted R^2 is 0.69, indicating that SPDR lambdas capture a considerable amount of the variation on the adverse selection costs of trading Broad-based ETFs. In the second column we employ monthly average lambda of Sector ETFs in each month as the dependent variable. Here too we see a positive and significant relation between SPDR lambdas and Sector lambdas. The magnitude of the estimate of β_0 for Sector lambdas is 1.48 and is over four times as large as the estimate of β_0 for Broad-based ETFs. This suggests that the level of market-wide information asymmetry is related to the adverse selection costs of individual assets. The lower adjusted R^2 (0.39) is consistent with variation in Sector ETFs that is related to idiosyncratic sector information. In the third column monthly average lambda for International ETFs are used as the dependent variable. As predicted, SPDR lambdas are not related to the lambdas of International ETFs. Since SPDR lambdas reflect asymmetry about the U.S. market and the lambdas of International ETFs reflect asymmetry about non-U.S. markets, there should be no relation between the lambda estimates.

Table 5: Commonality in Adverse Selection Cost of Trading

	Broad Based	Sector	International
(Constant)	0.0123**	0.0098	0.0502***
	(2.168)	(1.429)	(3.735)
□$_{spy}$/P$_{spy}$	0.3368***	1.4816***	1.3185
	(3.875)	(5.363)	(1.234)
ln (Vol)	0.0005	0.0002	-0.0014
	(1.605)	(0.33)	(-1.204)
ln (P)	-0.0037***	-0.0023**	-0.0070*
	(-4.522)	(-2.28)	(-1.701)
R^2	0.6903	0.3903	0.1113

This table estimates equation (4): $\left(\lambda_{ETF}/P_{ETF}\right) = \alpha + \beta_0\left(\lambda_{SPY}/P_{SPY}\right) + \beta_1 \ln\left(vol_{ETF}\right) + \beta_2 \ln\left(P_{ETF}\right) + \varepsilon$. Where The dependent variable is the *category average 'adverse selection cost component of the spread* λ_{ETF} *scaled by price* P_{ETF} *. The Independent variables are adverse selection cost of trading SPDR share* λ_{SPY} *, scaled by SPDR share price, the average trading volume* vol_{ETF} *and the natural logarithm of the average trading price* $\ln\left(P_{ETF}\right)$*. The numbers in the parenthesis present the t-statistics. ***, **, and * indicate significance at the 1, 5 and 10 percent levels respectively.*

The levels and correlation structure of the lambda estimates are consistent with there being a commonality in the adverse selection component of liquidity. Our next tests try to relate the common component to measures of overall uncertainty about the market. We begin by extracting the principal component of the lambdas from the various ETFs. Principal component analysis uses the information in all of the estimated ETF lambdas to find an index that best explains the variance in the original ETF's lambdas. We use only the first principal component as it explains 88%, 75%, and 45% of the variability of the average lambdas of Broad-based, Sector, and International ETFs respectively.

We use the following variables as proxies for the level of market wide uncertainty. Bessembinder, Chan, and Seguin (1996) interpret the open interest in S&P 500 futures contracts on the CBOE as a measure of cross sectional divergence of opinion. Open interest is a measure of net demand for the market, and if there are not shocks to tastes and endowments variation in open interest reflects differences in opinion. We use the open interest at the beginning of the month over which lambdas are estimated. We also control for the lagged return on the market. We do this for two reasons. First, Shleifer and Summers (1990) suggest that uncertainty about market sentiment is related to higher required rates of return and higher risk premiums. Market wide price increases are consistent with lower discount rates and a reduction in sentiment risk. Second, high market returns can result form positive feedback trading. Such returns draw uninformed investors into the market, which lowers the average amount of adverse selection. We present the result form the following regression in Table 6.

$$CF_t = \beta_0 + \beta_1 CF_{t-1} + \beta_2 Ln(OI)_{t-1} + \beta_3 r_{S\&P500,t-1} + \varepsilon_t \tag{5}$$

We control for the lagged common factor CF_{t-1} and are interested in the estimates of β_2, and β_3.

Table 6: Exploring the Common Factor Causality

	1	2	3	4	5
(Constant)	-50.66***	-0.01	-29.57***	-29.78***	-28.51***
	(-7.94)	(-0.10)	(-3.06)	(-3.28)	(-3.17)
CF			0.32*	0.40**	0.42***
			(2.08)	(2.65)	(3.21)
$Ln(OI)_{t-1}$	4.07***		2.30**	2.39***	2.29***
	(7.94)		(2.96)	(3.25)	(3.18)
$r_m - r_f$		-4.34*		-4.37**	
		(-1.68)		(-2.58)	
$r_{S\&P,500(t-1)}$					-4.90***
					(-3.07)
Adj. R^2	0.554	0.035	0.619	0.656	0.670

This table presents the results of estimating equation (5) $CF_t = \beta_0 + \beta_1 CF_{t-1} + \beta_2 Ln(OI)_{t-1} + \beta_3 r_{S\&P500,t-1} + \varepsilon_t$. CF (common factor) is the first *principal component extracted (by year) from the adverse selection cost components of various ETFs. It represents the crosssectional commonality in adverse selection among the sample ETFs. Ln(OI) is the natural logarithm of the numbrer of outstanding S&P open interest contracts. (r_m-r_f) is the excess return on the market, and $r_{S\&P,500(t-1)}$ is the lagged return on the S&P 500 index. The numbers in the parenthesis present the t-statistics. ***, **, and * indicate significance at the 1, 5 and 10 percent levels respectively.*

We begin by examining the impact of uncertainty and prior returns individually. The results in Column 1 show that the level of market wide adverse selection is positively and significantly related to the lagged open interest in the S&P 500 futures contract. Since this measure is associated with higher levels of disagreement about the direction of the market, this result is consistent with asymmetric information about systematic factors. We also note that this measure of market-wide uncertainty explains 55% of the time series variation in the common component of market-wide adverse selection risk. Column 2 shows the relation between the principal component and lagged excess return on the market. The coefficient is negative as predicted and the relation is significant at the 10% level. Lagged returns explain less of the time series variation in the principal component. The adjusted R^2 is 3.5%.

In Column 3 we include the control for the lagged common factor along with the lagged open interest variable. There is evidence of positive autocorrelation in the common factor. The estimate of β_1 is 0.32 and is significant at the 5% level. Controlling for the lagged common factor reduces the magnitude of the impact of the lagged open interest variable, but it is still positively and significantly related to market-wide adverse selection. In Columns 4 and 5 we control for the lagged common factor and include the open interest variable and lagged market returns. We again see evidence of positive autocorrelation in the common factor. We also observe that the relation between market-wide uncertainty and adverse selection is positive and significant. Finally, controlling for the autocorrelation in the common factor and market-wide uncertainty strengthens the relation between prior market returns and the common component of adverse selection. The p-values decrease from 0.098 to 0.012 when we employ the excess return on the CRSP value-weighted index and to 0.00 when we use the return on the S&P 500. The results in Table 6 are support our hypothesis that the measured adverse selection component of the trading costs of ETFs is related to asymmetric information about systematic factors. The common factor of market wide adverse selection increases with aggregate market uncertainty and decreases as the proportion of uninformed traders in the market increases. We now present evidence on the relation between the common component of liquidity related to adverse selection and the estimated lambdas of individual equities. Here we employ the 7,119 common stocks listed on the NYSE and NASDAQ over our sample period. We estimate a lambda for each stock in each month using a full month's trading record. We then relate the firm specific lambdas to (i) the SPDR lambda and (ii) the first principal component estimated from the time series of all the stocks and ETFs trading in the market. This may be interpreted as a proxy for market-wide adverse selection. We use the following regression models for studying the above two relations respectively:

$$\left(\lambda_{Stock} \big/ P_{Stock}\right) = \alpha + \beta_0 \left(\lambda_{SPY} \big/ P_{SPY}\right) + \beta_1 \ln\left(vol_{Stock}\right) + \beta_2 \ln\left(P_{Stock}\right) + \varepsilon \tag{6}$$

$$\left(\lambda_{Stock} \big/ P_{Stock}\right) = \alpha + \beta_0 CF + \beta_1 \ln\left(vol_{Stock}\right) + \beta_2 \ln\left(P_{Stock}\right) + \varepsilon \tag{7}$$

Table 7: Present Descriptive Statistics on Estimates of β_0 For Each Specification

Exchange		**Negative Beta**	**Positive Beta**	**Sum**
Table 7 (Panel A): Commonality in Adverse Selection Cost of Trading				
NYSE	Not Significant	395	375	770
	Significant	913	966	1,879
NASDAQ	Not Significant	522	727	1,249
	Significant	344	2,877	3,221
Total		2,174	4,945	7,119
Table 7 (Panel B): Commonality in adverse selection cost of trading				
NYSE	Not Significant	471	502	973
	Significant	495	1,181	1,676
NASDAQ	Not Significant	534	1,055	1,589
	Significant	173	2,708	2,881
Total		1,673	5,446	7,119

Panel A of this table presents the counts for β_0 *from equation (6):* $\left(\lambda_{Stock} \big/ P_{Stock}\right) = \alpha + \beta_0 \left(\lambda_{SPY} \big/ P_{SPY}\right) + \beta_1 \ln\left(vol_{Stock}\right) + \beta_2 \ln\left(P_{Stock}\right) + \varepsilon$ *Panel B presents the corresponding results from estimatng (7):* $\left(\lambda_{Stock} \big/ P_{Stock}\right) = \alpha + \beta_0 CF + \beta_1 \ln\left(vol_{Stock}\right) + \beta_2 \ln\left(P_{Stock}\right) + \varepsilon$ *.*

Panel A of Table 7 shows the results when the SPDR lambda is used to measure the common component of adverse selection risk. For NYSE firms there is an approximately half of the stocks have lambdas that are positively associated with the SPDR lambda and 72% of the positive estimates of β_0 are significant. Interestingly, a similar pattern emerges in NYSE stocks whose lambdas are negatively related to the SPDR lambda. Earlier we mentioned the possibility of a relation between the level of market-wide information asymmetry and the adverse selection component of the bid-ask spread on individual stocks. The negative relation between SPDR lambdas and firm specific lambdas also points to this possibility. The mean adjusted R^2 is 15.01% for NYSE firms. For the NASDAQ regressions the mean adjusted R^2 is 19.30%. The consistently high R^2 point to a commonality in the adverse selection component in liquidity.

Panel B of Table 7 presents summary statistics for estimates of β_0 when we use the common factor of ETF lambdas as our independent variable. We still observe some estimates of negative estimates. For NYSE firms the positive estimates of β_0 now make up 63% of the estimates (as opposed to 51% in Panel A) and only 50% of the negative estimates are significant (as opposed to 68% in Panel A). For NASDAQ stocks positive and significant estimates of β_0 make up 61% of the estimates. Only 3% of the estimates are negative and significant. The adjusted R^2 from these regressions are also high, consistent with commonality in the adverse selection component of liquidity.

CONCLUDING COMMENTS

This study provides an empirical investigation into the existence of market-wide (systematic) asymmetric cost of trading in the financial market. We examine three related hypothesis: (a) there exists asymmetric cost of trading even a highly diversified basket security; (b) this cost increases as the level of diversification of the basket security decreases; (c) the marketwide asymmetric cost of trading determines the asymmetric cost of trading individual stocks. Using intraday transaction level data on Standard and Poor's Depository Receipts (SPDRs), 145 other ETFs, and all common equities traded on the NYSE and NASDAQ, we provide evidence on commonality in the adverse selection component of liquidity. Our evidence is consistent with investors facing asymmetric information costs even when trading well diversified baskets of securities. The magnitude of these costs is inversely related to the degree of diversification. The SPDR is the most diversified of the ETFs we employ so we use its lambda as a measure of asymmetric information about market wide information.

We relate the lambdas on the other ETFs to the SPDR lambda and find that the SPDR lambda explains considerable time series variation in the lambdas of other ETFs. Further, we find that the SPDR lambda explains time series variation in the lambdas of individual equities. Finally, we present evidence that SPDR lambdas are reliably related to measures of aggregate market uncertainty. One limitation of this study is that due to its design which required the use of ETFs, the analysis is limited to five years only. Future research could extend the sample period by using closed end funds instead of ETFs as proxies for market-wide and sector level costs. Alternatively, principal component analysis could potentially be used to extract common factors from individual stock level data. These factors could potentially be used to proxy commonality in asymmetric information costs of trading.

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