5-2018

Essays on Short Selling

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To the Graduate Council:

I am submitting herewith a dissertation written by Peter Nephi Dixon entitled "Essays on Short Selling." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Business Administration.

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Essays on Short Selling

A Dissertation Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Peter Nephi Dixon
May 2018

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to Jean and Rolf Dixon, my mother and father for their unending support of my and my goals. I will never forget when as an eight-year-old child they bought me an entire encyclopedia set to cultivate my desire to learn. This dissertation is dedicated to them.

I also wish to extend a heartfelt thank you to my wife. She has been with me through the entire Ph.D. process and has provided invaluable copyediting support on all the papers I have written.

Lastly, I extend my heartfelt and deep gratitude to my advisers Dr. Eric Kelley, Dr. Andy Puckett, Dr. David Maslar, and Dr. Roberto Ragozzino. I can’t express how grateful I am to them for the support, guidance, council, advice, and correction that they have provided throughout this Ph.D. process.

ABSTRACT

This dissertation examines the role of short selling and short sellers in the process by which information is gathered and incorporated into stock prices. The first essay examines how the ability to short sell impacts adverse selection in financial markets through its impact on investors' incentives to gather costly information. The second essay examines how systematic changes across the business cycle affect what types of information – macro economic or firm specific – short sellers allocate attention to during recessions and expansions.

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INTRODUCTION

This dissertation examines the role of short selling and short sellers in the process by which information is gathered and incorporated into stock prices. The first essay explores the relation between short selling and adverse selection. Recent studies document that prohibiting short selling increases adverse selection in financial markets. This increase is puzzling given the prevailing view of short sellers as informed traders. In a simple rational expectations equilibrium model, I study the effect of short selling on adverse selection through its impact on traders' incentives to gather costly information. The model predicts an increase in adverse selection during a ban, but only for seller-initiated trades. Consistent with this prediction, I document that during the 2008 short selling ban the increase in adverse selection is concentrated almost exclusively on the seller-initiated side of the market, and also that this increase in adverse selection is the single largest factor contributing to increased transaction costs during the ban.

The second essay examines how systematic changes across the business cycle affect what types of information – macro economic or firm specific – short sellers allocate attention to during recessions and expansions. This essay documents that firm-level short interest predicts negative returns for individual stocks during economic expansions, while aggregate short interest predicts negative market returns during recessions. Viewing short sellers as informed traders, these findings are consistent with recent theory which argues that rational, yet cognitively constrained traders optimally allocate attention towards aggregate (firm-specific) information in recessions (expansions) because these times are marked by higher (lower) aggregate volatility and price of risk.

CHAPTER I

Short Selling and Liquidity, Why do Bans Increase Adverse Selection?

Peter Dixon, is the sole author of this chapter. He extends a special thank you to his advisers, Eric Kelley, Andy Puckett, David Maslar, and Roberto Ragozzino for their invaluable insights and assistance with this paper. He also thanks Kyoung-Hun Bae, Chelsea Chen, Philip Daves, Kaitlyn Dixon, Ryan Farley, Corbin Fox, Michael Goldstein, Matthew Serfling, Eric Sirri, and Tracie Woidtke for their valuable comments and insights

ABSTRACT

Recent studies document that prohibiting short selling increases adverse selection in financial markets. This increase is puzzling given the prevailing view of short sellers as informed traders. In a simple rational expectations equilibrium model, I study the effect of short selling on adverse selection through its impact on traders' incentives to gather costly information. The model predicts an increase in adverse selection during a ban, but only for seller-initiated trades. Consistent with this prediction, I document that during the 2008 short selling ban the increase in adverse selection is concentrated almost exclusively on the seller-initiated side of the market, and also that this increase in adverse selection is the single largest factor contributing to increased transaction costs during the ban.

1. Introduction

During the 2008 financial crisis, the United States (US) Securities and Exchange Commission (SEC) imposed a temporary ban on short selling for US listed financial stocks. Boehmer, Jones, and Zhang (2013) and Kolasinski, Reed, and Thornock (2013) observe that adverse selection increases during the ban for those stocks subject to it. As I document, this increase in adverse selection had a significant effect on financial markets and was the single largest factor contributing to lower levels of liquidity[1] experienced by those stocks subject to the ban.

[1] As measured by transaction costs

Adverse selection occurs in a transaction when one party has more precise information about the value of the asset being transacted than does the other. In such a transaction the less informed party usually loses money on the trade. Adverse selection affects liquidity because market makers are generally uninformed, and so as the fraction of informed traders in the market increases, so too do the losses that the market maker experiences due to adverse selection. When faced with increased adverse selection, market makers will compensate by decreasing liquidity and making it more expensive to transact (Kyle (1985), Glosten and Milgrom (1985)).[2]

The finding that adverse selection increases during a ban highlights a significant gap in our understanding of the role that short selling plays in financial markets. To date there exists no suitable explanation for this effect and given that short sellers are generally viewed as informed traders, their removal being associated with an increase in adverse selection is counter intuitive. Short selling is becoming a more prevalent component of financial markets[3] and is a topic of significant discussion amongst regulators around the globe.[4] It is therefore imperative ask the question, why do short selling bans increase adverse selection? Failing to answer this question leaves financial economists with an incomplete view of the role of short selling in modern financial

[2] A large literature of both theoretical and empirical work has grown which examines the role of adverse selection in as a key component of liquidity, see for example: Copeland and Galai (1983), Kyle (1985), Glosten and Milgrom (1985), Diamond and Verrecchia (1987), Glosten and Harris (1988), Stoll (1989), Eom, Ok, and Park (2007), Chung, Elder, and Kim (2010), Riordan and Storkenmaier (2012), Fotak, Raman, and Yadav (2014)
[3] Comerton-Forde, Jones, and Putniņš (2016) report in their sample of NYSE and Nasdaq trades that short selling is involved in 39% of all trades. Rapach, Ringgenberg, and Zhou (2016) document that average short interest outstanding per stock has been linearly increasing over the past four decades.
[4] For example, in the United States, short selling regulations have changed significantly over the past decade or so. Prior to 2005, short selling was only allowed on an uptick, this restriction was partially removed in 2005 and then fully removed in 2007. During the financial crisis, short selling was prohibited for a time then reallowed, and more recently the SEC has imposed a 'modified uptick rule' which sets a circuit breaker restricting short selling to upticks if a stock experiences a severe price decline.

markets, and regulators vulnerable to enacting short selling policies which may have unintended – and potentially detrimental – effects.[5]

Adverse selection also impacts many other aspects of finance and financial markets. If unaddressed, adverse selection can cause markets to fail (Akerlof (1970)). It also plays a role in many firm decisions, such as capital structure (Leland and Pyle (1977)), dividend policy (Miller and Rock (1985)), contracting (Jullien (2000)), management incentives (Ross (1977)), investment decisions (Morellec and Schürhoff (2011)), banking relationships (Sharpe (1990)), and others.

The finding that adverse selection increases during a short selling ban runs counter to intuitive expectations. There is a large body of research characterizing short sellers as informed traders.[6] Therefore, the intuitive expectation would be that removing short sellers during a ban should decrease adverse selection by removing informed traders from the market thus mitigating the information asymmetries that cause adverse selection. Further, this intuition leads to the expectation that the decline in adverse selection should be concentrated on the *sell* side of the market, because that is where informed short sellers transact (Comerton-Forde, Jones, & Putniņš (2016)). The finding that a short selling ban increases adverse selection is counter to this intuition and suggests the need to consider additional perspectives on the relationship between short selling and adverse selection.

[5] For example, after the 2008 short selling ban, SEC Chairman Christopher Cox remarked to reporters that "Knowing what we know now, I believe on balance the commission would not do it again" see http://www.reuters.com/article/us-sec-cox-idUSTRE4BU3GG20081231, accessed August 1, 2017

[6] See for example: Figlewski (1981), Desai et al. (2002), Cohen, Diether, and Malloy (2007), Boehmer, Jones and Zhang (2008), Diether, Lee, & Werner (2009), Boehmer, Huszar, and Jordan (2010), Karpoff and Lou (2010), Christophe, Ferri, and Hsieh (2010), Drake, Rees, and Swanson (2011), Kecskés, Mansi, and Zhang (2013), Boehmer and Wu (2013), Henry, Kisgen, and Wu (2015), Rapach, Ringgenberg, and Zhou (2016), Comerton-Forde, Jones, & Putniņš (2016), Kelley and Tetlock (2017) among others.

The finding that a short selling ban hurts liquidity by increasing adverse selection highlights a gap in the current literature linking short selling to liquidity. There are many studies linking short selling to liquidity;[7] however, these studies tend to link short selling to liquidity through the role of short sellers as liquidity providers. As articulated by Boehmer, Jones, and Zhang (2013), a short selling ban can hurt liquidity through the liquidity provision channel because *"Banning short sellers could reduce competition in liquidity provision, worsening the terms of trade for liquidity demanders."* (p1366).

However, this liquidity provision channel between short selling and liquidity is incomplete because it does not explain the apparent adverse selection link between short selling and liquidity. The importance of this link is highlighted in this study as I find that, during the 2008 short selling ban, the adverse selection channel between short selling and liquidity dominates the liquidity provision channel in terms of the magnitude of its effect on transaction costs. Another point concerning the liquidity provision channel is that it comes with the heretofore untested empirical prediction that the decline in liquidity during a short selling ban will be concentrated on the buy side of the market since short sellers only provide liquidity when they trade passively with an active buyer, a prediction that I test in section (4.c.ii).

Lastly, an increase in adverse selection during a ban is not consistent with the theoretical predictions of Diamond and Verrecchia (1987), the seminal theoretical work in the area. In their model, prohibiting short selling does not affect adverse selection because "*the prohibition applies*

[7] Other studies linking short selling to liquidity through the liquidity provision channel include: Diether, Lee, and Werner (2009), Boehmer and Wu (2013), Beber and Pagano (2013), Kaplan, Moskowitz, and Sensoy (2013), and Comerton-Forde, Jones, & Putniņš (2016).

to informed and uninformed alike…As a result, it leaves unchanged the information of actually observing [a sell].” (p289).

In pursuing a potential mechanism to explain the apparent adverse selection link between short selling and liquidity, I begin by examining the effect that short selling has on the incentives to gather costly information. When an investor chooses to expend resources to become informed they are acting under the assumption that they will be able to trade on the information they acquire. When short selling is prohibited, investors who do not already own the asset are unable to trade on negative information –decreasing the incentive for them to gather information. In contrast, by rendering them the only investors able to trade on negative information, a short selling ban increases the relative benefit to becoming informed for investors who already own the asset.

By changing the incentives that various investors have to become informed, a short selling ban may alter the distribution of informed traders in the market and thus impact the adverse selection that market makers face. I explore the implications of this mechanism in the context of a simple rational expectation equilibrium model based on Glosten and Milgrom (1985) and Diamond & Verrecchia’s (1987) seminal models. Exactly opposite to my initial intuition, the model predicts that a short selling ban will be associated with an increase in adverse selection that is concentrated on the sell side of the market.

This occurs because the inability to short sell increases the incentive for investors who own the asset to become informed and decreases it for those who do not own the asset. Consequently, the inability to short sell skews the distribution of informed traders in the market towards having a greater fraction of investors who own the asset who are informed and a smaller fraction of informed investors among investors who do not own the asset.

The total amount of adverse selection in the market is determined by the sum of the adverse selection on the buy and sell sides of the market. On the sell side of the market the only traders allowed to transact during a short selling ban are those who already own the asset, and because of the increased incentives to become informed an increased fraction of these investors are informed during a ban. Consequently, the probability a market maker trades with an informed seller increases relative to when short selling is allowed, and so adverse selection increases on the sell side of the market.

On the buy side of the market, the effect of the ban on adverse selection is muted. Since both investors who do and do not own the asset can still buy during a ban, the increase in informed trading by investors who own the asset is offset by the decrease in informed trading by investors who do not own the asset. Consequently, the effect of the ban on buy side adverse selection is comparatively small, and the change in overall adverse selection is driven primarily by the increase in adverse selection on the sell side of the market. This leads to the model's primary prediction. During a short selling ban, overall adverse selection will increase, but the increase will be concentrated on the sell side of the market.

I test these predictions empirically using data from the 2008 short selling ban in the United States. For these tests, each stock subject to the ban is matched to a control stock following the procedure described in Boehmer, Jones, and Zhang (2013). The adverse selection portion of the effective spread is measured for both banned and control stocks and is used in difference-in-difference-in-difference (DDD) regressions that measure the effect of the ban on adverse selection for both the buy and sell sides of the market.

The empirical analysis produces three important results that help illuminate the relation between short selling and adverse selection. First, consistent with the predictions of the model, I document that the increase in adverse selection during the short selling ban is concentrated almost exclusively on the sell side of the market.

Second, I find that the adverse selection channel between short selling and liquidity dominates the liquidity provision channel in terms of its effect on overall liquidity during the 2008 short selling ban. This result highlights the economic magnitude of the adverse selection channel linking short selling and liquidity, and thus the need to better understand the adverse selection link between short selling and liquidity.

Third, the increase in sell side adverse selection leads total transaction costs to increase 50% more for seller-initiated trades than for buyer-initiated trades during the ban – i.e. liquidity declines significantly more on the sell side of the market than the buy side during the ban. This finding has potential regulatory implications. Maintaining sell side liquidity during periods of downward price pressure is important to maintaining market stability (Huang and Wang (2008)), and regulations which restrict short selling during periods of downward price pressure may have the unintended effect of diminishing sell side liquidity when it is most needed.

In additional analysis, I explore the effects of the ban on the other component of the effective spread, the realized spread. The realized spread is the portion of the effective spread that market makers earn after adverse selection losses are accounted for. It compensates market makers for the non-adverse selection costs of market making – such as inventory and order processing costs – and provides the market maker’s profit.

If a short selling ban hurts liquidity by decreasing competition among liquidity providers – as the liquidity provision channel suggests – then this effect should manifest through an increase in the realized spread during the ban. However, this increase should be concentrated on the buy side of the market since short sellers only provide liquidity to buyers. Consistent with this prediction, I document that the increase in realized spread during the short selling ban is concentrated on the buy side of the market.

The analysis provided in this study contributes to multiple areas of finance. First, the result that the effect of the 2008 short selling ban on adverse selection is the single largest determinate of decreased liquidity during the ban highlights the magnitude of the adverse selection link between short selling and liquidity and thus the importance of better understanding this channel. This study also provides an explanation for why we may expect this link to exist; specifically, a short selling ban may impact adverse selection through how it affects the incentives to gather costly information.

Also, as noted earlier, the finding that sell side liquidity deteriorates more than buy side liquidity during the ban has potential regulatory implications and suggests that restricting short selling during periods of downward price pressure may have the unintended effect of diminishing sell side liquidity when it is most needed.

Next, the model's prediction that the inability to short sell will influence the characteristics of the investors who choose to become informed may have implications beyond liquidity. If fewer outside investors choose to become informed because of an inability to trade on negative information, then the role of outside investors as monitors of the firm may diminish when short selling is restricted. Fang, Huang, and Karpoff (2015) find evidence consistent with this notion. They document that easing short selling restrictions is associated with an increased likelihood of a firm being caught for misdeeds which occurred before the easing took place suggesting that when short selling restrictions are relaxed, more outside investors choose to gather information.

Lastly, this study has potential implications for how researchers approach the study of the determinates of liquidity. The asymmetry between the effect of the ban on buy and sell side liquidity documented in this study shows that additional insights can be gained by disaggregating liquidity measures and studying the buy and sell sides of the market separately.

2. Background Information

In the context of financial markets, adverse selection represents the risk that one party in a transaction knows more about the asset than the other. It is costly to market makers, because informed traders only transact when the asset is mispriced, leaving the market maker to bear the cost of the mispricing. As the fraction of informed traders in the market increases, so too does the likelihood that the market maker will lose money on a given transaction. Market makers will respond to increases in adverse selection by decreasing liquidity. Decreasing liquidity has the dual effect of both decreasing the value of information – mitigating somewhat the level of adverse selection in the market – and also increasing the average revenue per trade – which helps offset the losses due to adverse selection.[8]

Empirically, adverse selection is frequently measured using the price impact of a trade. As discussed in Kyle (1985) and Glosten and Milgrom (1985), when there are informed traders in the market, order flow conveys information about the value of the asset. Market makers respond to the information in order flow by adjusting subsequent prices to incorporate the information in the signal. When adverse selection increases – implying a greater fraction of informed traders in the market – the strength of the signal obtained from order flow is stronger, and the subsequent price

[8] See for example: Glosten and Milgrom (1985), Kyle (1985), Glosten and Harris (1988), Stoll (1989), Rubin (2007), Chung, Elder, and Kim (2010), Riordan and Storkenmaier (2012), and Fotak, Raman, and Yadav (2014)

change – or price impact – increases. Consequently, the literature uses the price impact of a trade as a measure of adverse selection.

The connection between adverse selection (measured by price impact) and liquidity can be seen clearly by analyzing the effective spread. The effective spread paid on trade *i* which occurs at time *t* is presented in equation (1). It is the signed (s_i) proportional distance between the trade price (P_i) and the prevailing midpoint at the time of the trade (M_t). It represents the cost that an active trader pays to the market maker to execute a trade.

$$Effective\ Spread_{it} = 2 * s_i * \frac{(P_i - M_t)}{M_t} \tag{1}$$

By adding and subtracting the midpoint at some future time $t + \Delta t$, as shown in equation (2), the effective spread can be decomposed into two components. The first component is the price impact of the trade and measures the proportional distance that the midpoint moves after the trade. It is an empirical measure of adverse selection and the literature uses the terms price impact and adverse selection interchangeably to refer to this portion of the effective spread.[9] The second component is the realized spread. It is the portion of the spread that the market maker 'realizes' after adverse selection costs are accounted for. The realized spread compensates the market maker for all non-adverse selection related costs as well as provides the market maker's profit.

[9] See for example: Sandås (2001), Barclay and Hendershott (2004), and Hendershott, Jones, and Menkveld (2011) among others

$$Effective\ Spread_i = 2 * s_i * \frac{(P_i - M_t + M_{t+\Delta t} - M_{t+\Delta t})}{M_t}$$

$$Effective\ Spread_i = 2 * s_i * \frac{(M_{t+\Delta t} - M_t)}{M_t} + 2 * s_i * \frac{(P_i - M_{t+\Delta t})}{M_t} \qquad (2)$$

$$Effective\ Spread_i = Adverse\ Selection_{it} + Realized\ Spread_{it}$$

Decomposing effective spreads into adverse selection and realized spread components provides a method for testing the economic channels through which an event or situation may impact financial markets. Events that affect the information environment will affect financial markets through changes in the adverse selection component of the effective spread, while events that affect non-adverse selection related market maker costs, as well as competition among market makers, will impact effective spreads by impacting the realized spread.

The prevailing view linking short selling to liquidity provision emphasizes the role of short sellers as liquidity providers and argues that removing short sellers hurts liquidity by decreasing competition among liquidity providers. By impacting competition among market makers – and thus market maker profits – the effects of the liquidity provision channel should manifest through changes in the realized spread. Decomposing the effective spread into its adverse selection and realized spread components allows me to differentiate between the affects due to the liquidity provision and adverse selection channels.

3. The Model

a. **Diamond and Verrecchia** (1987)

The seminal theoretical work examining the relation between short selling and adverse selection is Diamond and Verrecchia (1987) (hereafter DV). DV explore the effect of a short selling ban on the bid-ask spread in the context of a Glosten and Milgrom (1985) (hereafter GM) model. In both models, market makers are perfectly competitive and zero profit, and there are no other frictions in the market other than adverse selection. The assumption of perfectly competitive market makers implies that market makers earn zero profit and that the bid and the ask prices are set equal to the expected value of the asset given past order flow. Zero profit market makers together with the absence of other frictions (such as order processing costs or inventory costs) also implies that the realized spread in the economy is zero. Consequently, the entire bid-ask spread in these models is determined by adverse selection.

When a trade arrives, the market maker updates the prices for future trades to incorporate the information contained in the trade that just arrived. As the fraction of informed investors in the economy increases, adverse selection increases, and the price impact of a trade will also increase. As the market maker observes more trades, he becomes increasingly confident about the true value of the asset. This increasing confidence causes spreads to narrow and prices to converge to fundamentals.

In DV, a short selling ban has the effect of converting some trading rounds that would have experienced a sell into rounds where no trade occurs. A no trade event is less informative to the market maker than a trade, and so the expected speed at which spreads narrow and prices converge to fundamentals slows. This slowing of the market during a ban provides the mechanism driving their analysis of the effect of a short selling ban on financial markets. However, even though it takes longer for spreads to narrow and prices to converge, a short selling ban does not affect the level of adverse selection faced by the market maker in their model. This occurs because, "*the prohibition applies to informed and uninformed alike…As a result, it leaves unchanged the information of actually observing [a sell]*." (p289).

Although DV predicts no change in the actual level of adverse selection, their analysis does suggest that the *measured* level of adverse selection in financial markets may actually decline. This is because empirical measures of price impact keep the time horizon used to measure adverse selection constant (usually at 5 minutes). Consequently, even though the strength of the signal extracted from a given trade is unchanged, fewer trades arriving means that the expected price change over a given time horizon will decline. Consequently, the analysis in DV suggests that empirical measures of price impact that keep the time horizon constant may report a *decline* in adverse selection during a short selling ban due to fewer trades arriving. However, both DV's prediction that total adverse selection does not change, and the suggestion that observed adverse selection may decline are counter to the empirical observation that adverse selection appears to increase during a short selling ban suggesting the need for additional analysis.

b. Setup

The setup I use to explore short selling and adverse selection follows closely that used in DV and GM, with the key exception that I will allow the fraction of informed traders in the economy to be endogenously determined. Allowing the fraction of informed investors to be endogenously determined in the model allows me to explore a perspective on the relation between short selling and liquidity not considered previously. Specifically, I am able to consider how a short selling ban impacts liquidity through its effect on the incentives that traders face to become informed in the first place.

In the economy there exists one asset which has an equally likely value of either zero or one i.e. $v \epsilon[0,1]$. There exists a continuum of traders and perfectly competitive market makers. All trade occurs in one round, and then the asset is liquidated. Some fraction γ of these traders own the asset. Any trader can pay a cost $c < .5$ to learn the value of the asset prior to trading. The fraction of informed investors in the market is determined endogenously, with the fraction λ_e of investors who own the asset choosing to become informed, and the fraction λ_n of investors who do not own the asset choosing to become informed. Uninformed traders will buy or sell (or short) with equal probability. Informed traders always buy if the asset value is equal to one and sell (or short) if the asset value is equal to zero. Market makers cannot distinguish which traders are informed and which are not, but they do know the distribution of traders in the economy. Traders and market makers are risk neutral and transact one share.

To understand how the model measures the effect of short selling on adverse selection, it is important to note that prior to a trade arriving the expected value of the asset is equal to ½. This is also the bid and ask price that would be in force if none of the traders were informed – i.e. if there were zero adverse selection. To the extent that a market maker faces adverse selection on a given side of the market the bid or ask price will deviate from ½. Consequently, the absolute difference between the bid or ask price and ½ provides a measure of the amount of adverse selection that market makers face on a given side of the market.

To study the effect of short selling on adverse selection, I will first solve the model for the case where short selling is allowed, and then for the case where short selling is prohibited. I will then compare adverse selection in the two cases to determine the effect of prohibiting short selling on adverse selection.

c. The Baseline Case Where Short Selling is Allowed

In the absence of a short selling ban traders can buy and sell regardless of whether or not they own the asset. When a market maker trades, they know that the trade originated from one of four types of trader: informed investors who own the asset, uninformed investors who own the asset, informed investors who do not own the asset, and uninformed investors who do not own the asset. The probability that a market maker transacts with one of these four categories of investors is presented below as π_1, π_2, π_3, and π_4 (γ is the fraction of investors who own the asset, and λ_e and λ_n indicate the fraction of investors who do and do not own the asset who are informed).

Type of Trader	Probability of Event
Informed who own the asset	$\pi_1 = \gamma\lambda_e$
Uninformed who own the asset	$\pi_2 = \gamma(1 - \lambda_e)$
Informed who do not own the asset	$\pi_3 = (1 - \gamma)\lambda_n$
Uninformed who do not own the asset	$\pi_4 = (1 - \gamma)(1 - \lambda_n)$

Given this information, the market makers set the bid and ask price equal to the expected value of the asset given that a buy or sell arrives as shown in equations (3) and (4).

$$Ask_{noban} = E[v|uninformed\ Buy] * P(uninformed\ trader)$$
$$+ E[v|informed\ Buy] * P(informed\ trader)$$
$$= \frac{1}{2}(\pi_2 + \pi_4) + 1 * (\pi_1 + \pi_3) \tag{3}$$
$$= \frac{1}{2}[\gamma(1 + \lambda_e) + (1 - \gamma)(1 + \lambda_n)]$$

$$Bid_{noban} = E[v|uninformed\ Sell] * P(uninformed\ trader)$$
$$+ E[v|informed\ Sell] * P(informed\ trader)$$
$$= \frac{1}{2}(\pi_2 + \pi_4) + 0 * (\pi_1 + \pi_3) \tag{4}$$
$$= \frac{1}{2}[\gamma(1 - \lambda_e) + (1 - \gamma)(1 - \lambda_n)]$$

Prior to trading, a trader may pay a cost c to learn the value of the asset. Traders will become informed until the marginal benefit to becoming informed equals the marginal cost. I model the benefit to information as having two components. The first is the expected trading profits that can be earned if the trader becomes informed. If the asset is worth zero the trader can either sell the asset if they own it, or they can short sell the asset if they do not, doing so earns the trader a profit equal to the bid price minus the liquidation value – zero in this case. If the asset is worth one the trader can buy the asset, earning the trader the liquidation price – one in this case – minus the ask price. Both outcomes are equally likely, so the expected trading profit to becoming informed is the average of the two cases.

The other component that affects the benefit to becoming informed draws from the literature showing that as more investors become informed, implementing an information based trade becomes more difficult and the value of information declines.[10] Drawing from this literature, the trading profits are multiplied by a coefficient $(1 - \overline{\lambda}) \equiv 1 - (\gamma\lambda_e + (1 - \gamma)\lambda_n)$ which is one minus the total fraction of informed traders in the market. This coefficient captures the dynamic that as more investors become informed, it becomes more difficult to capture the potential trading

[10] Prominent studies in this literature include: Holden and Subrahmanyam (1992), Foster and Viswanathan (1994), (1996), Back, Cao, and Willard (2000), Akins, Ng,and Verdi (2012), Di Mascio, Lines, and Naik (2015)

profits that being informed makes possible. Equation (5), captures both these dynamics which affect the benefit to becoming informed.[11]

$$Benefit\ to\ being\ informed_{noban} = \left(1-\bar{\lambda}\right)\left(\frac{1}{2}[1-Ask]+\frac{1}{2}[Bid-0]\right)$$

$$= \left(1-\bar{\lambda}\right)\left(\frac{1}{2}\left[1-\frac{1}{2}[\gamma(1+\lambda_e)+(1-\gamma)(1+\lambda_n)]\right]+\frac{1}{2}\left[\frac{1}{2}[\gamma(1-\lambda_e)+(1-\gamma)(1-\lambda_n)]\right]\right) \quad (5)$$

$$= \left(1-\bar{\lambda}\right)\left(\frac{1}{2}[\gamma(1-\lambda_e)+(1-\gamma)(1-\lambda_n)]\right)$$

In equilibrium the marginal benefit to becoming informed must equal the marginal cost of becoming informed. However, since there is no difference in the benefit to becoming informed for investors who do and do not own the asset there is only one equation and two unknowns. To solve for the optimal values of λ_e and λ_n I assert that, since there is no difference in the benefit to becoming informed for investors who do and do not own the asset, both types of investors will behave in the same manner i.e. $\lambda_e = \lambda_n \equiv \lambda$. In this case, the benefit to becoming informed simplifies to the expression in equation (6) with one equation and one unknown.

$$Benefit\ to\ being\ informed = (1-\lambda)\frac{1}{2}[\gamma(1-\lambda)+(1-\gamma)(1-\lambda)] \quad (6)$$

[11] If an investor chooses not to become informed, then the investor will on average earn a negative profit equal to one half the bid ask spread. A natural question to ask is, why would the uninformed traders transact in the first place? Most studies, including Kyle (1985), GM, and DV (and many others) simply assume that investors who are not informed must trade for liquidity reasons. However, this justification is less applicable to the current analysis because uninformed investors must proactively choose to not become informed and then to trade anyways. Another perspective on this question is that the decision to become informed (or not) is similar in spirit to the decision that fund managers must make when deciding whether or not to be a passively or an actively managed fund. A passive fund that perfectly tracks a given index will earn a benchmark adjusted return equal to zero minus transaction costs (1/2 the bid ask spread). If there is a market for passively managed funds then managers of such funds will still find it beneficial to remain in business, even though their benchmark adjusted returns are negative by the amount of transaction costs. These indexing fund managers earn an outside benefit that compensates them for the transaction cost losses. In equilibrium managers should be indifferent between the two choices.

$$= \frac{(1-\lambda)^2}{2}$$

Setting the benefit to becoming informed from equation (6) equal to the cost to becoming informed (c) and solving for λ provides the equilibrium fraction of investors who choose to become informed when short selling is allowed as shown in equation (7b).

$$cost\ of\ becoming\ informed\ \ = Benefit\ to\ being\ informed$$

$$c \ = \frac{(1-\lambda)^2}{2} \tag{7a}$$

$$\lambda_1 = \lambda_2 \equiv \ \lambda = \ 1 - \sqrt{2c} \tag{7b}$$

The assumption $c < .5$ ensures that the fraction of investors choosing to become informed is positive. In (7b) the fraction of investors in the economy that become informed is a monotonic function of the cost to becoming informed. If the cost were zero, then the fraction of investors becoming informed would equal one. If the cost were ½ (the maximum allowed), then the fraction informed would equal zero. Consequently, adverse selection in the economy will be a monotonic and decreasing function of the cost to becoming informed. To find the equilibrium bid and ask prices when short selling is allowed, the equilibrium fraction of investors becoming informed from equation (7b) is inserted into the equilibrium bid and ask prices from equations (3) and (4) to find the equilibrium bid and ask prices, as well as the bid ask spread in effect when short selling is allowed, as shown in equation (8).

$$Ask_{noban} = 1 - \frac{\sqrt{2c}}{2}$$

$$Bid_{noban} = \frac{\sqrt{2c}}{2} \quad (8)$$

$$Spread_{noban} = 1 - \sqrt{2c}$$

As expected, the equilibrium bid and ask prices in force when short selling is allowed are monotonic functions of the cost of becoming informed. This makes intuitive sense. If the cost to becoming informed were ½ (the maximum allowed), then no investors would choose to become informed and the spread would be equal to 0; as the cost declines, more investors become informed and the bid ask spread increases to compensate market makers for the increased adverse selection risk they face. To measure the amount of adverse selection on both sides of the market I simply take the absolute difference between the bid or ask and 1/2. Doing so reveals that the adverse selection that the market maker faces is symmetric on both sides of the market, and the total adverse selection is equal to $1 - \sqrt{2c}$. This provides a baseline case for which to compare adverse selection in the market when short selling is prohibited.

d. Case Where Short Selling is Prohibited

A short selling ban will change the dynamics of trade by prohibiting traders who do not own the asset from transacting at the bid. Consequently, if a sell arrives then the market maker knows that it must come from an investor that already owns the asset. In this setting, the probability that a market maker faces an informed trader at the bid changes from $\pi_1 + \pi_3$ in the case where short selling is allowed to $\frac{\pi_1}{\pi_1+\pi_2}$, and the probability that a market maker faces an uninformed trader at the bid changes from $\pi_2 + \pi_4$ in the case where short selling is allowed to $\frac{\pi_2}{\pi_1+\pi_2}$. Market makers update the bid price during a short selling ban accordingly as presented in equation (9).

$$\begin{aligned} Bid_{ban} &= E[v|uninformed\ Sell] * P(uninformed\ trader) + E[v|informed\ Sell] \\ &\quad * P(informed\ trader) \\ &= \frac{1}{2}\frac{\pi_2}{\pi_1+\pi_2} + 0 * \frac{\pi_1}{\pi_1+\pi_2} \qquad (9) \\ &= \frac{1-\lambda_e}{2} \end{aligned}$$

Since there are no restrictions on buying during a short selling ban, the expression characterizing the ask price – presented in equation (3) – does not change. Equations (10) and (11) give the bid and ask prices in force during a short selling ban.

$$Ask_{ban} = \frac{1}{2}[\gamma(1+\lambda_e) + (1-\gamma)(1+\lambda_n)] \qquad (10)$$

$$Bid_{ban} = \frac{1-\lambda_e}{2} \qquad (11)$$

The other aspect of the economy that changes during a short selling ban is the benefit to becoming informed. The inability to short sell prevents investors who do not own the asset from trading on their information if the value of the asset turns out to equal zero, diminishing the value of information for these investors. This effect on the benefit to being informed is reflected in equation (12) in the fact that the trading profit for these investors is limited to $1 - Ask$.

$$\textit{Benefit to being informed}_{\textit{do not own,ban}} = \left(1-\bar{\lambda}\right)\frac{1}{2}[1-Ask]$$

$$= \left(1-\bar{\lambda}\right)\frac{1}{2}\left[1-\frac{1}{2}[\gamma(1+\lambda_e)+(1-\gamma)(1+\lambda_n)]\right] \tag{12}$$

$$\textit{Benefit to being informed}_{\textit{own,ban}} = \left(1-\bar{\lambda}\right)\left(\frac{1}{2}[1-Ask]+\frac{1}{2}[Bid-0]\right)$$

$$= \left(1-\bar{\lambda}\right)\left(\frac{1}{2}\left[1-\frac{1}{2}[\gamma(1+\lambda_e)+(1-\gamma)(1+\lambda_n)]\right]+\frac{1}{2}\left[\frac{1-\lambda_e}{2}\right]\right) \tag{13}$$

By contrast, the inability of investors who do not own the asset to trade on negative information increases the relative benefit to becoming informed for those investors who own the asset by rendering them the only traders able to trade on negative information. The parameters λ_e and λ_n are found by setting the marginal benefit to becoming informed equal to the marginal cost for both types of traders – as shown in equations (14) and (15) – yielding two equations and two unknowns. It is then straightforward to solve this system of equations for the equilibrium values of λ_e and λ_n.

$$c = \textit{Benefit to being informed}_{\textit{own,ban}}$$

$$c = \left(1-\bar{\lambda}\right)\left(\frac{1}{2}\left[1-\frac{1}{2}[\gamma(1+\lambda_e)+(1-\gamma)(1+\lambda_2)]\right]+\frac{1}{2}\left[\frac{1-\lambda_e}{2}\right]\right) \tag{14}$$

$$c = \textit{Benefit to being informed}_{\textit{not endowed,ban}}$$

$$c = \left(1-\bar{\lambda}\right)\frac{1}{2}\left[1-\frac{1}{2}[\gamma(1+\lambda_e)+(1-\gamma)(1+\lambda_2)]\right] \tag{15}$$

The solution to the above system of equations for λ_1 and λ_2 is presented in equation (16)[12].

$$\lambda_e = 1 \quad , \quad \lambda_n = 1 - \frac{2\sqrt{c}}{1-\gamma} \tag{16}$$

It is immediately apparent from the solutions in equation (16) that when short selling is prohibited the fraction of investors who own the asset who choose to become informed increases as now all investors who own the asset choose to become informed. It is also straightforward to show that fewer investors who do not own the asset choose to become informed. Consequently, the effect of prohibiting short selling on information acquisition is to concentrate information acquisition among the investors who own the asset.

The equilibrium values of λ_e and λ_n presented in equation (16) are then inserted into equations (10) and (11) to yield the equilibrium bid and ask prices as well as the spread in force during a short selling ban as presented in equation (17).

$$Ask_{ban} = 1 - \sqrt{c}$$

$$Bid_{ban} = 0 \tag{17}$$

$$Spread_{ban} = 1 - \sqrt{c}$$

On the seller-initiated side of the market, the market maker knows that all the investors in the market are informed, so during a short selling ban a market maker faces the maximum value of

[12] Since there can never be a negative fraction of informed traders in the market, the solution presented in equation (16) is only when $\lambda_2 \geq 0$, i.e. when $\frac{2\sqrt{c}}{1-\gamma} < 1$. For parameter values of γ and c that violate this inequality, the equilibrium is obtained by setting $\lambda_n = 0$ in equation (14) and solving for the equilibrium value of λ_e. Then to ensure that this is a valid equilibrium, the equilibrium value of λ_e from the previous step is inserted into equation (15) and which is then solved for λ_n to verify that the investors who do not own the asset are not now better off becoming informed. This process yields an outcome that $\lambda_e = \frac{3\gamma+1-\sqrt{\gamma^2(16c+1)+\gamma(16c-2)+1}}{2\gamma(\gamma+1)}$, and $\lambda_n = 0$, this equilibrium yields the same predictions as the solution presented in equation (16) consequently, in the discussion moving forward I limit the discussion to those obtained from the values of λ_e and λ_n presented in equation (16).

adverse selection and so the bid is equal to zero, and the absolute difference between ½ and zero is one half. So there is an increase in adverse selection on the sell side of the market during a ban. On the buyer-initiated side of the market the effect of the ban on adverse selection is muted. While an increased fraction of investors who own the asset are informed, a smaller fraction of investors who do not own the asset choose to become informed. Consequently, the effect of the ban on buy side adverse selection is smaller than the effect of the ban on sell side adverse selection. The net effect is actually a small reduction in adverse selection on the buy side of the market during a short selling ban.

The combined effect of a large increase in sell side adverse selection with a small decline in buy side adverse selection combine to produce the net result that overall spreads increase from $1-\sqrt{2c}$ when short selling is allowed to $1-\sqrt{c}$ when short selling is prohibited. It is interesting to note that when short selling is allowed a total of $1-\sqrt{2c}$ fraction of the investors in the economy are informed. However, when short selling is prohibited that fraction declines to $1-2\sqrt{c}$. So even though market makers face increased levels of adverse selection, fewer total investors are becoming informed.

Although a formal analysis is outside the scope of this model, the finding that a short selling ban decreases overall information gathering would seem to suggest that a ban may harm price efficiency by increasing the amount of time it takes for information to become incorporated into stock prices – similar to what is observed in DV.

This seeming paradox of a decline in information acquisition occurring at the same time as an increase in adverse selection occurs because even though investors who own the asset only make up a fraction of the total traders in the market, during a ban they completely determine the amount of adverse selection that market makers face. Consequently, the ban's effect on these investors has a greater impact on adverse selection than does the ban's effect on investors who do not own the asset. In sum, the model's main predictions are that overall adverse selection will increase during a short selling ban, but that increase will be concentrated on the sell side of the market. In the following section I test this prediction empirically.

Insert Figure 1 Here

4. Empirical Analysis

a. Sample

The event that I use to study the effects of short selling on adverse selection is the 2008 short selling ban imposed by the US Securities and Exchange Commission. As the financial crisis deepened in August and September 2008 the SEC and other policy makers came under increasing pressure by executives to put a stop to what they believed was 'manipulative' short selling.[13] After the collapse of Lehman Brothers on September 15, and the subsequent stock market decline, the SEC imposed a short selling ban for a list of US financial stocks. The ban began on September 19 and lasted through October 8. The initial list of banned stocks comprised 799 US listed financial stocks but was eventually expanded to include a total of 931 stocks including non-financial blue chip stocks such as General Electric.

To study the effect of the ban on adverse selection, my primary data source is the NYSE Daily Trade and Quote (DTAQ) database for the months of August – October 2008. This dataset offers an improvement over the NYSE Monthly Trade and Quote (MTAQ) database employed in prior

[13] For example, then Treasury Secretary Henry Paulson reported in his memoir receiving multiple phone calls from executives complaining about short sellers.

studies.[14] As demonstrated in Holden and Jacobsen (2014) the differences in the two datasets can have a significant effect on the results obtained from empirical analysis. Most relevant to this study, Holden and Jacobsen (2014) document that compared to the more accurate DTAQ results, computations using MTAQ data can produce effective spreads that are 50% larger than the effective spreads computed using DTAQ. Consequently, where my analysis overlaps with that of Boehmer, Jones, and Zhang (2013) the pattern of results is similar, but the magnitudes presented here are smaller due to using DTAQ instead of MTAQ data. Other data sources include OptionMetrics from which I obtain data about the options status of the firm, and CRSP where I obtain stock specific data such as listing exchange, shares outstanding, and stock return data.

When the SEC published the list of stocks for which short selling was prohibited they did so by publishing a list of tickers. Of the 931 stocks subject to the ban I remove tickers that do not match to a permno in CRSP as well as those that ambiguously match to multiple permnos in CRSP leaving 910 tickers that pass the initial filter. 123 Tickers that are not common stocks (CRSP share codes 10 and 11) are removed leaving 787 tickers that pass the second filter. Of these 787 tickers 33 are not listed on NYSE or NASDAQ and are removed leaving 754. Stocks must also have complete CRSP volume and returns data for December 2007-July 2008 as well as DTAQ data from August 2008 – October 2008 leaving a total of 711 usable tickers from the published list of banned stocks from the SEC. Of these 653 are on the original list published by the SEC on September 19, 2008, and the remaining 58 were added to the ban later.

[14] The key differences between the MTAQ database and the DTAQ database are that the trade and quotes in the DTAQ database are time stamped at the millisecond whereas the MTAQ database is timestamped at the second. Also, the DTAQ database provides the national best bid and offer prices (NBBO) prices time stamped to the millisecond, whereas the MTAQ database requires the user to estimate the NBBO prices from the quotes database which are time stamped to the second.

Each banned stock is identified as either a large, small, or microcap based on its market cap as of December 31, 2007. Following Fama and French (2008), large stocks are defined as those stocks that are in the largest 5 NYSE size deciles as of December 31, 2007, small stocks are defined as those stocks that are in NYSE size deciles 3-5, and microcap stocks are those stocks that are in the smallest two NYSE deciles. This methodology results in 139 large stocks, 118 small stocks, and 454 microcap stocks.

Going forward, I omit microcap stocks from the analysis for a few reasons. First, measuring adverse selection requires signing order flow with some degree of accuracy. Microcap stocks trade infrequently, and the time between quote revisions can be significant. Consequently, signing order flow using algorithms which match trades to prior quotes – such as the Lee and Ready (1991) algorithm – for microcap stocks is likely to be highly noisy. Second, as Boehmer, Jones, and Zhang (2013) document, smaller stocks are lightly shorted and thus the effects of the short selling ban on smaller stocks is muted. Lastly, trading in microcap stocks accounts for only a tiny fraction of total trading volume, and a study whose results are strongly influenced by microcap stocks may lack generalizability.

Each banned stock is matched – with replacement – to a control stock based on market cap (calculated from CRSP) as of December 31, 2007, dollar trading volume in the first seven months of 2008 (calculated from CRSP), listing exchange (from CRSP), and options status (from Options Metrics). This matching procedure is similar to that employed by Boehmer, Jones, and Zhang (2013) and Brogaard, Hendershott, and Riordan (2017).

To determine the control stock, I take the universe of CRSP common stocks (share codes 10 and 11) which have complete DTAQ data for August-October 2008, and complete CRSP data for 2007 and 2008, as well as the same listing exchange and the same options status as the banned stock in question. I employ a distance measure like the one employed by Boehmer, Jones, and Zhang (2013) and Brogaard, Hendershott, and Riordan (2017) to determine which potential control stock is most similar to the banned stock in question. As shown in equation (18) where i indexes the banned stock, and j indexes the potential match, the distance between a banned stock and a potential control stock is the sum of the proportional distance between the banned stock and the control stock based on market cap and dollar volume. The control stock with the smallest distance measure becomes the assigned control stock for the banned stock under consideration. Following Boehmer, Jones, and Zhang (2013) the sampling is done with replacement. Table 1 presents descriptive statistics for the banned and control stocks used in this study.

$$Distance_{i,j} = \frac{\left|Mktcp_i - Mktcp_j\right|}{Mktcp_i} + \frac{\left|Dvol_i - Dvol_j\right|}{Dvol_i} \tag{18}$$

Insert Table 1 Here

b. Computation of Adverse Selection and Spread Measures

As discussed in section (2.a) adverse selection comprises a key component of the effective spread. The primary empirical objective in this section is to estimate the effect of the 2008 short selling ban on adverse selection on the buy and sell sides of the market. To estimate adverse selection and realized spread, I use DTAQ data for both banned and control stock and I compute the effective spread, and its constituent components of adverse selection and realized spread for all qualifying trades in August -October 2008. To be included in the sample a trade must not have a non-normal trade code.[15] Also, Reg NMS requires that brokers route orders to the best quote price, and so trades outside the current national best bid and offer (NBBO) prices should not occur

[15] Non-normal trades include those trades in the field tr_scond which have a value of J, L, N, O, P, T, Z, U, and Q.

and may be indicative of errors in the data. Consequently, I remove trades where the posted trade price is more than one cent outside of the NBBO prices in the millisecond prior to the trade. To eliminate trades associated with erroneous quotes I remove trades corresponding to quoted spreads (computed from the NBBO file) that are greater than 30% in the millisecond prior to the trade.

As shown in equation (2), the computation of adverse selection and realized spread require the use of a midpoint at some point Δt after the initial midpoint which occurs at time t. I eliminate trades in my computation of realized spread and adverse selection that are associated with quoted spreads at time $t + \Delta t$ that are greater than 30%. Lastly, trades associated with locked or crossed quotes are eliminated. These filters eliminate approximately 4% of trades from the sample.

For each remaining trade in the DTAQ database the effective spread, realized spread, and adverse selection measures are computed as displayed in equations (19) through (21). In these equations i indexes a given trade, s_i indexes the sign of the given trade as assigned by the Lee and Ready (1991) algorithm (1 indicates a buyer-initiated trade and -1 indicates a seller-initiated trade) using the prevailing NBBO midpoint in the millisecond prior to the trade provided by DTAQ as the reference midpoint in the algorithm. $P_{i,t}$ is equal to the transaction price for trade i which occurred at time t. M_{t-1} is the prevailing NBBO midpoint in the millisecond prior to trade i. $M_{t+\Delta t}$ is the prevailing NBBO midpoint at some time Δt after the arrival of the given trade.

When selecting a time horizon to measure adverse selection and realized spread there is unfortunately a lack of guidance in the literature. Perhaps the most common time horizon employed in the literature is five minutes, however, as O'Hara (2015) points out, five minutes in modern markets is a 'lifetime'. Consequently, in my analysis I will allow the time horizon used to measure adverse selection to vary from one to five minutes.

$$Effective\ Spread_i = \frac{2 * s_i\left(P_{i,t} - M_{t-1}\right)}{M_{t-1}} \tag{19}$$

$$Realized\ Spread_{i,\Delta t} = \frac{2 * s_i\left(P_{i,t} - M_{t+\Delta t}\right)}{M_{t-1}} \tag{20}$$

$$Adverse\ Selection_{i,\Delta t} = \frac{2 * s_i(M_{t+\Delta t} - M_{t-1})}{M_{t-1}} \tag{21}$$

The measurements from individual trades are aggregated and equally weighted daily averages for each of the three metrics are computed. These daily averages are computed in one of two ways. If the empirical specification is analyzing the total effect of the ban on adverse selection or spreads, then the dependent variable will be the equally weighted daily average across all trades – irrespective of sign – yielding one observation per stock per day. In specifications where the objective is to measure the differential effect of the ban on adverse selection or spreads for buy and sell sides of the market, then the dependent variable will be the equally weighted daily average across all buy or sell trades – producing two observations per stock per day. Adverse selection, realized spread, and effective spreads are converted to basis points for all analysis.

c. Empirical Results

The primary empirical methodology used to determine the effects of the ban on adverse selection and spreads is difference-in-difference (DD) regressions when estimating the overall effect of the ban, and difference-in-difference-in-difference (DDD) regressions for the signed analysis. In these regressions, the dependent variable is the difference in equally weighted daily average adverse selection (or realized spread or effective spread) between a banned stock and its matched control for the variable of interest. This effectively places the first difference in the DD, or DDD regressions on the left-hand side of the regression and allows the use of stock pair fixed effects in my model to control for systematic differences in the dependent variable between each banned stock and its matched control.

i. The Effect of the Ban on Adverse Selection

The primary prediction of the model presented in section 3 is that prohibiting short selling will lead to an overall increase in adverse selection, but that that increase will be concentrated on the sell side of the market. To study the effect of the short selling ban on adverse selection during the 2008 short selling ban, I use DD and DDD regressions presented in equations (22) and (23).

$$AS_{i,t}^{B,\Delta t} - AS_{i,t}^{C,\Delta t} = \eta_0 + \eta_1 Ban_t + \Gamma X_{it} + \nu_i + \varepsilon_{it} \tag{22}$$

$$AS_{i,t,s}^{B,\Delta t} - AS_{i,t,s}^{C,\Delta t} = \xi_0 + \xi_1 Ban_t + \xi_2 SI_s + \xi_3 Ban_t * SI_s + \Gamma X_{it} + \nu_i + \varepsilon_{it} \tag{23}$$

In these specifications, i indexes the banned stock, t indexes the day and s indexes which side of the market a given observation corresponds to – buyer or seller-initiated. In equation (22) the coefficient η_1 indicates the total effect of the short selling ban on adverse selection. Equation (23) is a DDD regression identifying the differential effect of the short selling ban on the buyer and seller-initiated sides of the market. The coefficient ξ_1 from equation (23) identifies the effect of the short selling ban on buyer-initiated adverse selection, and the sum of coefficients $\xi_1 + \xi_3$ identifies the effect of the short selling ban on adverse selection for seller-initiated trades. X_{it} is a matrix of control variables.[16] All models include stock pair fixed effects and standard errors are clustered at the date level.

[16] Control variables include the difference between banned and control stocks on dimensions of value weighted average price, market cap, dollar volume, number of trades, price volatility, and daily return, as well as the return on the CRSP value weighted index and level of the value weighted average price, market cap, dollar volume, number of trades, daily return, and price volatility for the banned stock.

Table 2 presents the regression estimates for the coefficient η_1 from equation (22) indicating the total effect of the short selling ban on adverse selection. In these specifications, the results for adverse selection are computed using horizons of one, two, three, four, and five minutes, and are presented in columns one through five of Table 2 respectively. Panel A presents the results for large stocks and panel B the results for small stocks. In both instances, the regressions reveal that the short selling ban is associated with a statistically significant increase in adverse selection. For large stocks, the measured increase in adverse selection is about 2.5-3.5 basis points, depending on the time horizon used. The pattern of results in panel B for small stocks is similar with adverse selection costs increasing by about 5-7 basis points. These results confirm the findings of Boehmer, Jones, and Zhang (2013) and Kolasinski, Reed, and Thornock (2013) that the ban is associated with an increase in adverse selection costs, and are consistent with the model's prediction that overall adverse selection will increase during a ban.

Insert Table 2 Here

Table 3 presents the results from the DDD regressions from equation (23) examining the differential effect of the short selling ban on adverse selection on the buy and sell sides of the market. The results presented in Table 3 are consistent with the predictions of the model as the effect of the short selling ban on adverse selection appears concentrated almost exclusively on the sell side of the market. For large stocks, there is not a single instance where the regressions indicate that the ban is associated with a statistically significant increase in buy side adverse selection, yet every time frame at which adverse selection is measured indicates a statistically significant increase in adverse selection costs of 4-6 basis points on the sell side of the market.

For small stocks, the pattern of results is similar. Across all time horizons the regressions indicate a statistically significant increase in adverse selection on the sell side of the market of between 8 and 14 basis points. The results identifying the effect of the ban on buy side adverse selection (ξ_1) indicate an increase of only about 2 basis points – which is not statistically significant in three of the five specifications.

To highlight the economic magnitude of the effect of the ban on adverse selection costs it is illustrative to note that the average effective spreads (of which adverse selection is a key component) paid by traders outside the ban for large (small) stocks is approximately 7 (15) basis points. Consequently, the increase in sell side adverse selection costs of 4-6 (8-12) basis points for large (small) represents an increase in transaction costs equal to approximately 60%-85 (50-90%) of total transaction costs paid outside the ban.

Figure 2 presents a graphical description of the regressions results presented in Tables 2 and 3. Each point in each series indicates the observed value of coefficient η_1, ξ_1, or the sum of coefficients $\xi_1 + \xi_3$ from a DD or DDD regressions corresponding to equations (22) and (23) and for a given time horizon used to compute adverse selection. Time horizons vary from 60 to 300 seconds. The vertical axis indicates the magnitude of the effect in basis points and the horizontal axis indicates the time horizon used to compute adverse selection. The dotted colored line in the figure shows the effect of the short selling ban on sell side adverse selection (coefficients $\xi_1 + \xi_3$ from equation (23)). The solid colored line indicates the effect of the ban on buy side adverse selection (coefficient ξ_1 from equation (23)), and the grey line indicates the aggregate effect of the ban on adverse selection (η_1 from equation (22)).

This figure provides a graphical illustration of effect of the ban on adverse selection which is documented in Tables 2 and 3. Consistent with the predictions of the model, for every time horizon used to measure adverse selection, the effect of the ban on adverse selection is concentrated almost exclusively on the sell side of the market.

Insert Table 3 Here

Insert Figure 2 Here

ii. The Effect of the Ban on Realized Spread

The other component of the effective spread paid by the liquidity demanders is the realized spread. This is the portion of the spread that compensates market makers for non-adverse selection costs and provides their profit. The literature examining the link between short selling and liquidity has primarily concentrated on studying the role that short sellers play as liquidity providers. As articulated by Boehmer, Jones, and Zhang (2013), the effect that a short selling ban may have on liquidity through the liquidity provision channel comes because *"Banning short sellers could reduce competition in liquidity provision, worsening the terms of trade for liquidity demanders."* (p1366).

A decline in competition among liquidity providers allows the remaining liquidity providers to charge higher rents. These higher rents should be discernable in the data through an increase in the realized spread portion of the effective spread. However, this liquidity provision channel comes with the heretofore untested prediction that the increase in realized spread during a short selling ban will be concentrated on the buy side of the market. This asymmetry comes because short sellers only provide liquidity when they trade passively with buyers, so the decline in competition due to prohibiting short sellers is likely to be concentrated on the buy side of the market – leading to an increase in buy side realized spread.

I examine the asymmetric effects of the short selling ban on buy and sell side realized spread employing DD and DDD regressions presented in equations (24) and (25) similar to those employed in the previous section. Equation (24) is used to determine the total effect of the short selling ban on realized spread and in this specification, the coefficient κ_1 indicates this overall effect. Equation (25) is used to study the differential effect of the short selling ban on realized spread for the buy and sell sides of the market. In equation (25) the coefficient ρ_1 indicates the effect of the short selling ban on buyer-initiated trades whereas the sum of coefficients $\rho_1 + \rho_3$ indicates the effect of the short selling ban on seller-initiated trades. In all specifications, the matrix of control variables X_{it} contains the same controls as those employed in the regressions in the prior analysis. All models include stock pair fixed effects, and standard errors are clustered at the date level.

$$RESP_{i,t}^{B,\Delta t} - RESP_{i,t}^{C,\Delta t} = \kappa_0 + \kappa_1 Ban_t + \Gamma X_{it} + \nu_i + \varepsilon_{it} \tag{24}$$

$$RESP_{i,t,s}^{B,\Delta t} - RESP_{i,t,s}^{C,\Delta t} = \rho_0 + \rho_1 Ban_t + \rho_2 SI_s + \rho_3 Ban_t * SI_s + \Gamma X_{it} + \nu_i + \varepsilon_{it} \tag{25}$$

Table 4 presents the regression estimates for the coefficient κ_1 from equation (24), which indicate the total effect of the short selling ban on realized spread. The results of the DD regressions indicate that for both large and small stocks, the short selling ban is associated with a statistically significant increase in realized spread at all time horizons used to compute realized spread – except for five-minute realized spread for large stocks. For large stocks, the increase is around 1 basis point. For small stocks, the increase in realized spread is approximately 5 to 6 basis points.

Insert Table 4 Here

Table 5 presents the DDD regression results indicating the effect of the short selling ban on realized spread for the buyer and seller-initiated sides of the market from equation (25). The coefficient ρ_1 from equation (25) measures the impact of the ban on buy side realized spread while the sum of coefficients $\rho_1 + \rho_3$ indicates the effect of the ban on sell side realized spread. Panel A of Table 5 presents the results for large stocks and panel B the results for small stocks.

Table 5 documents evidence consistent with the prediction that the increase in realized spread will be concentrated on the buy side of the market. On the buy side of the market, large (small) stocks experience an increase in realized spread of approximately 3 (7) basis points. Whereas on the sell side of the market the effect of the ban on realized spread is not clear. For large stocks, the sum of coefficients $\rho_1 + \rho_3$ indicating the effect of the short selling ban on sell side adverse selection is not significant in any specification, and negative in three of them. For small stocks, the effect of the ban on sell side realized spread is positive and significant when employing time horizons of one and two minutes but attenuates and is statistically indistinguishable from zero at longer time horizons.

Recall that outside the ban, the average effective spreads paid by traders for large (small) stocks is 7 (15) basis points. Consequently, the increase in buy side realized spread of approximately 3 (7) basis points for large (small) stocks represents an increase in transaction costs equal to approximately 40% (45%) of total transaction costs paid outside the ban, an economically meaningful increase, but smaller than the observed increase in adverse selection presented in the prior section – a difference that will be explored in greater depth in the next section.

Figure 3 presents a graphical description of the regression results presented in Tables 4 and 5 similar to Figure 2 in the prior section. Each point in each series indicates the observed coefficient κ_1, ρ_1, or the sum of coefficients $\rho_1 + \rho_3$ from the DD or DDD regressions corresponding to equations (24) and (25) for a given time horizon used to compute realized spread. Time horizons are varied from 60 to 300 seconds. The vertical axis indicates the magnitude of the effect in basis points and the horizontal axis indicates the time horizon used to compute realized spread. The dotted colored line presents the effect of the short selling ban on sell side adverse selection (coefficients $\rho_1 + \rho_3$ from equation (25)). The solid colored line indicates the effect of the ban on buy side adverse selection (coefficient ρ_1 from equation (25)), and the grey line indicates the aggregate effect of the ban on adverse selection (κ_1 from equation (24)). Figure 3 illustrates that the effect of the ban on buy side realized spread is positive and stable across all time horizons for both large and small stocks.

The finding that the increase in realized spread during the ban appears to be concentrated on the buy side of the market is consistent with the notion that removing short sellers is likely to hurt liquidity because short sellers only provide liquidity when they trade passively with a liquidity demanding buyer. Consequently, the removal of passive – liquidity providing – short sales during the ban produces a negative shock to liquidity supply on the buy side of the market resulting in wider realized spreads for buyers.

Insert Table 5 Here

Insert Figure 3 Here

iii. Comparing the Adverse Selection and Realized Spread Channels

The prior two sections document that the ban was associated with an increase in both adverse selection and realized spread. In this section I provide an analysis comparing the magnitude of these two effects with one another. The purpose of this analysis is to highlight the economic magnitude – and thus relevance – of the relatively unexamined adverse selection channel linking short selling and liquidity.

Empirically, liquidity can be affected through one of four channels: adverse selection on the buy and sell sides of the market and realized spread on the buy and sell sides of the market. Figure 4 displays the economic magnitude of the effect of the ban on each of these four channels with respect to one another by combining Figures 2 and 3 which plot the effect of the ban on adverse selection and realized spread using DD and DDD regressions.

What becomes apparent from this figure is that the largest single effect that the ban appears to have on transaction costs comes through sell side adverse selection. For large stocks, this effect is nearly twice as large as the second largest effect, that of buy side realized spread. This finding is important, because most of the literature linking short selling to liquidity highlights the liquidity provision role of short sellers, and Figure 4 shows that, in the context of the 2008 short selling ban, these effects were secondary in magnitude compared to the effect of the ban on adverse selection.

Insert Figure 4 Here

To more formally test the hypothesis that the informational effect of the ban on transaction costs, through its effect on adverse selection, is greater than the realized spread channel, I use DDD regressions. In these regressions, the dataset employed to test the effect of the ban on aggregated adverse selection, presented in Table 2, is combined with the dataset employed to test the effect of the ban on aggregated realized spread, presented in Table 4. DDD regression are then estimated to test whether the effect of the ban on transaction costs through the adverse selection channel is greater than its effect through the realized spread channel.

I omit the full results for brevity sake, and because the coefficients, indicating the differential effect of the ban can be obtained by simply subtracting the results in Table 2 from those in Table 4. What is of interest is the test of significance for the coefficient indicating the difference between the two economic channels. For both large and small stocks, the measured effect of the ban on adverse selection is larger than the effect of the ban on realized spread in every case except for small stocks at the 1-minute horizon. This difference is statistically significant across every time horizon employed to measure adverse selection and realized spread for large stocks. For small stocks the effect of the ban on adverse selection is statistically greater than the effect on adverse selection for time horizons longer than 2 minutes. With time horizons shorter than two minutes the difference is statistically insignificant. These tests document that during the 2008 short selling ban, the effect of the ban on liquidity through adverse selection appears to dominate the ban's effect on liquidity through the realized spread.

iv. **Effect of the Ban on Effective Spread**

Adverse selection and realized spread sum to equal the effective spread, which is the total cost paid to execute a trade and provides one of the primary indicators of liquidity in financial markets. The prior sections document that the ban's impact on the adverse selection portion of the effective spread is concentrated on the sell side of the market and that the ban's effect on the realized spread portion is concentrated on the buy side. In this section I explore how these two effects aggregate to impact the total transaction costs paid by liquidity demanders during the short selling ban.

I explore the effect of the ban on effective spreads using the same basic DD and DDD regression models that have been used previously. In these models, the dependent variable is the difference in equally weighted daily average effective spread between a banned stock and its matched control for a given day. In equation (26), which measures the aggregate effect of the ban, effective spreads are averaged across all trades irrespective of sign. In equation (27), effective spreads are averaged across the buy and sell sides of the market separately allowing me to study the differential effect that the ban has on the buy and sell sides of the market. The same control variables are used as in the prior sections, and both specifications include stock pair fixed effects and standard errors are clustered at the date level.

$$ESP_{i,t}^{B} - ESP_{i,t}^{C} = \gamma_0 + \gamma_1 Ban_t + \Gamma X_{it} + \nu_i + \varepsilon_{it} \tag{26}$$

$$ESP_{i,t,s}^{B} - ESP_{i,t,s}^{C} = \beta_0 + \beta_1 Ban_t + \beta_2 SI_s + \beta_3 Ban_t * SI_s + \Gamma X_{it} + \nu_i + \varepsilon_{it} \tag{27}$$

The coefficient identifying the aggregate effect of the short selling ban on effective spreads from equation (26) is γ_1, the coefficient identifying the buy side effect is β_1 from equation (27) and the sum of coefficients $\beta_1 + \beta_3$ (from equation (27)) indicate the effect of the ban on seller-initiated effective spreads. Table 6 presents the results from these regressions.

Insert Table 6 Here

Among large and small stocks, the total effect (γ_1) of the ban on effective spreads amounts to a statistically significant increase of 4.8 and 12.7 basis points respectively. Relative to the average effective spreads paid outside the ban, these magnitudes indicate that the ban is associated with an increase in effective spread of 68% and 84% for large and small stocks respectively.

When the effect of the short selling ban on effective spread is divided into its effect on the buy and sell sides of the market in equation (27), the results indicate that among both large and small stocks, seller-initiated trades experience an increase in effective spread that is approximately 50% larger than the increase experienced by buyer-initiated trades. This asymmetry is to be expected given the prior findings that the ban's effect on adverse selection appears to dominate the ban's effect on realized spread, and that the increase in adverse selection is concentrated on the sell side of the market.

For large stocks average seller (buyer) initiated effective spread increases by 5.6 (3.7) basis points. For small stocks, the effect of the ban on seller (buyer) initiated effective spread is equal to 15.3 (10.1) basis points. For large (small) stocks, this amounts to an increase in the cost of transacting of 53% and 70% (80% and 102%) on the buy and sell sides of the market respectively.[17]

The cost of transacting is a key indicator of liquidity in financial markets, and the finding that the short selling ban deteriorates sell side liquidity significantly more than buy side liquidity has potential regulatory implications. Maintaining sell side liquidity – particularly periods of downward price pressure – is important to maintaining market stability (Huang and Wang (2008)). Consequently, regulations which restrict short selling during periods of downward price pressure may have the unintended effect of diminishing sell side liquidity when it is most needed.

v. Summary of Empirical Findings

The key findings from the empirical analysis can be summed up as follows:

1) The 2008 short selling ban led to an increase in adverse selection that was concentrated almost exclusively on the sell side of the market

2) The ban led to an increase in realized spread that was concentrated on the buy side of the market.

3) The effect of the ban on liquidity through the adverse selection channel is significantly greater than its effect through the realized spread channel.

[17] Outside the ban I am unable to find systematic differences between buy and sell side transaction costs.

4) Total transaction costs increase more for seller-initiated trades than for buyer-initiated trades during the ban.

5. Extensions: Institutional Investors and Adverse Selection

In this section I test the hypothesis that the increase in sell side adverse selection, which causes the overall increase in overall adverse selection during a ban will be more pronounced among stocks with higher institutional ownership. This prediction arises because the core of the model presented in section (3) is a description of how the ability to short sell impacts investor behavior – specifically the decision to gather information. The model implicitly assumes two things about the characteristics of the investors in the economy. First that they are actively in the market for information, and second that they are willing to use short selling to execute their trading strategies.

These two characteristics seem more descriptive of institutional investors than of their retail counterparts. There is a large literature documenting that stocks with higher institutional ownership tend to incorporate new information more quickly suggesting that institutional investors are more active in the market for information than are their retail counterparts.[18] In addition to being less active in the market for information, retail investors are also less likely to actively use short selling in their trading strategies.

These characteristics lead me to conjecture that the behavior described in the model is likely to be more descriptive of the effect of a short selling ban on the behavior of institutional investors than it is of their retail counterparts, suggesting that the predictions of the model will be more pronounced among stocks with higher institutional ownership.

[18] For example: Badrinath, Kale, and Noe (1994), Sias and Starks (1997), El-Gazzar (1998), Bartov, Radhakrishnan, and Krinsky (2000), Balsam, Bartov, and Marquardt (2002), and Jiambalvo, Rajgopal, and Venkatachalam (2002) among others.

This prediction is essentially a cross sectional one, and testing a cross sectional hypothesis requires distilling the effect of the ban for each stock into one number and then determining the effect of institutional ownership on that number. To accomplish this, I define ΔAS_{ti} as the difference in equally weighted daily average adverse selection at the one-minute time horizon between a banned stock and its matched control on a given day. I then use regressions to estimate the relation between ΔAS_{ti} and a host of dependent variables selected to capture relevant components indicating the state of the market for both the banned and control stocks.[19]

The relation between ΔAS_{ti} and the state of the market is estimated individually for each stock pair using data from August – October 2008 utilizing all dates where the short selling ban is *not* in force. These regressions provide a baseline estimate of the relation between ΔAS_{ti} and the dependent variables when short selling is allowed.

The coefficients from these regressions are saved for each stock pair and are used to calculate the expected value of ΔAS_{ti} for each stock pair each trading day in August through October – including when the short selling ban is in place. Abnormal adverse selection experienced by the banned stock is defined simply as the difference between the observed value of ΔAS_{ti} and the predicted value. This abnormal adverse selection is then averaged for a given stock across all days that the short selling ban is in place for that stock producing a single number indicating the average effect of the ban on adverse selection.

This methodology produces estimates for the average effect of the ban on adverse selection across all stocks that are remarkably similar to those presented in Table 2 column 1 from DD

[19] Control variables include: price, dollar volume, price volatility, return, and market cap. For each of these variables I include both Control the level of the given variable for the banned stock as well as the difference between the banned stock and its matched control.

regressions based on equation (22). In these regressions, the estimated effect of the ban on one-minute adverse selection is 2.5 and 4.5 basis points for large and small stocks respectively. Averaging the abnormal adverse selection calculated in this section across stocks suggests an average effect of the ban of 2.5 and 4.3 basis points for large and small stocks respectively.

To measure institutional holdings, I use 13 (f) filings to determine the fraction of a stock's shares held by institutional investors. These holdings are then standardized to give the number of standard deviations above or below the mean institutional holdings across all stocks in a given quarter. Dividing by the standard deviation across all stocks, as opposed to just those subject to the ban, does not affect the statistical significance or sign of any of the coefficients in the following tests. It does however convert the effect of the ban on adverse selection into one that is relative to the variation in institutional holdings across the broader market as opposed to just the variation in institutional ownership among just financial stocks, which may not be representative of the market as a whole. Standardized institutional holdings are then matched to each banned stock as of the closest observation on or prior to September 2008.

I estimate the relation between average abnormal adverse selection and institutional holding using cross-sectional regressions presented in equations (28) and (29).

$$Abnormal\ AS_i = \beta_0 + \beta_1 Inst\ Hldngs_i + \Gamma X_i + \varepsilon_i \tag{28}$$

$$Abnormal\ AS_{i,s} = \gamma_0 + \gamma_1 Inst\ Hldngs_i + \gamma_2 Inst\ Hldngs_i * SI_{is} + \gamma_3 SI_{is} + \Gamma X_i + \varepsilon_i \tag{29}$$

Equation (28) estimates the effect of institutional holdings on aggregate abnormal adverse selection while equation (29) estimates the effect of institutional holdings on adverse selection for the buy and sell sides of the market separately. In equation (28) the coefficient $\beta_1$indicates the effect of a one standard deviation increase in institutional holdings on average abnormal adverse selection. Equation (29) measures the signed effect. In this specification, the coefficient γ_1 identifies the effect a one standard deviation increase in institutional holdings has on buy side adverse selection while the sum of $\gamma_1 + \gamma_2$ indicates the effect of a one standard deviation increase in institutional holdings on sell side adverse selection. The hypothesis that the effects of the model will be more pronounced among stocks with higher institutional ownership suggests that both β_1 and the sum $\gamma_1 + \gamma_3$ will be statistically greater than zero. Table 7 presents the results from these tests.

The results presented in Table 7 indicate that a one standard deviation increase in institutional ownership is associated with a 2.6 basis point increase in overall abnormal adverse selection during the ban. This increase in adverse selection also appears concentrated on the sell side of the market. Buy side abnormal adverse selection declines by a statistically insignificant 3.7 basis points with a one standard deviation increase in institutional ownership while sell side abnormal adverse selection experienced during the ban increases by a statistically significant 9.4 basis points. These findings are consistent with the idea that the effects of the ban on adverse selection are more pronounced for stocks with greater institutional ownership, because the model is more likely to describe the behavior of institutional investors than their retail counterparts.

Insert Table 7 Here

6. Conclusion

This study investigates theoretically and empirically the relation between short selling and adverse selection. Prior studies indicate that the 2008 short selling ban was associated with an increase in adverse selection. This finding is puzzling, however, given the prevailing view of short sellers as informed traders and the lack of theoretical explanation for such an outcome.

I address the relation between short selling and adverse selection by noting that the ability to short sell changes the benefit of information differently for investors who do and do not own the asset. By rendering them unable to transact on negative information, a short selling ban decreases the benefit to information for investors who do not own the asset leading fewer of them to become informed. For investors who own the asset a short selling ban increases the relative value of information by rendering them the only investors able to trade on negative information, and consequently a greater fraction become informed. During a short selling ban, only investors who own the asset are allowed to sell, and more of these investors are informed relative to the no ban case. Consequently, the probability that a sell order originates from an informed trader increases leading to increased adverse selection on the sell side of the market. This dynamic leads to the prediction that a short selling ban will lead to an increase in adverse selection, but only on the sell side of the market.

Empirical tests provide evidence consistent with this prediction. I find that the observed increase in adverse selection during the 2008 short selling ban is concentrated almost exclusively on the sell side of the market. Additionally, I observe that the increase in sell side adverse selection is the largest component contributing to the increase in effective spreads observed during the ban and leads effective spreads to increase 50% more on the sell than buy side of the market during the ban.

This analysis has implications for multiple areas of finance. First, the study helps to fill a gap in the understanding of the link between short selling and liquidity. Prior explanations of the link between short selling and liquidity do provide for adverse selection. In this study, I suggest that an adverse selection link between short selling and adverse selection may exist through a ban's impact on the incentives to gather information. The need to better understand this channel is highlighted by the finding that the 2008 short selling ban's effect on liquidity through adverse selection dominates the ban's effect on realized spread.

The finding that sell side liquidity deteriorates more than buy side liquidity during the ban has potential regulatory implications and suggests that restricting short selling during periods of downward price pressure may have the unintended effect of diminishing sell side liquidity when it is most needed.

Also, the model's prediction that the inability to short sell will influence the characteristics of the investors who choose to become informed may have implications beyond liquidity. If fewer outside investors choose to become informed because of an inability to trade on negative information, then the role of outside investors as monitors of the firm may diminish when short selling is restricted. Fang, Huang, and Karpoff (2015) find evidence consistent with this notion. They document that easing short selling restrictions is associated with an increased likelihood of a firm being caught for misdeeds which occurred before the easing took place suggesting that when short selling restrictions are relaxed, more outside investors choose to gather information.

Lastly, this study has potential implications for how researchers approach the study of the determinates of liquidity. The asymmetry between the effect of the ban on buy and sell side liquidity documented in this study shows that additional insights can be gained by disaggregating liquidity measures and studying the buy and sell sides of the market separately.

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Appendix: Figures and Tables

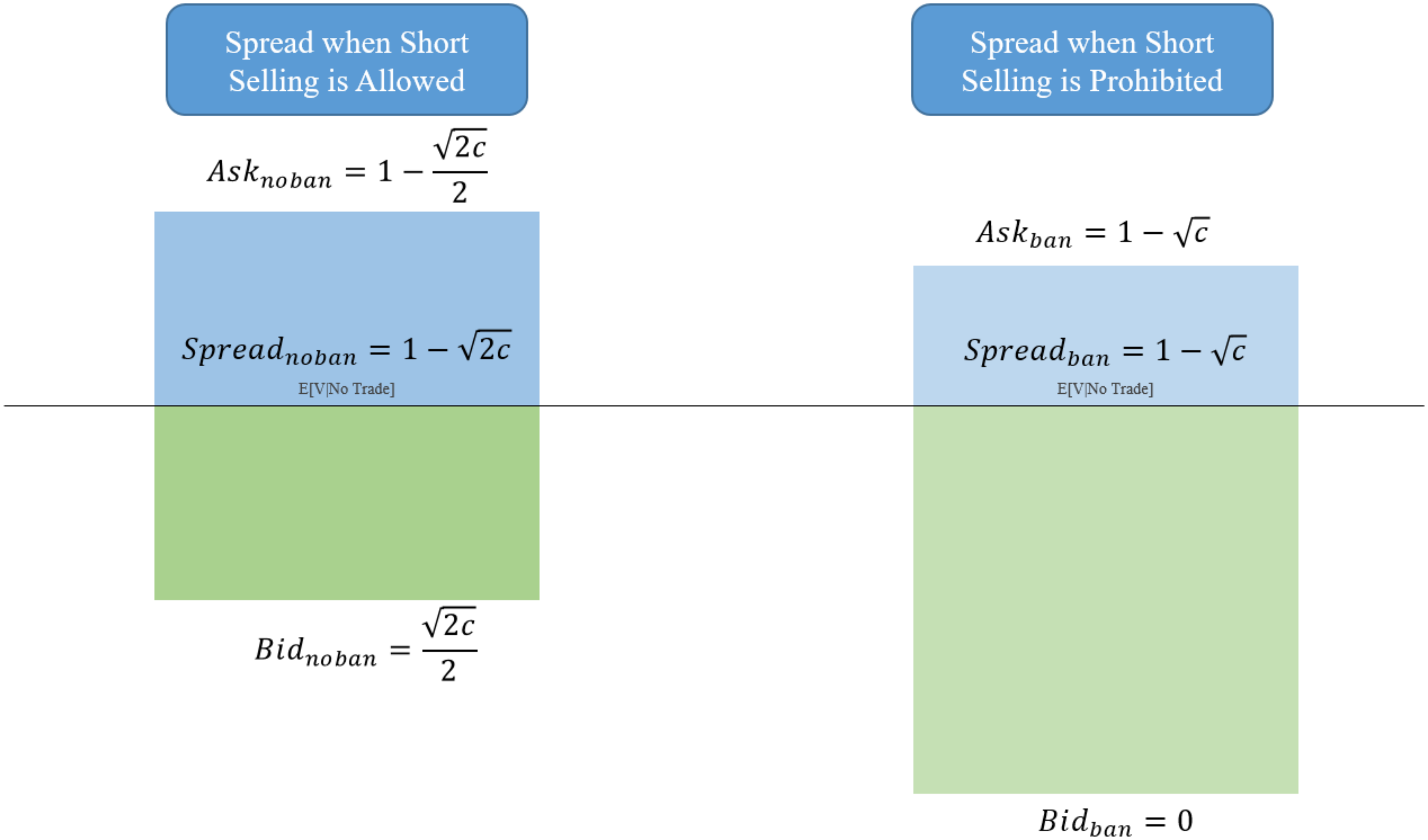
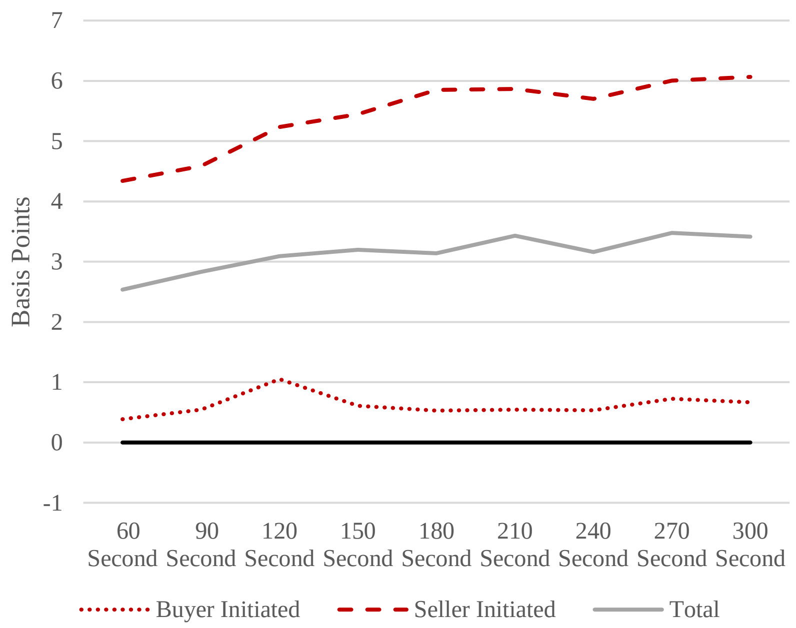
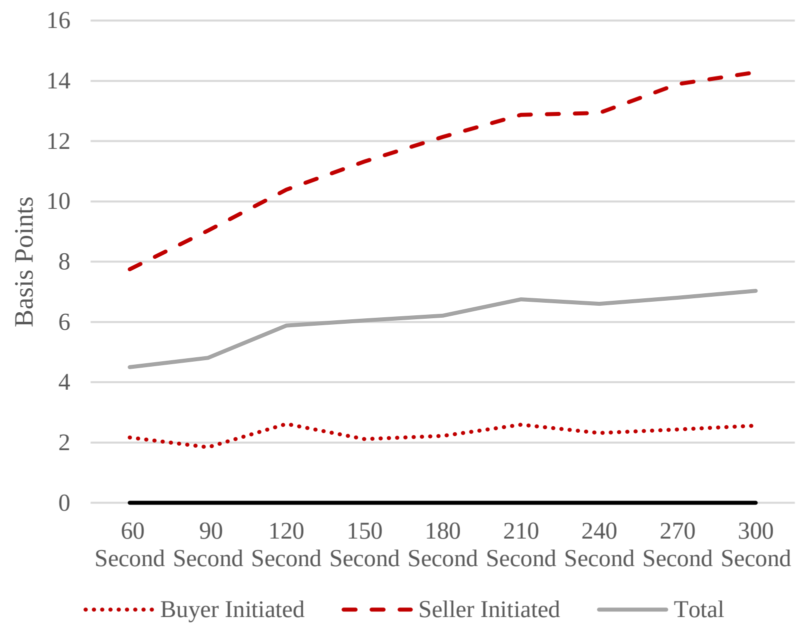


Figure 1: Comparison of the Bid-Ask Spread When Short Selling is Allowed and When it is Prohibited. This figure presents a graphical representation of the bid and ask prices predicted in the model both short selling is and is not allowed.

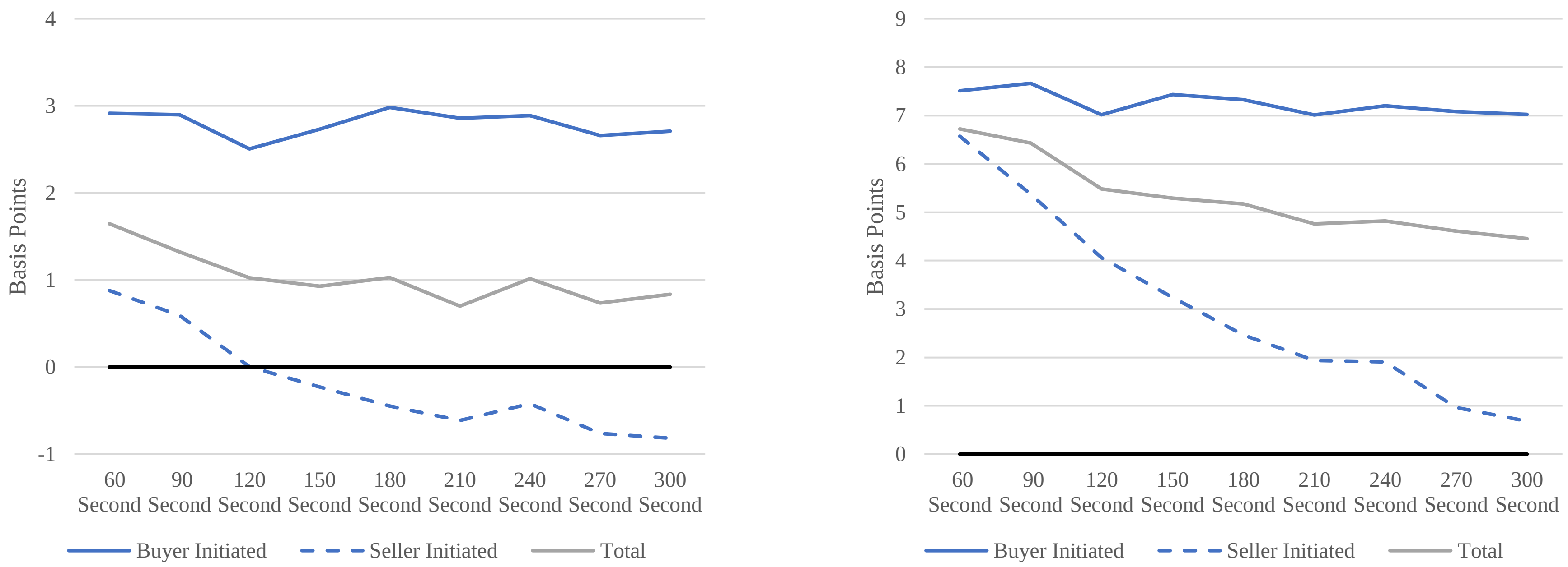




Panel A: Large Stocks

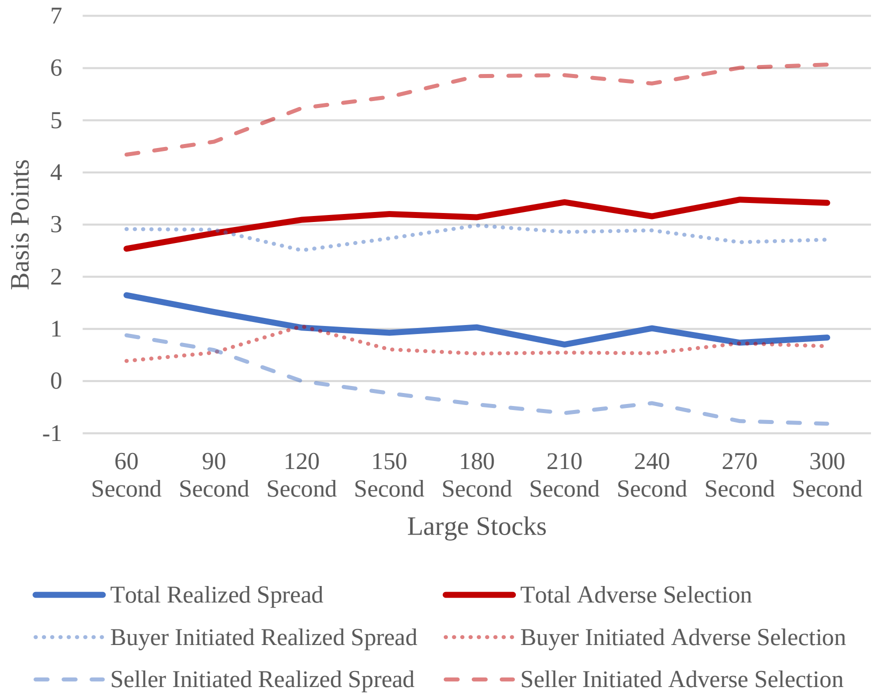
Panel B: Small Stocks

Figure 2: Regression Results for the Empact of the Short Selling Ban on Adverse Selection. This figure presents the regression coefficients from regressions estimating the effect of the short selling ban on adverse selection. Adverse selection is measured from DTAQ data employing time horizons from 60 seconds to 300 seconds as described in section (4.b). The effect of the ban on aggregate and buyer and seller-initiated adverse selection are estimated using equations (22) and (23). Coefficients from these regressions are saved and plotted in this figure. The effect of the ban on aggregate adverse selection is indicated by the coefficient η_1 from equation (22) which are plotted as the solid grey line. The effect of the ban on buyer-initiated adverse selection is indicated by the coefficient ξ_1 from equation (23) and are presented as the dotted colored line. The effect of the ban on seller-initiated adverse selection is the sum of coefficients $\xi_1 + \xi_3$ from equation (23) and are shown as the dashed colored line. The horizontal axis indicates the time frame used to measure adverse selection, and the vertical axis indicates the observed value of the indicated coefficients in basis points. Panel A presents the results for large stocks and Panel B presents the results for small stocks.

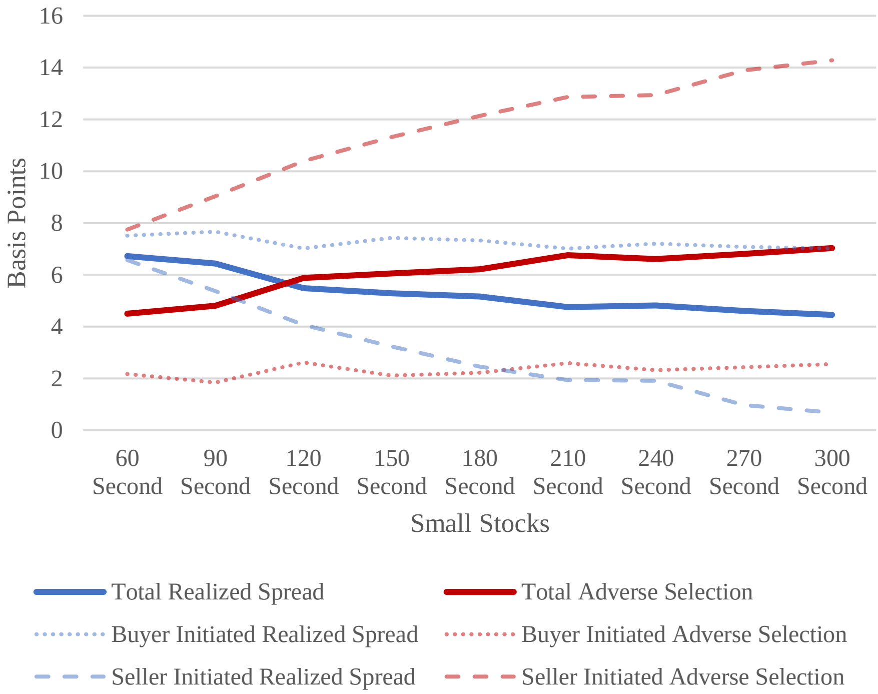


Panel A: Large Stocks Panel B: Small Stocks

Figure 3: Regression Results for the Impact of the Short Selling Ban on Realized Spread. This figure presents the coefficients from regressions estimating the effect of the short selling ban on realized spread. Realized spread is measured from DTAQ data employing time horizons from 60 seconds to 300 seconds as described in section (4.b). The effect of the ban on aggregate and buyer and seller-initiated realized spread are estimated using equations (24) and (25). Coefficients from these regressions are plotted in this figure. The effect of the ban on aggregate realized spread is indicated by the coefficient κ_1 from equation (24) which are plotted as the solid grey line. The effect of the ban on buyer-initiated realized spread is indicated by the coefficient ρ_1 from equation (25) and are presented as the dotted colored line. The effect of the ban on seller-initiated realized spread is the sum of coefficients $\rho_1 + \rho_3$ from equation (25) and is shown as the dashed colored line. The horizontal axis indicates the time frame used to measure realized spread, and the vertical axis indicates the observed value of the indicated coefficients in basis points. Panel A presents the results for large stocks and Panel B presents the results for small stocks.



Panel A: Large Stocks



Panel B: Small Stocks

Figure 4: Comparing the Adverse Selection and Realized Spread Channels. This figure combines Figures 2 and 3 to compare the effect of the ban on transaction costs through both the adverse selection and realized spread channels. Each point represents the estimated coefficient indicating the effect of the short selling ban on one of the given channels obtained from DD and DDD regressions estimated from equations (22) through (25). The time horizon used to measure adverse selection and realized spread varies from 60-300 seconds as indicated on the horizontal axis, the vertical axis indicates the magnitude of the observed effect in basis points. The red lines show the effect of the ban on adverse selection and the blue lines indicate the effect of the ban on realized spread. The solid lines present the aggregate effect of the ban, the dashed lines present the effect on the seller-initiated side of the market, and the dotted lines present the effect of the ban on the buyer-initiated side of the market. Panel A presents the results for large stocks and Panel B presents the results for small stocks.

Table 1
Summary Statistics for Matched Sample

This table presents descriptive statistics for the 257 stocks used in the regression analysis. Each stock subject to the ban is matched, with replacement, to a stock not subject to the ban that has the same listing exchange and options status. The match is based on market cap as of December 31, 2007, and average dollar trading volume over the first seven months of 2008 based on the distance measure below.

$$Distance_{i,j} = \frac{|Mktcp_i - Mktcp_j|}{Mktcp_i} + \frac{|Dvol_i - Dvol_j|}{Dvol_i}$$

Stocks are divided into three groups based on their market cap as of December 31, 2007. Large stocks are those stocks with market caps in the top five NYSE deciles, small stocks are those stocks with market caps in NYSE deciles 3-5. Results are provided both in aggregate and by size group. Average dollar volume and market cap statistics are reported for the total as well as for each of the three size groups separately. T statistics and p values for a t-test on the difference between the banned and matched stocks are performed and the results provided below.

	Total		**Large**		**Small**	
N	257		139		118	
Average Distance	0.142		0.171		0.108	
	Banned	**Matched**	**Banned**	**Matched**	**Banned**	**Matched**
Average Monthly Dollar Volume (Millions)	2,838	2,421	5,046	4,271	260	259
t statistic	(0.75)		(0.81)		(0.02)	
p value	0.451		0.421		0.981	
Market Cap (Millions)	12,547	13,049	22,363	23,301	1,081	1,075
t statistic	(-0.16)		(-0.16)		(0.15)	
p value	0.876		0.87		0.881	

Table 2
Effect of the Ban on Adverse Selection

This table presents the results from DD regressions indicating the effect of the short selling ban on adverse selection for large stocks (Panel A) and small stocks (Panel B) using time horizons of one minute to five minutes to compute adverse selection in basis points. Small stocks are those stocks which have a market cap in NYSE deciles 3-5, and large stocks are those stocks subject to the short selling ban which have a market cap in the largest 5 NYSE deciles as of December 31, 2007. Each banned stock is matched to a control stock based on listing exchange, options status, dollar volume, and market cap. Equally weighted adverse selection is computed for each stock each day. Then the difference in daily average adverse selection between a banned stock and its matched control is computed and is the dependent variable used in the following DD regression.

$$AS_{i,t}^{B,\Delta t} - AS_{i,t}^{C,\Delta t} = \eta_0 + \eta_1 Ban_t + \Gamma X_{it} + \nu_i + \varepsilon_{it}$$

Presented in the table are the estimated coefficients from the above regression for the effect of the short selling ban on one to five-minute adverse selection in columns one through five respectively. In this specification, the coefficient κ_1 indicates the effect of the short selling ban aggregate realized spread. P values testing the hypothesis that κ_1 is equal to zero are presented in parentheses.

Panel A: Large Stocks

	1-Minute (1)	2-Minute (2)	3-Minute (3)	4-Minute (4)	5-Minute (5)
Ban (η_1)	2.536***	3.092***	3.138***	3.161***	3.416***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	9452	8000	8000	8000	8000
RSQ	0.257	0.238	0.228	0.205	0.187
Stock FE	Yes	Yes	Yes	Yes	Yes
Date Clustered SE	Yes	Yes	Yes	Yes	Yes

Panel B: Small Stocks

	1-Minute (1)	2-Minute (2)	3-Minute (3)	4-Minute (4)	5-Minute (5)
Ban (η_1)	4.500***	5.876***	6.209***	6.604***	7.032***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	8000	8000	8000	8000	8000
RSQ	0.395	0.389	0.397	0.392	0.371
Stock FE	Yes	Yes	Yes	Yes	Yes
Date Clustered SE	Yes	Yes	Yes	Yes	Yes

* p<.1, **p<.05, ***p<.01

Table 3
Effect of the Ban on Signed Adverse Selection

This table presents the results from DDD regressions indicating the effect of the short selling ban on signed adverse selection for large stocks (Panel A) and small stocks (Panel B) using time horizons of one minute to five minutes to compute adverse selection in basis points presented in columns one through five respectively. Small stocks are those stocks which have a market cap in NYSE deciles 3-5, and large stocks are those stocks subject to the short selling ban which have a market cap in the largest 5 NYSE deciles as of December 31, 2007. Each banned stock is matched to a control stock based on listing exchange, options status, dollar volume, and market cap. The equally weighted adverse selection is computed for each stock each day. Then the difference in daily average adverse selection and adverse selection between a banned stock and its matched control is computed and is the dependent variable used in the DDD regressions. Presented in the table are the estimated coefficients from the below regression for the effect of the short selling ban on adverse selection.

$$AS_{i,t,s}^{B,\Delta t} - AS_{i,t,s}^{C,\Delta t} = \xi_0 + \xi_1 Ban_t + \xi_2 SI_s + \xi_3 Ban_t * SI_s + \Gamma X_{it} + \nu_i + \varepsilon_{it}$$

In this specification, the coefficient ξ_1 indicates the effect of the short selling ban on buyer-initiated adverse selection, the sum of coefficients $\xi_1 + \xi_3$ indicates the seller-initiated effect, and the coefficient ξ_3 indicates the difference between the buyer and seller-initiated effect. P values testing the hypothesis that the relevant coefficients are equal to zero are presented in parentheses.

Panel A: Large Stocks

	1-Minute (1)	2-Minute (2)	3-Minute (3)	4-Minute (4)	5-Minute (5)
Buyer (ξ_1)	0.386	1.051	0.528	0.534	0.666
	(0.656)	(0.336)	(0.674)	(0.722)	(0.706)
Seller ($\xi_1 + \xi_3$)	4.340***	5.232***	5.874***	5.702**	6.065*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Difference (ξ_3)	3.954**	4.181*	5.319**	5.168	5.399
	(0.019)	(0.056)	(0.050)	(0.114)	(0.163)
N	18904	18904	18904	18904	18904
R-sq	0.035	0.035	0.032	0.030	0.027
Stock FE	Yes	Yes	Yes	Yes	Yes
Date Clustered SE	Yes	Yes	Yes	Yes	Yes

Panel B: Small Stocks

	1-Minute (1)	2-Minute (2)	3-Minute (3)	4-Minute (4)	5-Minute (5)
Buyer (ξ_1)	2.166***	2.616**	2.217	2.316	2.554
	(0.009)	(0.034)	(0.146)	(0.262)	(0.299)
Seller ($\xi_1 + \xi_3$)	7.747***	10.393***	12.135***	12.936***	14.284**
	(0.030)	(0.014)	(0.015)	(0.008)	(0.043)
Difference (ξ_3)	5.581***	7.777***	9.918***	10.62**	11.73**
	(0.001)	(0.004)	(0.003)	(0.019)	(0.025)
N	16000	16000	16000	16000	16000
R-sq	0.171	0.144	0.126	0.108	0.095
Stock FE	Yes	Yes	Yes	Yes	Yes
Date Clustered SE	Yes	Yes	Yes	Yes	Yes

* p<.1, **p<.05, ***p<.01

Table 4
Effect of the ban on Realized Spread

This table presents the results from DD regressions indicating the effect of the short selling ban on signed realized spread for large stocks (Panel A) and small stocks (Panel B) using time horizons of one minute to five minutes to compute realized spread in basis points. Small stocks are those stocks which have a market cap in NYSE deciles 3-5, and large stocks are those stocks subject to the short selling ban which have a market cap in the largest 5 NYSE deciles as of December 31, 2007. Each banned stock is matched to a control stock based on listing exchange, options status, dollar volume, and market cap. Equally weighted realized spread is computed for each stock each day. Then the difference in daily average realized spread between a banned stock and its matched control is computed and is the dependent variable used in the DD regressions.

$$RESP_{i,t}^{B,\Delta t} - RESP_{i,t}^{C,\Delta t} = \kappa_0 + \kappa_1 Ban_t + \Gamma X_{it} + \nu_i + \varepsilon_{it}$$

Presented in the table are the estimated coefficients from the above regression for the effect of the short selling ban on one to five-minute realized spread in columns one through five respectively. In this specification, the coefficient κ_1 indicates the effect of the short selling ban aggregate realized spread. P values testing the hypothesis that κ_1 is equal to zero are presented in parentheses.

Panel A: Large Stocks

	1-Minute (1)	2-Minute (2)	3-Minute (3)	4-Minute (4)	5-Minute (5)
Ban (κ_1)	1.646***	1.023***	1.028**	1.013**	0.837
	(0.000)	(0.005)	(0.019)	(0.036)	(0.101)
N	9452	9452	9452	9452	9452
RSQ	0.175	0.135	0.111	0.095	0.080
Stock FE	Yes	Yes	Yes	Yes	Yes
Date Clustered SE	Yes	Yes	Yes	Yes	Yes

Panel B: Small Stocks

	1-Minute (1)	2-Minute (2)	3-Minute (3)	4-Minute (4)	5-Minute (5)
Ban (κ_1)	6.722***	5.483***	5.169***	4.819***	4.455***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	8000	8000	8000	8000	8000
RSQ	0.257	0.238	0.228	0.205	0.187
Stock FE	Yes	Yes	Yes	Yes	Yes
Date Clustered SE	Yes	Yes	Yes	Yes	Yes

* p<.1, **p<.05, ***p<.01

Table 5
Effect of the Ban on Signed Realized Spread

This table presents the results from DDD regressions indicating the effect of the short selling ban on signed realized spread for large stocks (Panel A) and small stocks (Panel B) using time horizons of one minute to five minutes to compute realized spread in basis points presented in columns one through five respectively. Small stocks are those stocks which have a market cap in NYSE deciles 3-5, and large stocks are those stocks subject to the short selling ban which have a market cap in the largest 5 NYSE deciles as of December 31, 2007. Each banned stock is matched to a control stock based on listing exchange, options status, dollar volume, and market cap. The equally weighted adverse selection and realized spread is computed for each stock each day. Then the difference in daily average adverse selection and realized spread between a banned stock and its matched control is computed and is the dependent variable used in the DDD regressions. Presented in the table are the estimated coefficients from the below regression for the effect of the short selling ban on realized spread.

$$RESP_{i,t,s}^{B,\Delta t} - RESP_{i,t,s}^{C,\Delta t} = \rho_0 + \rho_1 Ban_t + \rho_2 SI_s + \rho_3 Ban_t * SI_s + \Gamma X_{it} + \nu_i + \varepsilon_{it}$$

In this specification, the coefficient ρ_1 indicates the effect of the short selling ban on buyer-initiated realized spread, the sum of coefficients $\rho_1 + \rho_3$ indicates the seller-initiated effect, and the coefficient ρ_3 indicates the difference between the buyer and seller-initiated effect. P values testing the hypothesis that the relevant coefficients are equal to zero are presented in parentheses.

Panel A: Large Stocks

	1-Minute (1)	2-Minute (2)	3-Minute (3)	4-Minute (4)	5-Minute (5)
Buyer (ρ_1)	2.914***	2.506**	2.982**	2.888*	2.709
	(0.001)	(0.021)	(0.018)	(0.056)	(0.127)
Seller ($\rho_1 + \rho_3$)	0.878	0.002	-0.449	-0.421	-0.817
	(0.000)	(0.021)	(0.239)	(0.460)	(0.817)
Difference (ρ_3)	-2.036	-2.504	-3.431	-3.309	-3.526
	(0.210)	(0.251)	(0.207)	(0.312)	(0.362)
N	18904	18904	18904	18904	18904
R-sq	0.012	0.010	0.010	0.009	0.009
Stock FE	Yes	Yes	Yes	Yes	Yes
Date Clustered SE	Yes	Yes	Yes	Yes	Yes

Panel B: Small Stocks

	1-Minute (1)	2-Minute (2)	3-Minute (3)	4-Minute (4)	5-Minute (5)
Buyer (ρ_1)	7.510***	7.013***	7.328***	7.200***	7.024***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.007)
Seller ($\rho_1 + \rho_3$)	6.571***	4.060**	2.462	1.910	.0681
	(0.001)	(0.002)	(0.008)	(0.007)	(0.025)
Difference (ρ_3)	-0.939	-2.953	-4.866	-5.290	-6.343
	(0.563)	(0.206)	(0.111)	(0.193)	(0.192)
N	16000	16000	16000	16000	16000
R-sq	0.099	0.082	0.063	0.053	0.046
Stock FE	Yes	Yes	Yes	Yes	Yes
Date Clustered SE	Yes	Yes	Yes	Yes	Yes

* p<.1, **p<.05, ***p<.01

Table 6
Effect of the Ban on Effective Spread

This table presents the results for regressions testing the effect of the short selling ban on effective spreads for large and small stocks. Effective spread is computed as the equally weighted daily average effective spread. The total effect of the short selling ban on effective spreads is estimated using the difference-in-difference regression from equation (26). In this regression, the dependent variable is the difference in daily average effective spread between a banned stock and its matched control. The effect of the short selling ban on buyer and seller-initiated effective spread is estimated using the following difference-in-difference-in-difference regression from equation (27). In this regression, equally weighted average effective spread is computed daily for buyer and seller-initiated trades, where trades are signed using the Lee and Ready (1991) algorithm. The dependent variable is the difference in equally weighted average effective spread between a banned stock and its matched control on a given day for either all buy or sell trades. This table presents only the coefficients indicating the effect of the short selling ban on effective spreads. The coefficient γ_1 from equation (26) indicates the total effect of the short selling ban on transaction costs. The coefficient β_1 from equation (27) indicates the effect of the ban on buyer-initiated trades, and the sum of $\beta_1 + \beta_2$ indicates the effect of the ban on seller-initiated trades. Significance for the seller-initiated effect is determined by an F test of joint significance. Panel A presents the aggregate effect of the ban on effective spread, and panel B presents the signed effect of the ban on effective spread. P values are provided in parentheses.

Panel A: Aggregate Effect

	Large Stocks (1)	Small Stocks (2)
Total Effect (γ_1)	4.770***	12.66***
	(0.000)	(0.000)
N	9452	8000
R-sq	0.618	0.469
Stock FE	Yes	Yes
Date Clustered SE	Yes	Yes

Panel B: Signed Effect

	Large Stocks (1)	Small Stocks (2)
Buyer-initiated Effect (β_1)	3.773***	10.11***
	(0.000)	(0.000)
Seller-initiated Effect ($\beta_1 + \beta_3$)	5.596***	15.317***
	(0.000)	(0.000)
Difference (β_2)	1.823***	5.207***
	(0.000)	(0.000)
N	18904	16000
R-sq	0.581	0.434
Stock FE	Yes	Yes
Date Clustered SE	Yes	Yes

* p<.1, **p<.05, ***p<.01

Table 7

Institutional Ownership and Abnormal Adverse Selection

This table presents results from regressions indicating the effect of institutional holdings on abnormal adverse selection. Abnormal adverse selection is estimated following the process described in section 5. Institutional ownership is estimated using data from 13f filings and is standardized so that it indicates the number of standard deviations above or below the mean a given stock's level of institutional ownership is. Columns 1 and 2 present the effect of institutional ownership on aggregate adverse selection as estimated from equation (28). Columns 3 and 4 present the effect of institutional ownership on signed adverse selection as estimated from equation (29). Adverse selection is measured in basis points employing a 60 second horizon. T statistics are provided in parentheses except where the seller effect is estimated, where it is the f statistic from an f test of joint significance of the variables $\gamma_1 + \gamma_2$ from equation (29). Even numbered columns include control variables while odd numbered columns do not.

	(1)	(2)	(3)	(4)
$Total\ Effect\ (\beta_1)$	2.611**	2.585**		
	(2.25)	(2.22)		
$Buyer\ Effect\ (\gamma_1)$			-3.749	-3.677
			(-0.82)	(-0.79)
$Seller\ Effect\ (\gamma_1 + \gamma_2)$			9.401**	9.473**
			(4.21)	(4.09)
$Difference\ (\gamma_2)$			13.15**	13.15**
			(2.03)	(2.01)
N	257	257	514	514
R-sq	0.019	0.098	0.012	0.017
Control Variables	No	Yes	No	Yes

* p<.1, **p<.05, ***p<.01

CHAPTER II

Short Selling and Attention Around the Business Cycle

PETER N. DIXON AND ERIC K. KELLEY

Peter Dixon served as a research assistant to Eric Kelley during the production of this chapter. The ideas presented are the joint work of both Peter and Eric. The empirical analysis was primarily executed by Peter. Eric was the primary writer of section I.

ABSTRACT

We show that firm-level short interest predicts negative returns for individual stocks during economic expansions, while aggregate short interest predicts negative market returns during recessions. Viewing short sellers as informed traders, these findings are consistent with Kacperczyk, Van Nieuwerburgh, and Veldkamp's (2016) model in which rational yet cognitively constrained traders optimally allocate attention among firm-specific and systematic signals. In their model, traders collect aggregate (firm-specific) information in recessions (expansions) because these times are marked by higher (lower) aggregate volatility and price of risk.

1. Introduction

When faced with information processing constraints, even the most sophisticated and capital rich investor must allocate the scarce resource of attention. The resulting allocation choices directly influence the composition and performance of managed portfolios. More broadly, since information acquisition—or the lack thereof—drives price efficiency (e.g., Grossman and Stiglitz (1980)), attention allocation has implications for the welfare of market participants, the severity and duration of mispricing, and the extent to which stock prices may guide firms' real investment decisions (Dow and Gorton (1997), Chen, Goldstein, and Jiang (2007)).

Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), hereafter KVV, model a multi-asset framework in which rational yet cognitively constrained traders optimally choose which types of information to observe prior to forming portfolios. Signals that are either systematic or firm-specific in nature represent these different types of information. Since recessions coincide with greater aggregate volatility and an elevated price of risk, constrained information processors allocate relatively more attention to signals affecting all firms than to signals affecting only a single firm. The opposite prediction holds for expansionary times. In short, the marginal benefit of collecting systematic (as opposed to idiosyncratic) signals is greatest during recessions, and rational agents respond accordingly.

We offer a novel test of the rational inattention model by analyzing the trading decisions of short sellers. This laboratory is appealing because empirical evidence portrays short sellers as informed investors. First, Saffi and Sigurdsson (2010) and Boehmer and Wu (2012) show that stocks with lower shorting constraints and higher shorting activity, respectively, have more efficient prices. These findings are consistent with a Grossman and Stiglitz (1980) world in which short sellers represent informed traders. Second, a large literature relates shorting activity to low future stock returns, again suggesting short sellers possess information relevant to future prices. Most of this work uses cross-sectional tests to show that stocks with greater short selling experience lower future returns than those with less shorting. Prominent studies that document this effect using monthly or bi-monthly short interest include Figlewski (1981) and Boehmer, Huszar, and Jordan (2010), hereafter BHJ. Those employing daily data on equity lending and shorting flow include Cohen, Diether, and Malloy (2007) and Diether, Lee, and Werner (2009). In addition, Boehmer, Jones, and Zhang (2008) and Kelley and Tetlock (2016) show that both institutional and retail short sellers correctly anticipate future negative returns. Recent work by Rapach, Ringgenberg, and Zhou (2016) complements the cross-sectional literature by demonstrating that short interest aggregated across stocks predicts market returns over the subsequent year. Short sellers' ability to anticipate aggregate cash flows primarily drives this predictability.

While the literature generally agrees that short sellers successfully anticipate stock returns, the timing and nature of this predictability is largely unexplored. We examine how short sellers' ability to predict aggregate and firm-specific stock returns varies across the business cycle and offer new insights into the attention allocation decisions of informed traders. To the extent that switching attention from aggregate to firm-specific signals drives time variation in short sellers' cross-sectional and aggregate return predictability, our two main results are consistent with the rational attention allocation theory of KVV. In our first set of tests, we examine a portfolio that is long stocks with low short interest and short stocks with high short interest. Consistent with prior literature, this portfolio has a positive alpha over the full time series from 1973 to August 2015. More importantly, the alpha is over twice as large in expansions as it is during recessions, suggesting that short sellers' trades convey less firm-specific information during recessions compared to expansions.

Our second set of tests examines the relation between Rapach, Ringgenberg, and Zhou's (2016) short interest index (*SII*) and future aggregate market returns. We show that aggregate short interest predicts future market returns economically and statistically more strongly during economic recessions than during economic expansions. Specifically, we find that during a recession (expansion), a one standard deviation increase in *SII* is associated with a future three-month excess return of -1.7% (-0.4%), -1.4% (-0.2%), and -1.3% (-0.2%) on the CRSP value weighted index, the CRSP equal weighted index, and the S&P 500 respectively. During recessions, the relation between each of the three indices and the SII is highly significant. However, for the S&P 500 and the CRSP value weighted index the observed relation is statistically insignificant during expansions. Taken as a whole, our results are consistent with one class of informed investors – short sellers – shifting their attention from firm-specific information in expansions to aggregate information in recessions.

These results are robust to a number of alternative specifications. First, our cross-sectional results hold when we allow factor loadings to vary with the business cycle and when we measure abnormal returns using Daniel, Grinblatt, Titman, and Wermers (1997) characteristic adjustments (DGTW). Second, our findings are robust to two alternative real-time recession indicators: the probability of recession based on the work of Chauvet and Piger (2008) and a measure based on the Chicago Fed's National Activity Index. Finally, we divide our sample in June 1988 and verify our results in both subsamples.

Our paper joins a budding empirical literature on rational attention allocation. Most closely related is the analysis in KVV. These authors test their model by examining the covariances between actively managed mutual funds' quarterly position changes and future aggregate and firm-level fundamentals. They find that during expansions, funds tilt their holdings in the cross-section of stocks toward those with strong future earnings. In contrast, during recessions, funds tend to shift into and out of equities in a manner that anticipates future aggregate earnings shocks. This evidence speaks directly to how certain traders allocate attention but is silent on the extent to which the attention reallocation is profitable. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), in contrast, show certain funds switch from stock selection strategies in expansions to market timing strategies in recessions and that these particular funds generate positive alpha. In other words, these authors identify skilled investors as those who switch focus from firm-specific to aggregate information across the business cycle. Because we study short interest aggregated across all short sellers, we conduct no analysis at the trader level. Rather, in our analysis, we speak to business cycle variations in an entire class of investors' ability to identify firm-specific and market-wide mispricing.

Other authors provide empirical evidence that attention allocation matters for prices. Ben-Rephael, Da, and Israelsen (2016) show that institutional attention facilitates the incorporation of information in earnings announcements and analyst recommendation changes. In a similar vein, DellaVigna and Pollet (2009) and Hirshleifer, Lim, and Teoh (2009) show that markets respond sluggishly to earnings announcement information when investors are likely distracted by other stimuli. A key difference between these studies and ours is that they relate attention to efficient incorporation of *public* information. We consider how informed traders allocate attention by observing the manner in which their trades convey *private* information and predict returns.

Our analysis also suggests potential real implications of rational attention allocation. Kempf, Manconi, and Spalt (2016) argue that investors who allocate attention elsewhere play a diminished monitoring role. Firms with such "distracted" shareholders are more likely to announce value-destroying acquisitions, cut dividends, and retain CEOs in the wake of poor performance. Other work shows short sellers are effective monitors. For example, Karpoff and Lou (2010) show that short sellers are able to identify financial misconduct well in advance of other market participants and Fang, Huang, and Karpoff (2015) relate short-selling constraints to greater earnings management. As short-sellers allocate attention away from firm-specific signals in recessions, managers may engage in more value-destroying and nefarious behavior in these states of the world. This is particularly concerning in recessions because some combination of greater operating and financial leverage, weak fundamental performance, and underdiversified managers may facilitate inefficient outcomes ranging from excessive risk-taking to underinvestment (e.g., Jensen and Meckling, (1976); Myers, (1984)).

2. Hypothesis Development

In KVV's model, investors make two rounds of choices. In the first, they allocate attention amongst firm-specific and aggregate signals. In the second, they form portfolios. While this model is static in nature, its rich predictions highlight how investors optimally reallocate attention across the business cycle as the price of risk and volatility evolve. In particular, since aggregate volatility and the price of risk both tend to rise during recessions[20], investors in this model find it more valuable to allocate attention to aggregate (firm-specific) signals in recessions (expansions). Intuitively, recessions are times when aggregate shocks have the greatest effects on overall portfolios, and it is during these times when investors most value the reduction in risk that results from learning aggregate signals. Since attention is a scarce resource in the model, investors who learn more about aggregate signals must necessarily learn less about firm-specific signals.

In standard information asymmetry models (e.g, Kyle (1985)), informed traders gain at the expense of the uninformed. KVV's model implies the nature of these gains varies across the business cycle. This reasoning leads to our main hypotheses regarding short sellers' ability to predict future stock returns which we refer to as the *Stock Selection Hypothesis* and the *Market Timing Hypothesis*. According to the *Stock Selection Hypothesis*, short interest will be a stronger cross-sectional predictor of stock returns during expansions than recessions. During expansions, informed traders, as proxied by short-sellers, should allocate attention to firm-specific signals, and

[20] KVV summarize this literature in their Section 3.2.

the profitability of their trading strategies should manifest cross-sectionally via the stocks they trade. According to the *Market Timing Hypothesis*, short interest will be a stronger time-series predictor of stock returns during recessions than expansions. This is because during recessions, informed traders should reallocate attention to aggregate signals, and their trading should better predict future aggregate stock returns.

3. Data

We analyze short interest data for NYSE, AMEX, and NASDAQ listed stocks as compiled and reported by the exchanges from 1973 to 2015. Exchanges reported outstanding short interest once per month (as of the 15th) from 1973 through August, 2007 and twice per month (as of the 15th and 30th) from September, 2007 until present. We limit our analysis to the mid-month reports for consistency over the entire time series. We obtain these data primarily from Compustat, which provides short interest data for NYSE and AMEX listed firms from 1973 to 2015 and for NASDAQ listed firms from 2004 to 2015.We supplement the Compustat data with monthly short interest for NASDAQ-listed securities obtained directly from NASDAQ for the years 1988-2003.[21] For each stock-month, we normalize short interest by computing the fraction of shares held short as the number of shares held short divided by the number of shares outstanding. Henceforth, we refer to this fraction as short interest.

We obtain stock specific information on shares outstanding, returns, delisting returns, price, and trading volume from CRSP. We consider only ordinary common stocks that have traded for at least one year and require non-missing data for return, trading volume, shares outstanding, and share price. To measure recessions, we use official business cycle dates published by the

[21] The NASDAQ short interest dataset is not perfectly complete as noted also by Chen and Singal (2003) and Boehmer, Huszar, and Jordan (2010) data is missing for February and July of 1990.

National Bureau of Economic Research (NBER). Since the NBER establishes these dates *ex post* and our hypotheses describe real-time attention allocation decisions of short-sellers, we employ two real-time business cycle measures similar to those used in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014). The first is the probability of recession (*Pr_REC*), as estimated by Chauvet and Piger (2008) using a dynamic-factor-Markov-switching model applied to four monthly macroeconomic variables. We obtain the time series of recession probabilities from Marcelle Chauvet's website.[22] The second alternative measure for the business cycle is based on the Chicago Fed's National Activity Index (*CFNAI*).

In Table 8 we present descriptive statistics for our sample. In our descriptive statistics, we split our sample into two periods with the first period beginning in January 1973 and ending in May 1988 and the second period beginning in June 1988 and running through August 2015. This partition ensures that both periods have approximately the same number of recession months (34 in the first period and 38 in the second period). We also note that since the NASDAQ short interest data begins in June 1988, our subsample procedure facilitates a cursory analysis of the exclusion of NASDAQ securities.

Insert Table 8 Here

In Panel A of Table 8, we present descriptive statistics for the 25th, 50th, and 75th percentiles, as well as the mean value of short interest for the two time periods considered. In Panels B and C, we present similar statistics for stock price and market cap (in thousands) for the two periods. Panel D presents other statistics, including the average number of stocks with zero and non-zero reported short interest each month and the number of NBER recession months in a given subsample. From Table 8 we observe that average short interest has increased over time. Further,

[22] https://sites.google.com/site/marcellechauvet/u-s-probabilities-of-recession-chauvet-and-piger-2008

the median stock price declines in the latter period coincident with the addition of NASDAQ securities. Also, we find that the addition of NASDAQ securities increases our average number of observations each month from just over a thousand to over four thousand.

4. Empirical Analysis

In our empirical analysis, we test the *Stock Selection* and *Market Timing Hypotheses* by examining how the relation between short selling and future returns varies with the business cycle. We proceed with a cross-sectional analysis of the information content of short sales around the business cycle. This analysis follows the established literature documenting that in the cross section of stocks, high short selling conveys information about low future returns of individual stocks.[23] We then consider the relation between short interest and aggregate stock returns by building on the recent work of Rapach, Ringgenberg, and Zhou (2016) who document that detrended aggregate short interest strongly predicts future returns on the S&P 500 index.

a. Cross Sectional Results

Our first set of analysis tests the *Stock Selection Hypothesis*. Specifically, we assess how short sellers' ability to explain the cross-section of individual security returns varies around the business cycle. A large literature documents the informed nature of short sells, and our tests most closely follows those relating the cross-section of short interest to future stock returns such as Figlewski (1981), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2005), and BHJ. To test the hypothesis that short interest better predicts firm-specific returns during expansions than during recessions, we begin with the framework of BHJ. They find

[23] See for example Figlewski (1981), BHJ, Cohen, Diether, and Malloy (2007) , Diether, Lee, and Werner (2009), Boehmer, Jones, and Zhang (2008), and Kelley and Tetlock (2016)

that a portfolio with long exposure to lightly shorted stocks and short exposure to highly shorted stocks earns a positive abnormal return over the subsequent month during the 1988 to 2005 time period.

We sort stocks each month according to short interest on the 15th of the prior month. We then form portfolios of lightly and heavily shorted stocks as those with short interest below (above) some extreme threshold percentile in the prior month's cross-sectional short-interest distribution. Following BHJ, we consider the 10th, 5th, and 1st percentiles as the thresholds for lightly shorted stocks and the 90th, 95th, and 99th percentiles as thresholds for heavily shorted stocks. We then compute equal-weighted returns for the three lightly and heavily shorted stock portfolios over the h months following the formation month. For $h > 1$, we overlap returns in calendar time as in Jegadeesh and Titman (1993). Lastly, we compute three spread portfolio returns corresponding to portfolios that buy and sell the 10th and 90th short interest percentile portfolios, the 5th and 95th short interest percentile portfolios, and the 1st and 99th short interest percentile portfolios.

We evaluate the profitability of these strategies using the Carhart (1997) four-factor model augmented with a recession dummy:

$$ret_{t+1:t+h}^{p} = \alpha_e + \alpha_r Rec_t + \beta MKTRF_t + \ sSMB_t + hHML_t + mMOM_t + \varepsilon_t \qquad (1)$$

The dependent variable $ret_{t+1:t+h}^{p}$ corresponds to the excess return on portfolio p where p indexes the percentile $p\ \varepsilon\ (10,5,1,90,95,99, 10-90, 5-95, 1-99))$. The indicator variable Rec_t equals 1 during NBER recession months and 0 during expansion months. The variables $MKTRF_t$, SMB_t, HML_t, and MOM_t correspond to the monthly factors in the Carhart (1997) four factor model.[24] The coefficient α_e denotes the four-factor alpha for the given portfolio during an

[24] We obtain the monthly market, SMB, HML, and momentum factors as well as the risk-free rate from Ken French's website.

expansion. The coefficient α_r indicates the incremental four-factor alpha during a recession. The sum of $\alpha_e + \alpha_r$ indicates the alpha of the portfolio during a recession.

To establish a baseline and connect with prior literature, we first estimate the model under the restriction $\alpha_r = 0$ and report the results in Table 9. Columns one through three contain results corresponding to one-month calendar time portfolio returns (h = 1), and columns four through six contain the results for three-month calendar time portfolio returns (h = 3). These unconditional results cohere with prior findings. First, across all six models, the spread portfolios produce significantly positive alphas; lightly-shorted firms tend to out-perform heavily-shorted firms on a risk-adjusted basis. Second, portfolios formed using more extreme short interest cutoffs experience more extreme alphas. Specifically, we find that for one (three) month calendar time portfolios the alphas are 1.8 (1.7), 2.1 (2.1), and 2.9 (2.6) percent monthly for portfolios that are long and short stocks in the most extreme 10%, 5%, and 1% of high and low short interest respectively. These findings also demonstrate that the alphas decay in event time as in every case the alphas for the portfolios with three month holding periods produces smaller risk adjusted alphas than their corresponding one month portfolios. Finally, the significantly negative market betas for the spread portfolios are consistent with the known finding that investors tend to short high-beta stocks.

Insert Table 9 Here

We present our main cross-sectional results in Table 10. Across all six specifications in Table 10 we observe that the expansion alpha is positive and significant at the one-percent level. In column 1 (4) the monthly alpha generated by the one- (three-) month calendar time portfolio that goes long stocks below the 10^{th} percentile and short stocks above 90^{th} percentile is 2.0 percent (2.0 percent). Similarly, in column 2 (5) the monthly alpha generated by the one (three) month calendar time portfolio that goes long stocks below the 5^{th} percentile and short stocks above 95^{th}

percentile is 2.3 percent (2.3 percent). Lastly, in column 3 (6) we observe the monthly alpha generated by the one (three) month calendar time portfolio based on the most extreme short interest cutoffs is 3.1 percent (2.9 percent). These results suggest that during an expansion the trades of short sellers in individual securities contain significant information about future firm-specific returns. Moreover, these findings are consistent with the unconditional results from Table 9 and prior literature. This is not surprising given the U.S. economy has experienced far more months in expansions than recessions over the sample period.

Insert Table 10 Here

Examining the point estimate on the *Rec* variable, we observe that in each of the six specifications, alpha diminishes significantly during recession months. These findings provide strong support for the *Stock Selection Hypothesis*. The decrease in alpha is economically meaningful as point estimates decrease by about one-half during recessions. For the one-month calendar time portfolios, monthly alpha falls from 2.0 percent, 2.3 percent, and 3.1 percent in expansions to 0.8 percent, 0.9 percent, and 1.6 percent in recessions. The changes in point estimates for the three-month calendar time portfolios are similar. Table 5 summarizes these results. The blue bars represent spread portfolio alphas for one-month calendar time portfolios, and the green bars represent those for the three-month calendar time portfolios. The dark bars indicate the expansion alpha as indicated by the coefficient α_e from Equation (1), and the light bars indicate the recession alpha computed as the sum of the coefficients $\alpha_e + \alpha_r$ from Equation (1).

Insert Table 5 Here

We next investigate separately each leg of the spread portfolio to better describe how short sellers reallocate attention across the business cycle. The attention theory suggests that highly shorted stocks should drive business cycle variation in alpha. High shorting activity in a stock implies attention; however, this attention may reflect the collection of either aggregate or firm-specific signals. Theory predicts the type of signals collected will vary with the business cycle. In contrast, low or zero shorting activity is more difficult to interpret. On the one hand, low shorting may reflect inattention. On the other hand, it may reflect attentive investors who have observed positive signals, potentially either aggregate or firm-specific in nature.[25] Thus, during a recession, as short sellers shift their attention from firm specific to macro information we expect that the individual short sales will become less informed about firm specific information, and alphas become smaller in magnitude for the portfolio of stocks with high short interest. It is not clear what, if any effect a recession will have on the alphas in the portfolios of lightly shorted stocks.

We study the effect of a recession on the alphas of heavily and lightly shorted stocks in Table 11. In this analysis, we employ the same specification from Equation (1) with the returns on the lightly and heavily shorted portfolios. In Panel A, we present the results for the portfolios of heavily shorted securities. Across all specifications, the portfolios of highly shorted stocks produce a significantly negative four-factor alpha during expansions. This alpha diminishes significantly, and in some cases, disappears entirely, during a recession. For example, in column 4, the expansion alpha for the three-month calendar time returns for the portfolio of heavily shorted stocks is a statistically significant -0.8 percent. Thus, stocks with high short interest during expansions subsequently experience low future returns. However, the alpha for the high short interest portfolio during recessions is -0.8 + 1.0 = 0.2 percent. An *F*-test fails to reject the null hypothesis that $\alpha_e + \alpha_r = 0$ (p=0.72). Similar *F*-tests for each of the other five specifications in Panel A also

[25] As discussed by BHJ, a low level of short interest may indicate that there is a consensus among market participants that a stock is not overpriced, and thus not worth shorting. These lightly shorted stocks would therefore be less likely to experience negative future returns, and BHJ demonstrate that a portfolio of lightly shorted stocks does produce positive four factor alpha.

fail to reject the null hypothesis of zero recession alpha at the 10% level or better. These findings bolster our interpretation that short sellers pay more attention to macro information than firm-specific information during recessions.

Insert Table 11 Here

In Table 11 Panel B, we present results for lightly shorted stocks. In these specifications, we find, consistent with the unconditional results of BHJ, that the portfolios of lightly shorted stocks produce significant four factor alphas across all six specifications during expansions. The intercept in each of our specifications is significantly positive. Moreover, these alphas generally do not significantly change during recessions.

In sum, our findings demonstrate that high short interest is only an effective predictor of future firm-specific returns during economic expansions. During recessions, high short interest has no measurable ability to predict future stock returns. Consequently, the alphas on an arbitrage portfolio that is long low short interest stocks and short high short interest stocks is cut approximately in half during recessions. These finding are consistent with short sellers devoting less attention to firm-specific information during recessions than during expansions.

b. Aggregate Returns

According to the attention allocation theory of KVV, informed investors reallocate attention away from firm-specific signals and toward aggregate signals during recessions. Our results in the prior section are consistent with the first part of this theory; short interest does not correctly predict the cross-section of future stock returns during recessions. We now turn to the second part of the theory and examine how the relation between aggregate short interest and future market returns varies with the business cycle. If informed traders are reallocating attention to aggregate signals during recessions, we expect their positions to better predict aggregate market returns during these periods. This is the essence of the *Market Timing Hypothesis*.

Compared to the vast literature relating short selling to the future returns of individual stocks, few authors have examined short sellers' ability to anticipate aggregate returns. Rapach, Ringgenberg, and Zhou (2016) offer the first analysis covering a long time series. They construct a detrended aggregate short interest index (*SII*) that predicts future aggregate stock returns. They show that the *SII*'s ability to predict returns surpasses that of other variables widely studied in the literature (e.g., Welch and Goyal, 2008). The short interest index offers an ideal environment for testing whether investors shift from firm-specific signals to macroeconomic signals because the index aggregates the trading behavior of short sellers across stocks. If short sellers are, as an investor class, observing aggregate signals during recessions and firm-specific signals during expansions, then we expect *SII* to correlate more strongly with future market returns during recessions than during expansions. We construct *SII* as in Rapach, Ringgenberg, and Zhou (2016). We first restrict the sample to stocks with price exceeding $5 and those with market capitalization above the NYSE 5th percentile. Since the index is based on an equal-weighted average, these filters reduce the influence of the disproportionate number of stocks with little or no short interest, especially early in the time series. We then compute the equal weighted average short interest across all stocks each month ($EWSI_t$), leaving us with a monthly time series from 1973 through 2015. This series has a strong linear trend, so we detrend the series using the following regression:

$$\log(EWSI_t) = a + bt + u_t \tag{2}$$

We divide the time series of residuals u_t by their standard deviation σ_{u_t} to create the final *SII*. In Table 6, we present the computed *SII* time series from January 1973 through August 2015.

Insert Table 6 Here

Rapach, Ringgenberg, and Zhou (2016) demonstrate that *SII* has strong predictive properties for future realizations of the S&P 500 index by estimating the predictive regression:

$$ret_{t+1:t+h}^{S\&P500} = \alpha + \beta SII_t + \varepsilon_{t+1:t+h}, \tag{3}$$

where $ret_{t+1:t+h}^{S\&P500} = \left(\frac{1}{h}\right)\left(ret_{t+1}^{S\&P500} + \cdots + ret_{t+h}^{S\&P500}\right)$. In this specification, the coefficient β measures the relation between *SII* in month *t* and the S&P500 over the subsequent *h* months. In Table 11 we perform a similar analysis except that we allow the relation between the *SII* and future returns to vary with the state of the market. We augment Equation (3) with the *Rec* dummy and its interaction with *SII*:

$$ret_{t+1:t+h}^{m} = \alpha + \beta SII_t + \beta_r SII_t * Rec_t + \gamma Rec_t + \varepsilon_{t+1:t+h} \tag{4}$$

As before, the indicator variable Rec_t equals one during months identified by the NBER as recession months and zero otherwise. The variable $ret_{t+1:t+h}^{m}$ is the return on either the CRSP equal weighted index, the CRSP value weighted index, or the S&P 500. The coefficient β measures the relation between the *SII* and future aggregate returns during expansions, and the coefficient β_r measures the effect that being in a recession has on the relation between the *SII* and future returns. Because the *SII* is high when short interest is high, the *Market Timing Hypothesis* predicts β_r will be negative.

We estimate Equation (4) using future one-month and three-month market returns (*h* = 1, 3) and present the results in Table 12. In Panels A, B, and C the dependent variable is the return on the S&P 500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The first and third models restrict $\beta_r = 0$ to compare our results to Rapach, Ringgenberg, and Zhou (2016). Consistent with their findings, our unconditional models show a negative relation between *SII* and future market returns. This holds for one-month and three-month market returns and for all three market indices.

Insert Table 12 here

Turning to our models that include the recession indicator, we observe that in Column (2) in all three panels the coefficient on *SII* is statistically significant, indicating that we cannot reject the null hypothesis of no relation between *SII* and one month returns during expansion times. In contrast, during recessions, the relation between *SII* and future returns is negative and statistically significant. While β_r itself is not significant, the effect of *SII* during recessions, measured as the sum of the coefficient on the *SII* plus the interaction term $\beta + \beta_r$ is significant at the 5% level. This result holds when measuring the aggregate market with the S&P 500 as well as the equal and value weighted CRSP indices.

In Column (4), in which *SII* predicts three-month market returns, the results are statistically stronger. In particular, the coefficient on the interaction term is statistically significant in each of the three Panels. That is, for all three market indices, we observe a statistically significant increase in the magnitude of the relation between *SII* and aggregate returns during recessions. Moreover, for the S&P500 and the CRSP value weighted index, the relation between *SII* and the market return does not appear to be statistically significant during expansions.

We summarize how the relation between *SII* and future market return changes over the business cycle in Table 7. We plot the various coefficients from Columns (2) and (4) for the three measures of market returns. The blue bars present coefficients using one-month returns and the green bars present coefficients for the specifications using three-month returns. The lighter bars present the coefficient β, which indicates the relation between the *SII* and future returns during expansions. The darker bars present the sums of coefficients $\beta + \beta_r$ which represent the relation between the *SII* and future returns during expansions. For the analysis employing the S&P 500 index and the CRSP value weighted index, the observed relation between the *SII* and future one-month and three-month returns is four to six times stronger during recession months compared to expansion months. For the equal weighted index the relation between the *SII* and future returns is two to four times larger during recession months than during expansion months.

Insert Table 7 Here

The impact of the state of the market on the relation between the *SII* and future returns can also be seen by analyzing the increase in adjusted *R*-squared in the various regressions. For the three-month returns, adjusted *R*-squared nearly doubles across all three indices by allowing the relation between *SII* and future returns to be conditional on the state of the economy.

The results from this analysis suggest that the aggregate positions of short sellers, as an investor class, better anticipate aggregate market returns during recessions compared to expansions. This finding is consistent with the notion that short sellers allocate more attention to aggregate signals during recessions than during expansions. This result complements the analysis in the prior section to support the rational attention theory of KVV.

5. Robustness

In this section, we explore the robustness of the results obtained in Section IV. We first examine the robustness of our cross-sectional results from Section IV part (a) to alternative methods of risk adjusting returns. We then explore the robustness of both the cross-sectional and aggregate stock return results to two alternative measures of recession and to various sub-periods of the data.

a. Alternative Model Specification

The analysis in Section IV Part (a) demonstrates that a portfolio that purchases stocks with low short interest and sells stocks with high short interest generates positive four-factor alpha during expansions and that this alpha diminishes significantly, or disappears, during recessions. One potential concern with this approach is that factor loadings may change around the business cycle. In principle, factor loadings could change due to either changes in portfolio composition or time variation in stocks' factor loadings. Either way, if portfolio factor loadings systematically changes during recessions, then unconditional estimation of Equation (1) may produce biased estimates of the effect of a recession on alpha.

We address this potential issue in two ways. First, we estimate a variation of the four-factor model where each of the factors is interacted with the recession indicator *Rec*, which allows the relation between factors and returns to vary across the business cycle. Second, we use characteristic based benchmarks to adjust the returns of the stocks in each of our long-short portfolios based on a procedure similar to Daniel, Grinblatt, Titman, and Wermers (1997). In this procedure, we assign each stock to one of 125 benchmark portfolios formed using dependent sorts on firm size, book-to-market, and prior eleven-month return.[26] Since these benchmarks are estimated each month and the stock assignments are updated frequently, the characteristic-adjusted returns should account for dependency between factor sensitivity and the business cycle.

Insert Table 13 Here

Table 13 Panel A contains results from the four-factor model with time-varying factor loadings. As in Table 10, the dependent variable is the return on an equally weighted portfolio that purchases low short interest stocks and sells high short interest stocks. Columns one through three present the results from regressions with one month returns for portfolios that are long and short stocks in the lowest and highest 10, 5, and 1 percentiles respectively. Columns four through six

[26] Each June, we update size as June market equity and book-to-market as the ratio of the prior December market equity to prior year book equity. We update prior return each calendar quarter as the 11-month return ending the month prior to the calendar quarter end. Since our calendar-time analysis uses equal-weighted portfolios, we compute benchmarks as equal weighted returns as well.

present the results for three-month calendar time portfolios. Only the HML loading changes over the business cycle, and the interaction coefficients for this factor are modest at best. More importantly, in all cases the alphas for expansions and recessions are quite close to their values in the unconditional estimation from Table 10. Consequently, allowing the factor loadings to vary over the business cycle does not significantly affect the finding that portfolios that buy low short interest stocks and sell high short interest stocks produces positive alpha during expansion.

We present similar results using the characteristic-adjusted abnormal returns in Table 13 Panel B. These results are also consistent with the inferences from Table 10. Each of the six specifications produces a positive expansion alpha. The one (three) month calendar time portfolios produce positive monthly alpha of 1.4 (1.3), 1.7 (1.6), and 2.5 (2.1) percent respectively. These quantities are somewhat smaller than what is obtained using the four-factor regression framework but still reasonably similar. Further, one (three) month abnormal returns decrease in recessions a statistically significant 1.3 (1.2), 1.7 (1.4), and 1.8 (1.6) percent. In every case, an *F*-test fails to reject the null hypothesis that the characteristic-adjusted alpha is equal to zero during recessions.

b. Alternative Recession Variables

The underlying theory for our analysis describes how short sellers' attention allocation decisions change in real-time with the business cycle. As such, our utilizing NBER business cycle indicators, which are determined *ex post*, may overstate traders' abilities to optimally reallocate attention. To alleviate such concerns, we employ two alternative definitions of recession that can be estimated in real-time. The first is the probability of recession, *Pr_Rec*, studied by Chauvet and Piger (2008). This measure employs a dynamic-factor-Markov-switching model applied to four monthly macroeconomic variables to produce a variable ranging from zero to one indicating the likelihood of a recession. This metric has the advantage that it is a continuous time variable derived directly from time series of macro variables that are available in a timelier manner than are the official NBER recession turning points. Further, because this variable is a probability, we can substitute it in our prior regressions in place of the recession indicator without changing the inference of the coefficients.

The second alternative measure is based on the Chicago Fed's National Activity Index (CFNAI), which aggregates data from 85 macroeconomic time series. It is constructed to be mean zero and standard deviation of one such that a high value indicates economic output is 'high'. Because our main goal is to study the interaction between states of the world where economic output is abnormally 'low' and the nature of information contained in short sales, we set the indicator variable *CFNAI_Rec* to one if the value of the CFNAI is one standard deviation below the mean and zero otherwise. The pairwise correlations between the NBER *Rec* indicator and each of these alternatives are 0.87 and 0.79, respectively. In Table 8 we present the time series of *Pr_Rec* and *CFNAI_Rec* along with shaded bars denoting NBER recessions.

Insert Table 8 Here

We first repeat the calendar-time portfolio analysis from Table 10 using the two alternative recession variables. Table 14 presents point estimates for the spread portfolios with long exposure to low short interest stocks and short exposure to high short interest stocks. Panel A uses *Pr_Rec*, and Panel B uses *CFNAI_Rec*. In both Panel A and Panel B, we observe similar patterns as those described in Table 10. The spread portfolio alphas are positive and significant during expansions as denoted by the positive and significant intercepts. Across all specifications in Panel A, the alphas of the portfolios diminish significantly as the probability of recession increases. For both the 10%-90% and the 5%-95% short interest portfolios, alpha declines about 40% (80%) when the probability of recession is 0.5 (1.0). For the 1%-99% short interest portfolio, the decline is smaller but still economically meaningful.

Insert Table 14 Here

Panel B documents a similar pattern based on *CFNAI_Rec*. For both the 10%-90% and the 5%-95% one-month short interest portfolios, alpha declines about 50% when the *Rec* indicator equals one. For the one-month 1%-99% short interest portfolio, the point estimate for the recession is negative, consistent with prior results, but not statistically significant. For the three-month calendar time portfolios, the recession point estimates are negative, but they are not statistically significant in the 5%-95% and the 1%-99% portfolios. It is perhaps not surprising that the CFNAI results are slightly weaker than those in Table 10 and Table 14, Panel A; since it indicates economic output of one standard deviation below normal, the CFNAI dummy is a less extreme definition of recessions than our other two measures.

Insert Table 15 Here

In Tables 8 and 9 we perform similar robustness tests for the analysis of *SII* and aggregate stock market returns. In Table 15 we present results of a specification that interacts *SII* with *Pr_Rec*. Table 16 contains results from the same analysis employing *CFNAI_Rec* in place of the recession indicator. We observe in Table 15 that using the probability of recession to interact with *SII* as opposed to the NBER recession indicator strengthens the result that the relation between *SII* and aggregate returns strengthens as the economy heads towards recession. In each specification in Table 15, the interaction term between *SII* and the probability of recession is always negative and statistically significant, and the magnitude of the coefficient is larger than in the initial regressions.

In Table 16, we present results based on *CFNAI_Rec*. In all specifications, the interaction between the recession indicator and *SII* is negative, but the statistical significance of the point estimates are somewhat weaker than in the analysis employing the NBER recession dates or the probability of recession. Across all three measures of aggregate market returns, the interaction terms indicating how the relation between *SII* and future returns changes when *CFNAI_Rec* equals one are statistically significant when predicting three-month returns but insignificant when predicting future one-month returns. However, for the one month returns, *F*-tests for the joint significance of the *SII* and *SII* x *CFNAI_Rec* indicate that for each of the three indices the negative relation between *SII* and future one-month aggregate returns is statistically significant. Overall, the results employing either real-time measure – the probability of recession or the CFNAI index – are consistent with the main findings from Table 12.

Insert Table 16 Here

c. Subsamples

We next examine the robustness of our findings to different time periods. Since recessions are not evenly distributed across the sample, we split our sample in May 1988 so that approximately half of the recession months are in the first period (January 1973 through May 1988), and half of the recession months are in the second period (June 1988 through August 2015). We also note that since the NASDAQ short interest data begins in June 1988, our subsample procedure facilitates a cursory analysis of the exclusion of NASDAQ securities.

In Table 17, we report results from our main calendar-time analysis for each subperiod. Panel A of Table 17 presents four-factor regression results using the period of January 1973 through May 1988; Panel B present results for the period beginning June 1988. Across all specifications in both subperiods, the intercept, indicating the alpha during expansions, is positive and significant at the 1% level and the coefficient estimates for the *Rec* indicator variable are negative. The statistical significance of the decline in alpha during recessions is diminished relative to the whole sample analysis presented in Table 10, particularly in the early period. For the earlier sub-sample, two of the six *Rec* coefficients are significantly negative, while four of six are significantly negative in the later time period.

Insert Table 17 Here

The decline in statistical significance is not surprising given that the time series was already relatively short, and therefore dividing the sample results in a material loss in statistical power. *F*-tests in each of the six specifications in the earlier time period fail to reject the null hypothesis that the alpha of the long short portfolio during recession months is different from zero. The pattern of results presented in Table 17 are consistent with the decline in alpha during recessions existing in both sub-samples.

Insert Table 18 Here

We next explore the robustness of the relation between *SII* and future returns. In Table 18, we present the results for regressions estimating the relation between *SII* and future aggregate stock returns for the 1973-1988 sub-sample. Table 19 presents the same analysis for the latter sub-sample. Overall, our results from Table 19 hold in both subsamples. The *Rec* x *SII* interaction coefficient estimates are uniformly negative. As in the full sample, the interactions are generally only statistically significant for models predicting future three-month returns. Only one three-month return model, Table 18 Panel C, fails to find a statistically significant interaction coefficient. Taken as a whole, the results presented in Tables 11 and 12 document that the relation between the SII and future aggregate stock returns strengthens during recessions and that this relation appears to exist in both sub-samples.

Insert Table 19 Here

6. Conclusion

Sophisticated market participants play the important role of discovering and trading on private valuation signals. This activity provides a social good that can result in positive effects on real outcomes: it may lower firms' cost of capital, improve CEO incentives, and provide useful feedback in managerial decision making. Further, traders who discover and trade on private signals provide an additional source of external monitoring. Observing signals necessarily requires the scarce resource of attention (Kahneman, 1973); however, existing research offers few empirical explorations of factors influencing how large groups of traders allocate attention. We partially fill this void by studying the trading choices of short sellers, a group largely viewed as sophisticated, and the nature of how their revealed beliefs predict future stock returns.

Our findings that short sellers better anticipate firm-level returns during economic expansions and aggregate market returns during economic recessions are consistent with the rational attention allocation theory of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016). In short, their model predicts informed traders will shift their focus from firm-specific to aggregate signals during recessions because greater aggregate volatility and a higher price of risk increase the marginal benefit of collecting information that affects large portfolios during these times.

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Appendix: Figures and Tables

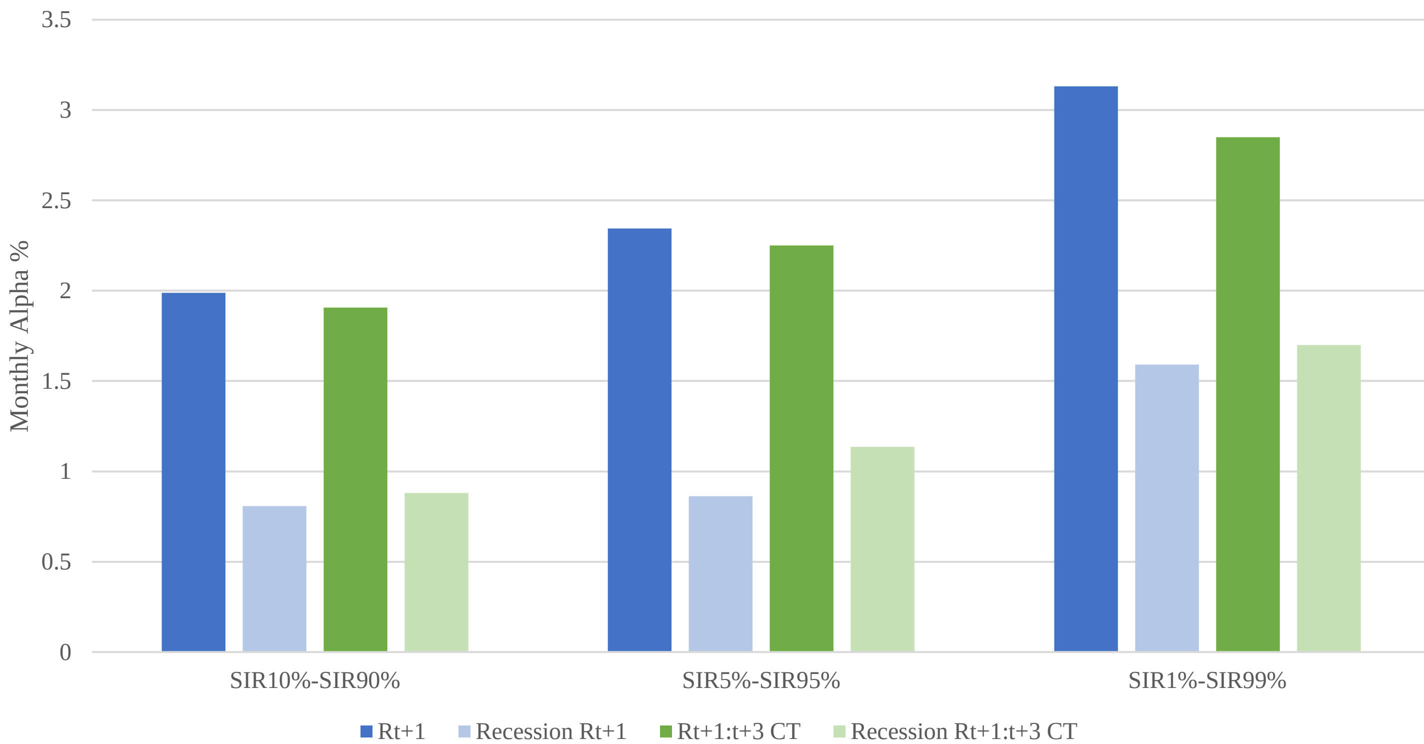

Figure 5: Four Factor Alpha During Recessions and Expansions. This figure presents the monthly alphas from Carhart (1997) four-factor regressions which include an additional intercept for recession months as in Equation (1). The first set of bars presents the monthly alphas from regressions where the dependent variable is either the one-month or three-month return on a calendar time portfolio that buys stocks with short interest below the 10th percentile and sells stocks with short interest above the 90th percentile. The middle and rightmost set of bars present the results for similar portfolios with thresholds for the long and short portfolios being 5% and 95% respectively for the middle set of bars, and 1% and 99% respectively for the rightmost set of bars. The green bars identify three-month calendar time portfolios and the blue bars one-month calendar time portfolios. The darkly shaded bars present the observed value of the coefficient α_e from Equation (1) which indicates the four-factor alpha for the given arbitrage portfolio during expansions. The darkly shaded bars present the observed value of the sum of coefficients $\alpha_e + \alpha_r$ from Equation (1) which indicates the magnitude of the four-factor alpha for the given arbitrage portfolio during NBER recession months.

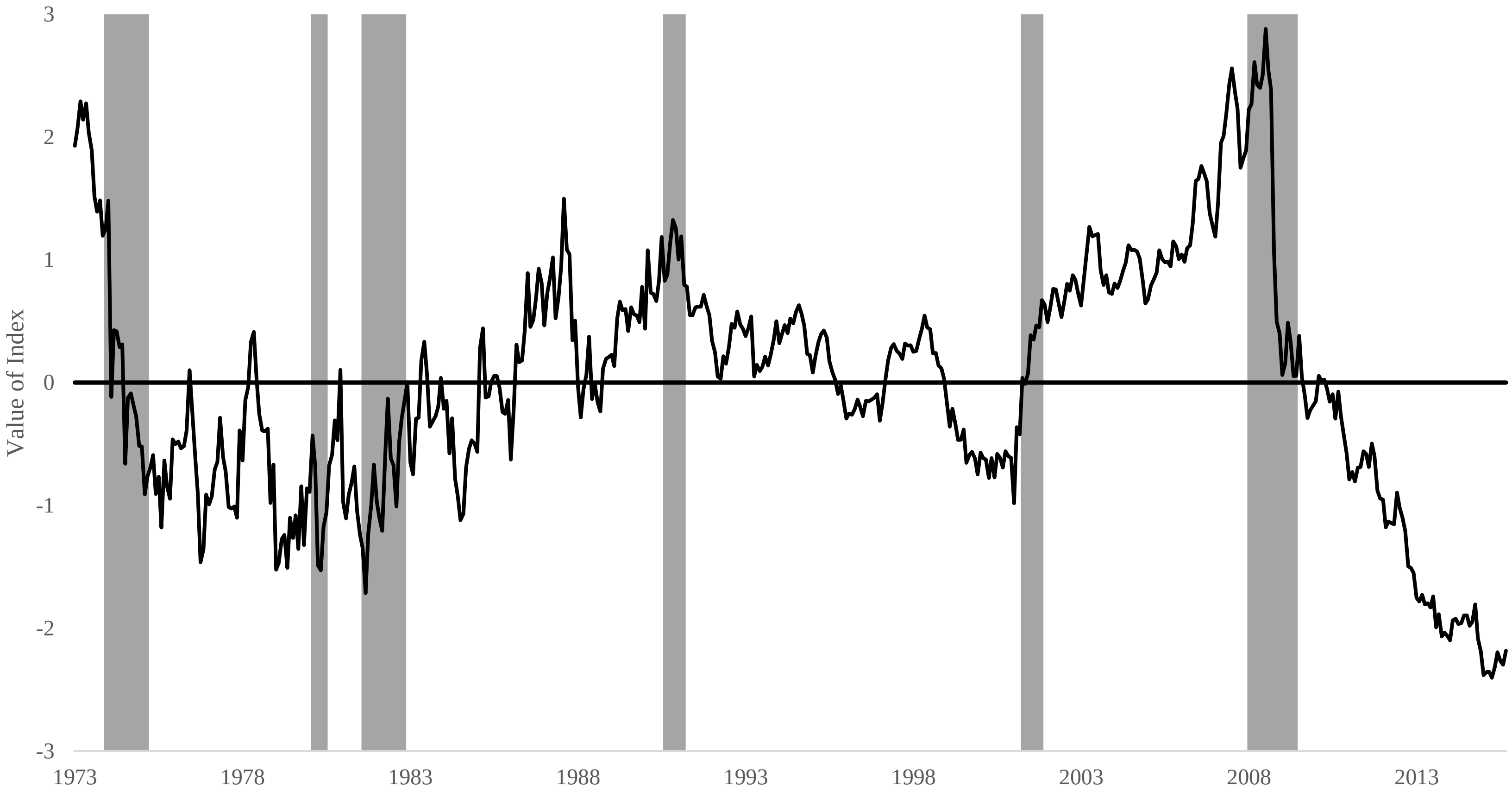

Figure 6: Short Interest Index from 1973-2015. This figure presents the monthly Short Interest Index as developed by Rapach, Ringgenberg, and Zhou (2016). Each month short interest is calculated for each stock as the number of shares held short divided by the number of shares outstanding. The long of the equally weighted average of short interest across all stocks is computed and the time trend is removed. The remaining series is divided by its standard deviation to produce the aggregate short interest index (*SII*). This figure presents the aggregate short interest index from 1973-2015. Recession bars are in grey.

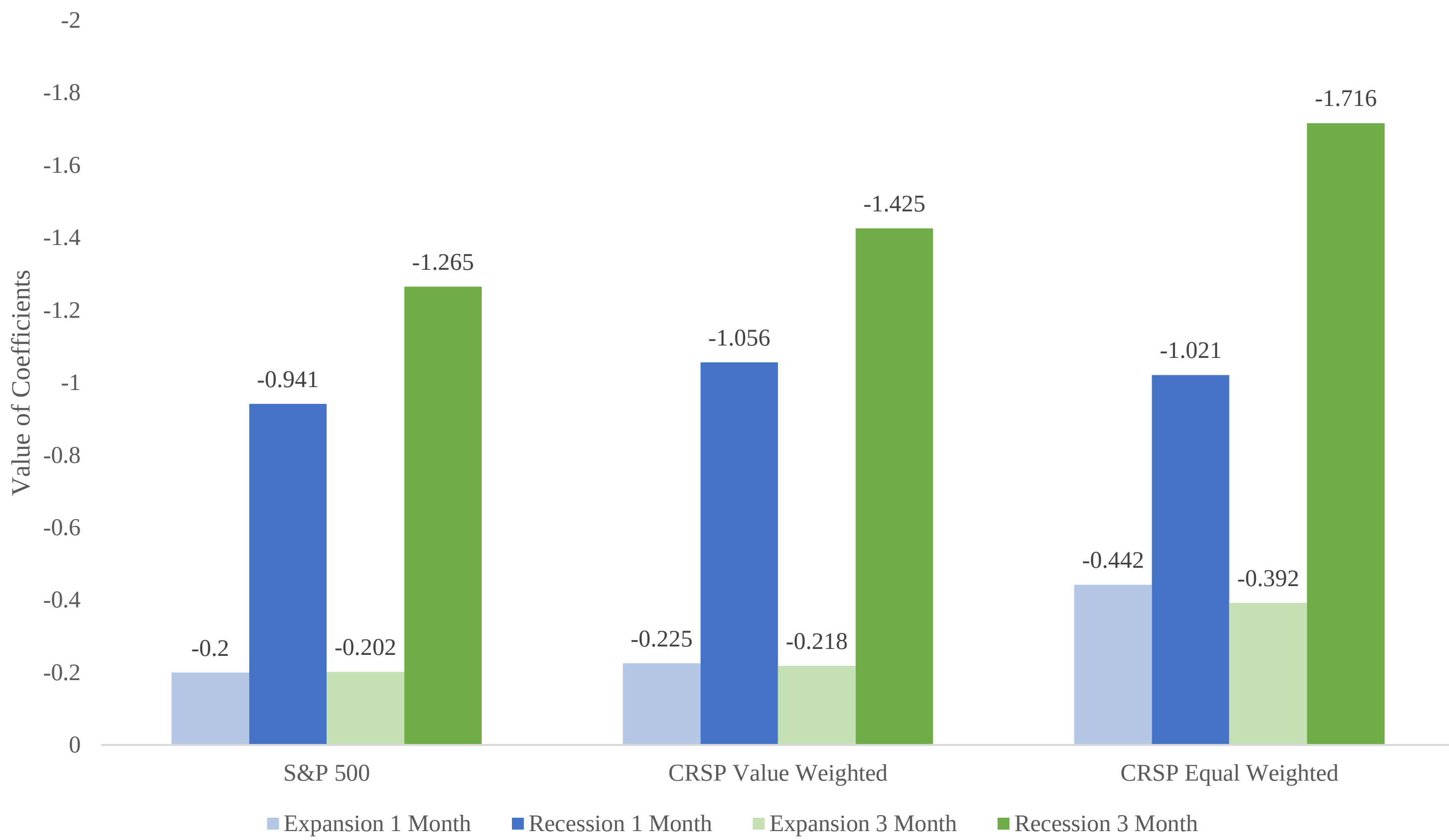

Figure 7: Relation Between SII and Aggregate Stock Returns During Recessions and Expansions. This Table presents a graphical description of the coefficients indicating the relation between *SII* and future aggregate stock returns from Equation (4). The first, second, and third set of bars present the results where the dependent variable is either the one-month or three-month return on the S&P 500 index, CRSP Value Weighted index, or the CRSP Equal Weighted index. The blue (green) bars correspond to specifications where the dependent variable is the one-month (three-month) return on the given index. The lightly shaded bars present the observed value of the coefficient β from Equation (4) which indicates the relation between *SII* and future returns during expansion periods, and the darkly shaded bars present the observed value of the sum of coefficients $\beta + \beta_r$ which indicates the magnitude of the relation between *SII* and future aggregate returns during NBER recession months.

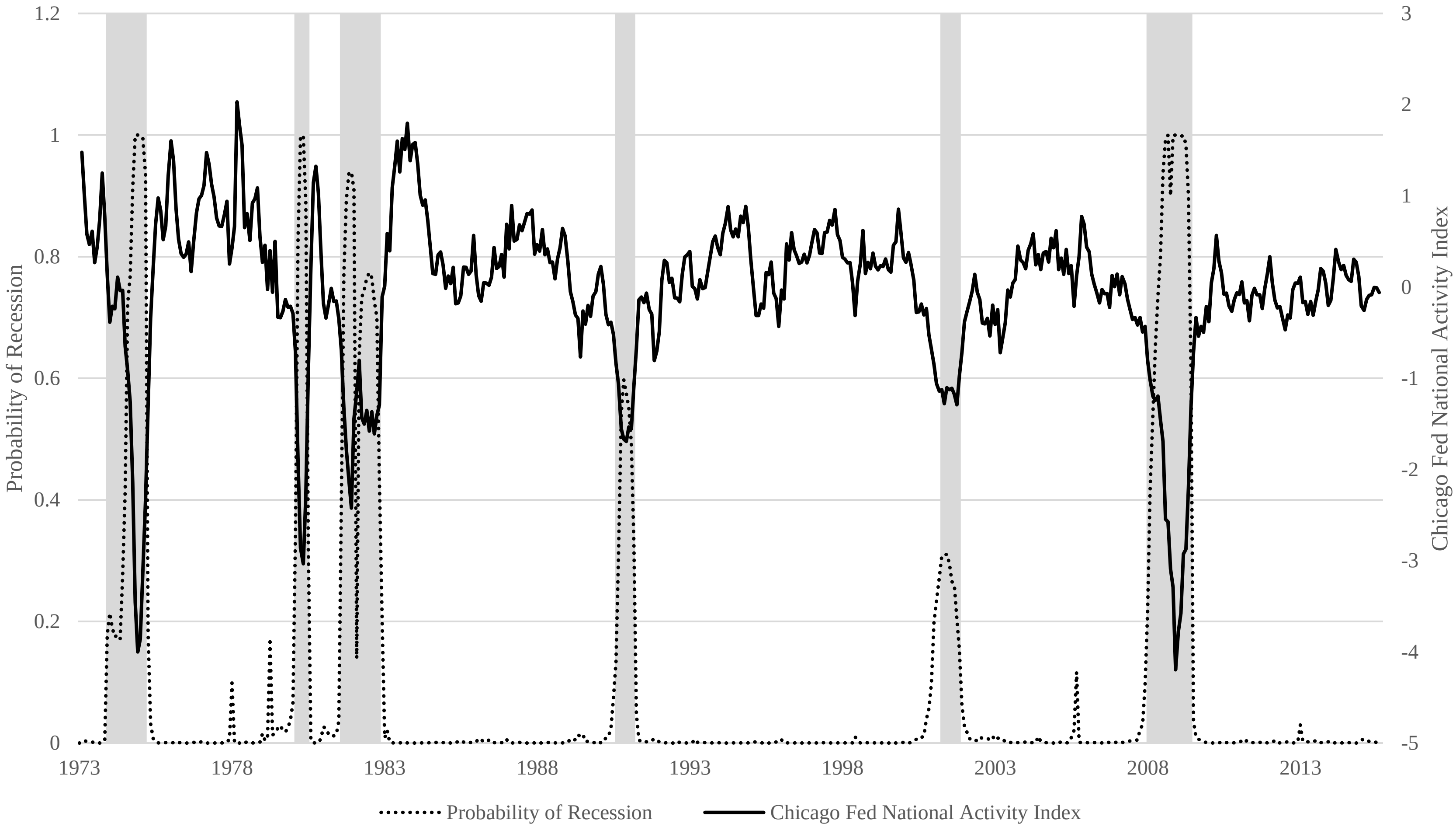

Figure 8: Alternative Recession Measures. This figure presents two alternative recession indicators. The dotted line indicates the probability of recession as described by Chauvet and Piger (2008). The solid line is the Chicago Fed National Activity Index (CFNAI). The grey bars indicate NBER recession dates.

Table 8

Summary Statistics

This table presents summary statistics for the short interest data employed in this study. Short interest is reported as shares held short and is reported once per month. We divide shares outstanding (from CRSP) to compute the short interest ratio (*SIR*) as the fraction of shares held short divided by the total shares outstanding. We divide our descriptive statistics into two periods, the first beginning in January 1973 and ending in May 1988 and the second beginning in June 1988 and continuing through August 2015. Since we only have short interest data for Nasdaq securities beginning in June 1988, this bifurcation separates our data into the two periods where we have only NYSE and Amex listed securities, and where we have NYSE, Amex, and Nasdaq securities. Panel A presents summary statistics for *SIR*. Panels B and C presents summary statistics for stock price and market capitalization. Panel D presents various other statistics.

Panel A: Short Interest		
	1973-May 1988	June 1988-Aug 2015
25th Percentile	0.04%	0.07%
Median	0.12%	0.65%
Mean	0.44%	2.45%
75th Percentile	0.37%	2.87%
Panel B: Price		
	1973-May 1988	June 1988- Aug 2015
25th Percentile	9.88	4.59
Median	19.25	12.71
Mean	23.85	19.75
75th Percentile	31.88	25.95
Panel C: Market Cap (Thousands)		
	1973-May 1988	June 1988-Aug 2015
25th Percentile	36,226	36,561
Median	164,456	156,969
Mean	883,753	2,294,219
75th Percentile	690,652	796,248
Panel D: Other Statistics		
	1973-May 1988	June 1988-Aug 2015
Average number of stocks with zero short interest per month	1	199
Average number of stocks with short interest data per month	1,017	4,674
Number of NBER Recession Months	34	38

Table 9

Calendar Time Analysis of Short Interest Portfolios

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month. Lightly shorted stocks correspond to those with *SIR* below the 10th, 5th, or 1st percentiles; heavily shorted stocks corresponding to those with *SIR* above the 90th, 95th, or 99th percentiles. Spread portfolios purchase an equal weighted portfolio of lightly shorted stocks and sell an equal weighted portfolio of highly shorted stocks. The first three columns consider a one month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with *t*-statistics in parenthesis. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR1*%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.624***	-0.676***	-0.753***	-0.664***	-0.730***	-0.814***
	(-18.83)	(-17.75)	(-12.69)	(-21.89)	(-21.14)	(-15.43)
SMB	-0.365***	-0.491***	-0.556***	-0.407***	-0.549***	-0.600***
	(-7.77)	(-9.09)	(-6.60)	(-9.45)	(-11.20)	(-8.02)
HML	0.152***	0.165***	0.252***	0.102**	0.106**	0.105
	(2.95)	(2.79)	(2.73)	(2.16)	(1.98)	(1.28)
MOM	0.0227	0.0389	0.0744	0.0395	0.0451	0.0685
	(0.70)	(1.04)	(1.28)	(1.33)	(1.33)	(1.32)
Intercept	1.809***	2.119***	2.896***	1.750***	2.080***	2.674***
	(12.40)	(12.64)	(11.08)	(13.08)	(13.67)	(11.50)
N	512	512	512	510	510	510
Adj. R^2	0.553	0.547	0.393	0.622	0.627	0.468

* p<.01 **p<.05 ***p<.01

Table 10

Calendar Time Analysis of Short Interest Portfolios in Expansions and Recessions

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month. Lightly shorted stocks correspond to those with *SIR* below the 10th, 5th, or 1st percentiles; heavily shorted stocks corresponding to those with *SIR* above the 90th, 95th, or 99th percentiles. Spread portfolios purchase an equal weighted portfolio of lightly shorted stocks and sell an equal weighted portfolio of highly shorted stocks. The first three columns consider a one- month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with *t*-statistics in parenthesis. The indicator variable *Rec* equals one if the given month is identified as a NBER recession month and zero otherwise. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.636***	-0.691***	-0.770***	-0.675***	-0.742***	-0.826***
	(-19.19)	(-18.18)	(-12.90)	(-22.21)	(-21.43)	(-15.57)
SMB	-0.357***	-0.481***	-0.545***	-0.400***	-0.541***	-0.593***
	(-7.64)	(-8.97)	(-6.49)	(-9.33)	(-11.09)	(-7.92)
HML	0.144***	0.155***	0.241***	0.0950**	0.0988*	0.0974
	(2.81)	(2.64)	(2.62)	(2.02)	(1.85)	(1.19)
MOM	0.0146	0.0288	0.0638	0.0325	0.0375	0.0606
	(0.45)	(0.78)	(1.10)	(1.10)	(1.11)	(1.17)
Rec	-1.182***	-1.482***	-1.546**	-1.027***	-1.115***	-1.158*
	(-2.93)	(-3.20)	(-2.13)	(-2.78)	(-2.65)	(-1.79)
Intercept	1.989***	2.345***	3.131***	1.907***	2.251***	2.850***
	(12.65)	(12.99)	(11.07)	(13.21)	(13.70)	(11.31)
N	512	512	512	510	510	510
Adj. R^2	0.560	0.555	0.397	0.627	0.631	0.471

* p<.01 **p<.05 ***p<.01

Table 11
Calendar Time Analysis of High and Low Short Interest Portfolios in Expansions and Recessions

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15^{th} of the prior month. Panel A analyzes equal weighted portfolios of heavily shorted stocks which have *SIR* above the 90^{th}, 95^{th}, or 99^{th} percentiles. Panel B analyzes equal weighted portfolios of lightly shorted stocks which have *SIR* below the 10^{th}, 5^{th}, or 1^{st} percentiles. The first three columns consider a one month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with *t*-statistics in parenthesis. The indicator variable *Rec* equals one if the given month is identified as a NBER recession month and zero otherwise. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

Panel A: Heavily Shorted Stocks

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	SIR 90%	*SIR* 95%	*SIR* 99%	*SIR* 90%	*SIR* 95%	*SIR* 99%
MKTRF	1.283***	1.308***	1.335***	1.242***	1.263***	1.315***
	(49.28)	(43.32)	(27.00)	(45.45)	(38.76)	(26.03)
SMB	0.975***	1.053***	1.128***	0.967***	1.066***	1.084***
	(26.58)	(24.76)	(16.19)	(25.10)	(23.21)	(15.21)
HML	0.161***	0.140***	0.0863	0.213***	0.197***	0.209***
	(3.99)	(3.00)	(1.13)	(5.05)	(3.91)	(2.67)
MOM	-0.125***	-0.144***	-0.156***	-0.139***	-0.161***	-0.162***
	(-4.92)	(-4.90)	(-3.23)	(-5.23)	(-5.07)	(-3.29)
Rec	0.806**	0.930**	0.738	0.981***	0.839**	1.377**
	(2.54)	(2.53)	(1.23)	(2.95)	(2.12)	(2.24)
Intercept	-0.893***	-1.054***	-1.667***	-0.825***	-1.015***	-1.646***
	(-7.23)	(-7.36)	(-7.11)	(-6.36)	(-6.56)	(-6.86)
N	512	512	512	510	510	510
Adj. R^2	0.896	0.874	0.737	0.881	0.850	0.715

Table 11 Continued

Panel B: Lightly Shorted Stocks

		Ret_{t+1}			$Ret_{t+1:t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	SIR 10%	*SIR* 5%	*SIR* 1%	*SIR* 10%	*SIR* 5%	*SIR* 1%
MKTRF	0.647***	0.616***	0.566***	0.533***	0.505***	0.472***
	(23.53)	(21.05)	(13.79)	(20.51)	(17.95)	(11.93)
SMB	0.618***	0.572***	0.583***	0.548***	0.481***	0.502***
	(15.96)	(13.87)	(10.09)	(14.94)	(12.12)	(9.00)
HML	0.305***	0.295***	0.328***	0.277***	0.267***	0.283***
	(7.17)	(6.52)	(5.17)	(6.89)	(6.15)	(4.63)
MOM	-0.110***	-0.115***	-0.0918**	-0.0890***	-0.116***	-0.108***
	(-4.12)	(-4.04)	(-2.30)	(-3.51)	(-4.21)	(-2.81)
Rec	-0.376	-0.551	-0.808	0.111	0.0631	0.159
	(-1.12)	(-1.55)	(-1.62)	(0.35)	(0.18)	(0.33)
Intercept	1.096***	1.291***	1.464***	1.059***	1.156***	1.278***
	(8.40)	(9.29)	(7.53)	(8.58)	(8.66)	(6.80)
N	512	512	512	510	510	510
Adj R^2	0.687	0.635	0.441	0.634	0.564	0.378

* p<.01 **p<.05 ***p<.01

Table 12

Short Selling Index and Aggregate Return Predictability

This table presents time series regressions of aggregate stock market returns on the short selling index (*SII*) of Rapach, Ringgenberg, and Zhou (2016). The dependent variable for the columns (1) and (2) is the future one-month return. The dependent variable for columns (3) and (4) is the future three-month return. The indicator variable Rec_t equals one when month *t* is an NBER recession month and zero otherwise. The return variables in Panels A, B, and C are the return on the S&P500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The regressions begin in January 1973 and run through August 2015. *t*-statistics appear in parenthesis, and one two and three stars indicates statistical significance at the ten, five, and one percent levels respectively.

Panel A: S&P 500 Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.363*	-0.200	-0.413***	-0.202
	(-1.84)	(-0.91)	(-3.56)	(-1.59)
SII_t * Rec_t		-0.741		-1.063***
		(-1.45)		(-3.61)
Rec_t		-0.705		-0.187
		(-1.23)		(-0.57)
Intercept	0.245	0.368*	0.263**	0.322***
	(1.25)	(1.74)	(2.30)	(2.64)
N	512	512	510	510
Adj. R^2	0.005	0.009	0.022	0.046

Panel B: CRSP Value Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.399*	-0.225	-0.450***	-0.218
	(-1.96)	(-1.00)	(-3.69)	(-1.62)
SII_t * Rec_t		-0.831		-1.207***
		(-1.57)		(-3.89)
Rec_t		-0.542		0.0114
		(-0.91)		(0.03)
Intercept	0.497**	0.600***	0.519***	0.553***
	(2.45)	(2.75)	(4.31)	(4.32)
N	512	512	510	510
Adj. R^2	0.006	0.009	0.024	0.050

Table 12 Continued

Panel C: CRSP Equal Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.553**	-0.442	-0.620***	-0.392**
	(-2.20)	(-1.58)	(-3.80)	(-2.18)
SII_t * Rec_t		-0.579		-1.324***
		(-0.89)		(-3.18)
Rec_t		-0.0681		0.849*
		(-0.09)		(1.82)
Intercept	0.339	0.367	0.776***	0.697***
	(1.36)	(1.36)	(4.82)	(4.05)
N	512	512	510	510
Adj. R^2	0.007	0.005	0.026	0.044

* p<.01 **p<.05 ***p<.01

Table 13

Calendar Time Analysis with Time Varying Factor Exposure

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month. Lightly shorted stocks correspond to those with *SIR* below the 10th, 5th, or 1st percentiles; heavily shorted stocks corresponding to with *SIR* above the 90th, 95th, or 99th percentiles. Spread portfolios purchase an equal weighted portfolio of lightly shorted stocks and sell an equal weighted portfolio of highly shorted stocks. The first three columns consider a one- month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with each factor loading interacted with the NBER recession indicator in Panel A. In Panel B, all returns are characteristic adjusted with benchmarks based on size, book-to-market, and prior 11-month return. *t*-statistics in parenthesis. The indicator variable *Rec* equals one if the given month is identified as a NBER recession month and zero otherwise. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

Panel A: Recession Varying Factor Loadings

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.617***	-0.669***	-0.706***	-0.673***	-0.736***	-0.818***
	(-15.90)	(-15.04)	(-10.07)	(-18.90)	(-18.12)	(-13.09)
*MKTRF * Rec*	-0.0249	-0.0139	-0.235*	0.0388	0.0360	-0.00446
	(-0.32)	(-0.15)	(-1.66)	(0.54)	(0.44)	(-0.04)
SMB	-0.336***	-0.439***	-0.569***	-0.378***	-0.513***	-0.610***
	(-6.57)	(-7.48)	(-6.15)	(-8.03)	(-9.56)	(-7.39)
*SMB * Rec*	0.00972	-0.0997	0.208	-0.0265	-0.0526	0.172
	(0.07)	(-0.66)	(0.87)	(-0.22)	(-0.38)	(0.80)
HML	0.216***	0.239***	0.235**	0.149***	0.150**	0.0747
	(3.61)	(3.49)	(2.18)	(2.72)	(2.40)	(0.78)
*HML * Rec*	-0.261**	-0.289**	0.0387	-0.197*	-0.177	0.0824
	(-2.23)	(-2.16)	(0.18)	(-1.84)	(-1.45)	(0.44)
MOM	-0.0140	-0.0130	0.0334	0.00746	0.000508	0.0236
	(-0.36)	(-0.29)	(0.47)	(0.21)	(0.01)	(0.38)
*MOM * Rec*	0.0905	0.119	0.0479	0.0938	0.126	0.143
	(1.20)	(1.37)	(0.35)	(1.35)	(1.59)	(1.17)
Rec	-1.131***	-1.378***	-1.731**	-0.961**	-1.051**	-1.286*
	(-2.76)	(-2.94)	(-2.34)	(-2.56)	(-2.46)	(-1.95)
Intercept	1.968***	2.324***	3.118***	1.902***	2.252***	2.885***
	(12.39)	(12.77)	(10.87)	(13.03)	(13.55)	(11.27)
N	512	512	512	510	510	510
Adj. R^2	0.563	0.560	0.397	0.630	0.633	0.469

Table 13 Continued

Panel B: Characteristic-Adjusted Returns

		Ret_{t+1}			$Ret_{t+1:t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
Rec	-0.814**	-1.166**	-1.240*	-0.714**	-0.920**	-0.994
	(-2.13)	(-2.57)	(-1.72)	(-1.99)	(-2.19)	(-1.54)
Intercept	1.212***	1.469***	2.221***	1.072***	1.295***	1.782***
	(8.44)	(8.65)	(8.22)	(7.98)	(8.20)	(7.34)
N	512	512	512	510	510	510
Adj. R^2	0.310	0.262	0.121	0.331	0.305	0.168

*p<.01 **p<.05 ***p<.01

Table 14

Calendar Time Analysis with Alternative Recession Metrics

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month. Lightly shorted stocks correspond to those with *SIR* below the 10th, 5th, or 1st percentiles; heavily shorted stocks corresponding to those with *SIR* above the 90th, 95th, or 99th percentiles. Spread portfolios purchase an equal weighted portfolio of lightly shorted stocks and sell an equal weighted portfolio of highly shorted stocks. The first three columns consider a one- month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with *t*-statistics in parenthesis. In Panel A, the variable *Pr_Rec* is equal to the probability of recession in a given month as computed by Chauvet and Piger (2008). In Panel B the variable *CFNAI_Rec* is equal to one if the value of the Chicago Fed National Activity Index is less than one standard deviation below the mean and zero otherwise. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

Panel A: Probability of Recession

		Ret_{t+1}			$Ret_{t+1:t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.633***	-0.688***	-0.763***	-0.673***	-0.740***	-0.824***
	(-19.12)	(-18.12)	(-12.81)	(-22.21)	(-21.45)	(-15.57)
SMB	-0.359***	-0.482***	-0.549***	-0.401***	-0.542***	-0.594***
	(-7.67)	(-9.00)	(-6.52)	(-9.35)	(-11.12)	(-7.93)
HML	0.143***	0.153***	0.242***	0.0934**	0.0968*	0.0956
	(2.79)	(2.61)	(2.62)	(1.99)	(1.81)	(1.17)
MOM	0.0122	0.0250	0.0630	0.0296	0.0339	0.0574
	(0.37)	(0.67)	(1.08)	(0.99)	(1.00)	(1.10)
Pr_Rec	-1.537***	-2.033***	-1.662	-1.452***	-1.632***	-1.631*
	(-2.67)	(-3.09)	(-1.61)	(-2.76)	(-2.73)	(-1.78)
Intercept	1.969***	2.330***	3.068***	1.901***	2.250***	2.843***
	(12.55)	(12.96)	(10.87)	(13.23)	(13.76)	(11.33)
N	512	512	512	510	510	510
Adj. R^2	0.558	0.555	0.395	0.627	0.631	0.471

Table 14 Continued

Panel B: CFNAI Index Measure

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.628***	-0.680***	-0.756***	-0.668***	-0.733***	-0.817***
	(-19.01)	(-17.92)	(-12.72)	(-22.04)	(-21.23)	(-15.47)
SMB	-0.361***	-0.486***	-0.553***	-0.404***	-0.546***	-0.597***
	(-7.71)	(-9.04)	(-6.56)	(-9.39)	(-11.15)	(-7.97)
HML	0.138***	0.149**	0.241***	0.0899*	0.0956*	0.0941
	(2.66)	(2.51)	(2.60)	(1.90)	(1.77)	(1.14)
MOM	0.0128	0.0279	0.0675	0.0314	0.0378	0.0610
	(0.39)	(0.74)	(1.15)	(1.05)	(1.11)	(1.17)
CFNAI_Rec	-0.974**	-1.094**	-0.685	-0.802**	-0.718	-0.744
	(-2.28)	(-2.23)	(-0.89)	(-2.05)	(-1.61)	(-1.09)
Intercept	1.945***	2.271***	2.991***	1.862***	2.181***	2.777***
	(12.39)	(12.59)	(10.59)	(12.93)	(13.29)	(11.06)
N	512	512	512	510	510	510
Adj. R^2	0.557	0.551	0.393	0.625	0.628	0.469

* p<.01 **p<.05 ***p<.01

Table 15

Aggregate Return Predictability and the Probability of Recession

This table presents time series regressions of aggregate stock market returns on the short selling index (*SII*) of Rapach, Ringgenberg, and Zhou (2016). The dependent variable for the columns (1) and (2) is the future one-month return. The dependent variable for columns (3) and (4) is the future three-month return. The indicator variable Pr_Rec_t is equal to the probability of recession in a given month as computed by Chauvet and Piger (2008). The return variables in Panels A, B, and C are the return on the S&P500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The regressions begin in January 1973 and run through August 2015. *t*-statistics appear in parenthesis, and one two and three stars indicates statistical significance at the ten, five, and one percent levels respectively.

Panel A: S&P 500 Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.363*	-0.140	-0.413***	-0.150
	(-1.84)	(-0.65)	(-3.56)	(-1.20)
SII_t * Pr_Rec_t		-1.618**		-1.919***
		(-2.39)		(-4.96)
Pr_Rec_t		-0.424		0.142
		(-0.53)		(0.31)
Intercept	0.245	0.301	0.263**	0.267**
	(1.25)	(1.44)	(2.30)	(2.22)
N	512	512	510	510
Adj. R^2	0.005	0.013	0.022	0.064

Panel B: CRSP Value Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.399*	-0.148	-0.450***	-0.157
	(-1.96)	(-0.66)	(-3.69)	(-1.20)
SII_t * Pr_Rec_t		-1.850***		-2.157***
		(-2.65)		(-5.31)
Pr_Rec_t		-0.122		0.457
		(-0.15)		(0.95)
Intercept	0.497**	0.527**	0.519***	0.495***
	(2.45)	(2.44)	(4.31)	(3.93)
N	512	512	510	510
Adj. R^2	0.006	0.015	0.024	0.073

Table 15 Continued

Panel C: CRSP Equal Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.553**	-0.323	-0.620***	-0.301*
	(-2.20)	(-1.17)	(-3.80)	(-1.71)
$SII_t * Pr\_Rec_t$		-1.756**		-2.446***
		(-2.04)		(-4.50)
Pr_Rec_t		0.681		1.836***
		(0.67)		(2.86)
Intercept	0.339	0.293	0.776***	0.624***
	(1.36)	(1.09)	(4.82)	(3.70)
N	512	512	510	510
Adj. R^2	0.007	0.012	0.026	0.072

* p<.01 **p<.05 ***p<.01

Table 16

Aggregate Return Predictability and CFNAI Recessions

This table presents time series regressions of aggregate stock market returns on the short selling index (*SII*) of Rapach, Ringgenberg, and Zhou (2016). The dependent variable for the columns (1) and (2) is the future one-month return. The dependent variable for columns (3) and (4) is the future three-month return. The indicator variable $CFNAI\_Rec_t$ is equal to one if the value of the Chicago Fed National Activity Index is less than one standard deviation below the mean and zero otherwise. The return variables in Panels A, B, and C are the return on the S&P500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The regressions begin in January 1973 and run through August 2015. *t*-statistics appear in parenthesis, and one two and three stars indicates statistical significance at the ten, five, and one percent levels respectively.

Panel A: S&P 500 Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.363*	-0.261	-0.413***	-0.242*
	(-1.84)	(-1.20)	(-3.56)	(-1.92)
$SII_t * CFNAI\_Rec_t$		-0.658		-1.046***
		(-1.25)		(-3.44)
$CFNAI\_Rec_t$		0.543		0.600*
		(0.90)		(1.74)
Intercept	0.245	0.191	0.263**	0.208*
	(1.25)	(0.91)	(2.30)	(1.72)
N	512	512	510	510
Adj. R^2	0.005	0.005	0.022	0.044

Panel B: CRSP Value Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.399*	-0.274	-0.450***	-0.259*
	(-1.96)	(-1.23)	(-3.69)	(-1.96)
$SII_t * CFNAI\_Rec_t$		-0.838		-1.193***
		(-1.54)		(-3.75)
$CFNAI\_Rec_t$		0.913		0.891**
		(1.48)		(2.47)
Intercept	0.497**	0.400*	0.519***	0.430***
	(2.45)	(1.85)	(4.31)	(3.39)
N	512	512	510	510
Adj. R^2	0.006	0.010	0.024	0.054

Table 16 Continued

Panel C: CRSP Equal Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.553**	-0.473*	-0.620***	-0.429**
	(-2.20)	(-1.72)	(-3.80)	(-2.45)
SII_t * $CFNAI\_Rec_t$		-0.711		-1.338***
		(-1.07)		(-3.17)
$CFNAI\_Rec_t$		1.976***		2.146***
		(2.60)		(4.48)
Intercept	0.339	0.107	0.776***	0.533***
	(1.36)	(0.40)	(4.82)	(3.17)
N	512	512	510	510
Adj. R^2	0.007	0.018	0.026	0.071

* p<.01 **p<.05 ***p<.01

Table 17

Calendar Time Analysis: Subperiods

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month for two sub-samples of the data. Panel A presents the analysis for the period of January 1973-May 1988, and panel B presents the analysis for the period of June 1988-August 2015. Lightly shorted stocks correspond to those with *SIR* below the 10th, 5th, or 1st percentiles; heavily shorted stocks corresponding to those with *SIR* above the 90th, 95th, or 99th percentiles. Spread portfolios purchase an equal weighted portfolio of lightly shorted stocks and sell an equal weighted portfolio of highly shorted stocks. The first three columns consider a one- month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with *t*-statistics in parenthesis. The indicator variable *Rec* equals one if the given month is identified as a NBER recession month and zero otherwise. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

Panel A: 1973-1988

		Ret_{t+1}			$Ret_{t+1:t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.460***	-0.505***	-0.585***	-0.547***	-0.626***	-0.665***
	(-10.41)	(-8.57)	(-5.37)	(-13.96)	(-12.21)	(-6.82)
SMB	-0.257***	-0.380***	-0.304*	-0.380***	-0.522***	-0.436***
	(-3.64)	(-4.04)	(-1.74)	(-6.04)	(-6.35)	(-2.79)
HML	0.274***	0.290***	0.628***	0.199***	0.202**	0.364**
	(3.67)	(2.92)	(3.42)	(3.01)	(2.33)	(2.21)
MOM	-0.0716	-0.0607	0.0661	-0.0389	-0.0467	-0.0812
	(-1.40)	(-0.89)	(0.52)	(-0.86)	(-0.79)	(-0.72)
Rec	-0.897*	-1.269**	-1.753	-0.609	-0.837	-0.922
	(-1.91)	(-2.03)	(-1.51)	(-1.46)	(-1.54)	(-0.89)
Intercept	1.725***	2.008***	2.222***	1.507***	1.849***	2.141***
	(7.64)	(6.69)	(4.00)	(7.51)	(7.04)	(4.29)
N	185	185	185	183	183	183
Adj. R^2	0.594	0.517	0.320	0.715	0.669	0.384

Table 14 Continued

Panel B: 1973-1988

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.766***	-0.828***	-0.888***	-0.762***	-0.814***	-0.914***
	(-16.38)	(-16.31)	(-12.34)	(-17.27)	(-16.90)	(-14.27)
SMB	-0.436***	-0.560***	-0.710***	-0.429***	-0.572***	-0.719***
	(-7.26)	(-8.59)	(-7.67)	(-7.56)	(-9.23)	(-8.73)
HML	0.0819	0.0968	0.0501	0.0567	0.0643	-0.0291
	(1.22)	(1.33)	(0.49)	(0.90)	(0.93)	(-0.32)
MOM	0.0183	0.0339	0.0500	0.0373	0.0522	0.0990*
	(0.45)	(0.76)	(0.79)	(0.96)	(1.24)	(1.77)
Rec	-1.528**	-1.706**	-1.268	-1.363**	-1.243*	-1.127
	(-2.49)	(-2.56)	(-1.34)	(-2.35)	(-1.96)	(-1.34)
Intercept	2.174***	2.566***	3.545***	2.140***	2.472***	3.179***
	(10.73)	(11.66)	(11.36)	(11.19)	(11.84)	(11.45)
N	327	327	327	327	327	327
Adj. R^2	0.582	0.601	0.479	0.606	0.621	0.549

*p<.1 **p<.05 ***p<.01

Table 18

Short Selling Index and Aggregate Return Predictability: 1973-1988

This table presents time series regressions of aggregate stock market returns on the short selling index (*SII*) of Rapach, Ringgenberg, and Zhou (2016). The dependent variable for the columns (1) and (2) is the future one-month return. The dependent variable for columns (3) and (4) is the future three-month return. The indicator variable Rec_t equals one when month t is an NBER recession month and zero otherwise. The return variables in Panels A, B, and C are the return on the S&P500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The regressions begin in January 1973 and run through May 1988. t-statistics appear in parenthesis, and one two and three stars indicates statistical significance at the ten, five, and one percent levels respectively.

Panel A: S&P 500 Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.605	-0.454	-0.570**	-0.307
	(-1.39)	(-0.95)	(-2.28)	(-1.13)
$SII_t * Rec_t$		-1.299		-1.719**
		(-1.04)		(-2.43)
Rec_t		-1.134		-0.686
		(-1.05)		(-1.12)
Intercept	-0.220	-0.0858	-0.207	-0.181
	(-0.58)	(-0.21)	(-0.95)	(-0.76)
N	185	185	185	185
Adj. R^2	0.005	0.002	0.022	0.043

Panel B: CRSP Value Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.858*	-0.724	-0.793***	-0.524*
	(-1.91)	(-1.46)	(-3.04)	(-1.85)
$SII_t * Rec_t$		-1.225		-1.764**
		(-0.95)		(-2.39)
Rec_t		-1.182		-0.706
		(-1.06)		(-1.10)
Intercept	0.107	0.254	0.132	0.160
	(0.27)	(0.59)	(0.58)	(0.65)
N	185	185	185	185
Adj. R^2	0.014	0.010	0.043	0.062

Table 18 Continued

Panel B: CRSP Equal Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-1.432**	-1.554**	-1.450***	-1.300***
	(-2.56)	(-2.52)	(-4.18)	(-3.41)
$SII_t * Rec_t$		0.487		-0.802
		(0.30)		(-0.81)
Rec_t		-0.416		0.0330
		(-0.30)		(0.04)
Intercept	-0.283	-0.177	0.390	0.336
	(-0.58)	(-0.33)	(1.29)	(1.01)
N	185	185	185	185
Adj. R^2	0.029	0.021	0.082	0.077

*p<.1 **p<.05 ***p<.01

Table 19

Short Selling Index and Aggregate Return Predictability: 1988-2015

This table presents time series regressions of aggregate stock market returns on the short selling index (*SII*) of Rapach, Ringgenberg, and Zhou (2016). The dependent variable for the columns (1) and (2) is the future one-month return. The dependent variable for columns (3) and (4) is the future three-month return. The indicator variable Rec_t equals one when month t is an NBER recession month and zero otherwise. The return variables in Panels A, B, and C are the return on the S&P500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The regressions begin in June 1988 and run through August 2015. t-statistics appear in parenthesis, and one two and three stars indicates statistical significance at the ten, five, and one percent levels respectively.

Panel A: S&P 500 Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.361*	-0.157	-0.452***	-0.225
	(-1.65)	(-0.66)	(-3.51)	(-1.63)
SII_t * Rec_t		-1.234		-1.820***
		(-1.53)		(-3.98)
Rec_t		0.0915		1.080*
		(0.08)		(1.71)
Intercept	0.473**	0.569**	0.515***	0.567***
	(2.04)	(2.36)	(3.81)	(4.11)
N	327	327	325	325
Adj. R^2	0.005	0.012	0.034	0.080

Panel B: CRSP Value Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.294	-0.0765	-0.391***	-0.147
	(-1.30)	(-0.31)	(-2.85)	(-1.01)
SII_t * Rec_t		-1.500*		-2.110***
		(-1.81)		(-4.35)
Rec_t		0.482		1.478**
		(0.42)		(2.21)
Intercept	0.636***	0.719***	0.679***	0.719***
	(2.66)	(2.89)	(4.72)	(4.91)
N	327	327	325	325
Adj. R^2	0.002	0.011	0.021	0.074

Table 19 Continued

Panel C: CRSP Equal Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.324	-0.0855	-0.354*	-0.0809
	(-1.18)	(-0.29)	(-1.93)	(-0.42)
$SII_t * Rec_t$		-2.705***		-3.415***
		(-2.69)		(-5.33)
Rec_t		2.635*		3.760***
		(1.90)		(4.26)
Intercept	0.530*	0.519*	0.831***	0.773***
	(1.82)	(1.71)	(4.32)	(4.00)
N	327	327	325	325
Adj. R^2	0.001	0.017	0.008	0.084

*p<.1 **p<.05 ***p<.01

CONCLUSION

The first essay explores the relation between short selling and adverse selection. The theoretical analysis provided suggests that prohibiting short selling may increase adverse selection by impacting the incentives investors have to become informed. In the model, the distribution of informed investors in the market skews towards having more investors who own the asset becoming informed relative two when short selling is allowed. This skewing of the distribution of informed investors leads market makers to face increased adverse selection risk on the sell side of the market because only investors who own the asset can sell and a greater freaction of them are informed during the ban. Empirical analysis produces results consistent with the predictions of the model.

These findings have implications for various aspects of finance. First, the analysis highlights the magnitude of the adverse selection link between short selling and liquidity. Also, the finding that sell side liquidity deteriorates more than buy side liquidity during the ban has potential regulatory implications and suggests that restricting short selling during periods of downward price pressure may have the unintended effect of diminishing sell side liquidity when it is most needed.

Next, the model's prediction that the inability to short sell will influence the characteristics of the investors who choose to become informed may have implications beyond liquidity. If fewer outside investors choose to become informed because of an inability to trade on negative information, then the role of outside investors as monitors of the firm may diminish when short selling is restricted.

Lastly, this study has potential implications for how researchers approach the study of the determinates of liquidity. The asymmetry between the effect of the ban on buy and sell side liquidity documented in this study shows that additional insights can be gained by disaggregating liquidity measures and studying the buy and sell sides of the market separately.

The second essay examines how systematic changes across the business cycle affect what types of information – macro economic or firm specific – short sellers allocate attention to during recessions and expansions. This essay documents that firm-level short interest predicts negative returns for individual stocks during economic expansions, while aggregate short interest predicts negative market returns during recessions. Viewing short sellers as informed traders, these findings are consistent with recent theory which argues that rational, yet cognitively constrained traders optimally allocate attention towards aggregate (firm-specific) information in recessions (expansions) because these times are marked by higher (lower) aggregate volatility and price of risk.

This study suggests potential real implications of rational attention allocation. A large literature discusses the role of outside investors – such as short sellers – as monitors of the firm. Monitoring requires attention. As short-sellers allocate attention away from firm-specific signals in recessions, managers may engage in more value-destroying and nefarious behavior in these states of the world. This is particularly concerning in recessions because some combination of greater operating and financial leverage, weak fundamental performance, and underdiversified managers may facilitate inefficient outcomes ranging from excessive risk-taking to underinvestment.

VITA

Peter N. Dixon was born on March 19, 1986 in Murray, Utah to Rolf and Jean Dixon. He is the third child of eight. Shortly after birth, his family moved to Texas where Peter lived until High School when his family returned to Utah. He graduated from Bonneville High School in Ogden, Utah. Immediately after graduation, Peter embarked on a semester study abroad in Paris, France. Upon returning from France he served a two-year proselytizing mission for The Church of Jesus Christ of Latter-Day Saints in Phoenix, Arizona. Upon returning from missionary service, Peter enrolled at Brigham Young University-Idaho where he completed a Bachelors degree in Financial Economics in July 2009. Immediately upon graduation, Peter entered graduate studies at the University of Utah where he studied Statistics and Econometrics. He graduated from the University of Utah in 2011 with a Masters degree and was nominated by the faculty as the 2011 Masters of Statistics-Econometrics student of the year. Upon graduating from the University of Utah, Peter worked for a year as a Financial Analyst at Primary Children's Medical Center in Salt Lake City. In the Fall of 2012, Peter began his doctoral studies in Finance at the University of Maryland where he was until Summer of 2015 when he transferred to the University of Tennessee to complete his doctoral studies. At the University of Tennessee, Peter was pleased to work with Dr. Eric Kelley, who coincidentally grew up in the same small town of Canyon, Texas that Peter grew up in. Peter and Dr. Kelley were the authors of the second essay presented in this dissertation. Additionally, Peter was pleased to work with Dr. Andy Puckett and Dr. David Maslar whom he holds in the highest regard. Peter is Married to Kaitlyn Dixon they are the parents four beautiful children.