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Three Essays on Trading and Banking

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THREE ESSAYS ON TRADING AND BANKING

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ABSTRACT

This dissertation consists of three essays. The first essay, *Short Sales in the NYSE Batch Open and NASDAQ Opening Cross*, examines opening-trade short volume's relation to short volume for the rest of the trading day and to overnight, previous-day, and same-day price changes. We find that short volume in the batch open and opening cross increases with short volume for the rest of the day, with previous-day, open-to-close price changes, and with overnight price changes for S&P 500 stocks. Batch-open short volume increases with overnight price changes, and it increases (does not decrease) for firms making positive (negative) overnight earnings announcements. Opening-cross short volume increases with close-to-close, previous-day price changes and is negatively related to same-day price changes.

Our second essay, *Short Sales around Open-Market Repurchase Announcements*, studies short selling of a firm's stock during the five days after it announces an open-market repurchase. We conclude that a firm may be able to mislead normally-informed investors about its quality by announcing an open-market repurchase. Next, we conclude that open-market repurchase size does not possess positive signaling attributes. Lastly, we conclude that short sellers do not predict the repurchasing behavior of firms announcing an open-market repurchase.

The third essay, *Profit Efficiency and Big Bank Presence in Rural Markets*, studies the effect of big-bank presence on the profitability of rural one-market banks. We find that a small rural bank shows decreased profit efficiency and increased return on assets due to higher loan income when it competes with at least one big bank. If multiple big banks are competing with a small rural bank, the small bank shows a smaller decrease in profit efficiency and a smaller

increase in return on assets due to a smaller increase in loan income than if it competes with one big bank. From these results, we conclude that big banks choose to remain in rural markets where they possess some degree of market power, enabling them to earn higher returns while operating less efficiently, but market power is restricted when more than one big bank is present in a rural market.

DEDICATION

This work is dedicated to two people without whom I would have not completed my dissertation. First, I thank my loving wife, Julie Spurlin. She has been patient with me and supportive of my efforts during our marriage as I worked on my dissertation. I hope she is happy with the result. Second, but more so, I thank my personal Lord and Savior, Jesus Christ. Without Him, all of life and eternity would be meaningless. He loved and supported me through the entirety of this process, and I pray He is pleased with my efforts and the resulting product.

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ESSAY I: SHORT SALES IN THE NYSE BATCH OPEN AND NASDAQ OPENING CROSS

This paper looks at short sale volume that occurs as part of the batch open on the NYSE and as part of the opening cross on NASDAQ. The primary purpose of our study is to determine if short selling that occurs in a stock during these opening trades is predictive of short sale volume in that stock during the rest of the trading day and to determine whether short sales volume for a stock in the batch open or opening cross is related to its overnight price change or its previous day price change. We also examine how short sales that execute in the batch open and opening cross relate to price changes over the remainder of the trading day. We conduct this study to add to knowledge about daily-level short sales (e.g. Diether, Lee, and Werner, 2009, and Christophe, Ferri, and Angel, 2004) by examining short sales during the concentrated volume and high uncertainty of the market open (Madhavan and Panchapagesan, 2000). We are also motivated as trading at the open is considered crucial (Madhavan and Panchapagesan, 2000) and informative (Barclay and Hendershott, 2003). For the remainder of the paper, opening trade refers to the batch open on the NYSE and/or the opening cross on NASDAQ, and opening price refers to the price set by the NYSE specialist for the batch open and/or the price set by NASDAQ's electronic opening cross.

The opening price in a stock reflects both public and private information that has accumulated during the overnight period (Barclay and Hendershott, 2003). We examine whether short sales volume occurring in the opening trade is predictive of short sales volume over the rest of the day because total opening trade volume is positively related to total volume for the remainder of the day (Brooks and Moulton, 2004). Further, Diether, Lee, and Werner (2009) conclude that short sales are contrarian in contemporaneous returns and predictive of future negative returns. In our context of short sales in the opening trade, we consider overnight price changes (previous close to opening trade) and previous day price changes (close to close and open to close on the previous day) to correspond to contemporaneous returns, and we consider intraday price changes (opening trade to close) to correspond to future returns. Therefore, we suggest that opening trade short sales increase in overnight and previous day price changes and that opening trade short volume is inversely related to intraday price changes.[1]

We also examine short selling in the opening trade that follows a stock's earnings release made after the previous close but before the opening trade. We refer to these releases as non-trading period (NTP) earnings announcements. Barclay and Hendershott (2003) suggest earnings announcements made during this time frame will likely induce larger price reversals than earnings announcements made when markets are open due to lower price-discovery efficiency during the overnight period. Therefore, informed short sellers may attempt to profit on these reversals. Since Diether, Lee, and Werner (2009) find that short sellers are contrarian in contemporaneous returns, we believe that short volume may increase (decrease) in a stock's opening trade that follows an NTP earnings announcement with a positive (negative) surprise.

Blau and Pinegar (2010) show that daily short sales spike the day of and the day after positive earnings announcements. We differ from Blau and Pinegar (2010) since we do not look at *daily* short selling but focus on *opening trade* short sales, and we do not study their relation to

[1] We recognize the potential endogeneity issue with stating that short volume in the opening trade is related to overnight price change that is calculated using the opening price since any short sales in the opening trade affect the opening price. However, Barclay and Hendershott (2003) find that only 9% of price discovery from the previous close to the open occurs in the opening trade. So we suggest that any concerns should be small since very little price discovery for the overnight price change is determined by sales of any type in the opening trade.

all earnings announcements but only those made during the previous non-trading period.[2] For completeness, we study both positive and negative NTP announcements, but we focus on positive NTP announcements because they are more likely to affect the opening trade on the next day (Brooks, Patel, and Su, 2003). If short volume increases in the opening trade following positive NTP earnings announcements, it may add to the findings of Blau and Pinegar (2010) by indicating that increased short selling following positive earnings announcements begins as soon as short sellers have the opportunity to act during the trading day.[3]

Lastly, we study short sales of S&P 500 stocks during the opening trade on option-expiration Fridays. Stoll and Whaley (1991) find that S&P 500 stocks experience significant price reversals around the opening price when expiration values for S&P 500 option contracts are determined by the opening price of the component stocks on expiration Fridays. In light of these reversals around the opening price for S&P 500 stocks, the evidence that short sellers are contrarian in contemporaneous returns and that short sales predict negative returns (Diether, Lee, and Werner, 2009) leads us to examine whether opening trade short volume increases on option-expiration Fridays for S&P 500 stocks whose opening price is higher than the previous close.

This study's primary contribution is in determining how short sale volume during the market's opening trade is related to the day's short sale volume following the opening trade and in examining how short sale volume during the opening trade is related to overnight, previous day, and intraday price changes. We also examine short selling in the batch open and opening cross on two specific trading-day types. For days following non-trading period earnings

[2]To underscore the importance of studying the opening trade on days following non-trading period earnings announcements, we highlight that the practice of firms making after-hours earnings announcements is becoming common place. Berkman and Truong (2009) report earnings are announced after-hours more than 40% of the time for Russell 3000 index stocks over the period 2000-2004. The Russell 3000 index represents 98% of the United States equity market as it includes the 3,000 largest stocks according to market-cap.
[3] Holden and Subrahmanyam (1992) show that when large numbers of informed traders are active around an informational event, all of their information is revealed quickly as they aggressively and rapidly trade for profit around the event.

releases, we explore whether short selling during the opening trade is related to earnings surprises made known in the announcement, and for option-expiration Fridays, we look at the relation of opening-trade short volume to overnight price changes in S&P 500 stocks which, on average, demonstrate price reversals around the opening trade on option-expiration Fridays.

I. HYPOTHESES

Our first hypothesis considers the relation between opening-trade short volume and short volume over the remainder of the day. Barclay and Hendershott (2003) indicate that the opening trade is an informative trade, and Brooks and Moulton (2004) find that opening trade volume and total volume for the day are positively related. Based on these findings, we suggest that short volume in the opening trade is positively related to short volume over the remainder of the same day and question whether short selling during the opening trade for a stock is predictive of the level of short selling in that stock for the rest of the day. We state the following hypothesis:

H1: A stock's short volume in the NYSE batch open (NASDAQ opening cross) is positively related to that stock's short volume over the remainder of the trading day.

Diether, Lee, and Werner (2009) find that short sellers are contrarian in contemporaneous returns and that their increased activity precedes negative returns across trading days. However, they do not focus on the relation between daily returns and short sales executing in the day's opening trade. We believe the opening is a time when short sellers should be active since Diether, Lee, and Werner (2009) find that short sellers are opportunistic risk bearers, active in periods of uncertainty caused by information asymmetry and because the opening trade occurs in an atmosphere of uncertainty (Madhavan and Panchapagesan, 2000) and asymmetric information (Barclay and Hendershott, 2003).

Short sellers whose activity increases in positive returns and whose trades successfully predict negative returns across days (Diether, Lee, and Werner, 2009) may also be able to do the same within a trading day. The opening trade of the day is an attractive time for testing this possibility because it is an informative trade (Barclay and Hendershott, 2003) and because we can examine short sales in the NYSE batch open and the NASDAQ opening cross as they relate to overnight, previous day, and intraday price changes.

First, we examine short volume in the opening trade and price changes occurring overnight and on the previous day. When the opening price is higher than the previous close, there is more buy pressure than sell pressure during the opening trade. Diether, Lee, and Werner (2009) find evidence that short sellers step in to voluntarily provide liquidity when there is increased buy pressure. Therefore, we expect short volume in the opening trade to increase when the opening price is higher than the previous close. Since market participants can gather information during the pre-opening period (Barclay and Hendershott, 2003) and informed traders use market-on-open orders (Madhavan and Panchapagesan, 2000), we suggest that short sellers who are informed (e.g., Diamond and Verrecchia, 1987, and Dechow, Hutton, Meulbroek, and Sloan, 2001) will likely submit market-on-open orders in response to pre-open indications that the opening price will be higher than the previous close.[4] Their decisions may also be related to the previous day's price changes as short sellers attempt to profit from short-term price movements (Diether, Lee, and Werner, 2009). We examine whether opening-trade short volume increases when the opening price is higher than the previous close and when previous day price movements are positive, and state the hypothesis as follows:

[4] There may be concerns since short sales in the opening trade impact the opening price, but we think that any bias is against our suggested relation. We believe that short sales increase during the opening trade when pre-open indications are that the opening price will be higher, and since short sales push prices downward (Diamond and Verrecchia, 1987), not upward, our results concerning the relation between opening-trade short sale volume and the opening price should be interpreted considering the opening price would be higher if short sales that are part of the opening trade are not included.

H2: A stock's short volume in the NYSE batch open (NADSAQ opening cross) increases when the stock's opening price is higher than the previous close price (when previous day price changes are positive).

Next, we turn to the relation between short sales occurring as part of the opening trade and the intraday price change occurring from the opening trade to the close on the same day. Diether, Lee, and Werner (2009) show that short sales are informed trades, correctly predicting negative returns across days. The opening price is an informative price because it is based on accumulated public and private information (Barclay and Hendershott, 2003), some of which has been provided as informed short sellers impact the opening price by submitting market-on-open orders (Madhavan and Panchapagesan, 2000). Therefore, an increase in opening trade short volume could effectively predict negative intraday returns. We examine whether there is a negative relation between short volume in the opening trade and intraday price changes. We believe that any endogeneity inherent in testing our hypothesis is limited since price discovery occurs over the entire trading day (Barclay and Hendershott, 2003) so that trades occurring after the opening trade also contribute to intraday price changes. Our hypothesis follows:

H3: There is a negative relation between a stock's short volume in the NYSE batch open (NASDAQ opening cross) and that stock's intraday price change.

Barclay and Hendershott (2003) suggest earnings announcements made after the market closes will likely induce larger price reversals than earnings announcements made during the day because price changes when markets are closed are less informative than during normal trading. Their findings suggest that a non-trading period (NTP) earnings announcement that reveals a surprise may result in overreaction that will be corrected during the following day's trades.

According to Brooks, Patel, and Su (2003) surprise news from an overnight announcement results in an immediate price reaction in the following opening trade, and Holden and Subrahmanyam (1992) indicate that informed traders will aggressively and rapidly trade around information events in order to profit from their information. During the pre-open period, market participants have the opportunity to gather information from indications of the day's opening price (Barclay and Hendershott, 2003), so orders submitted to execute in the NYSE batch open or the NASDAQ opening cross are a prime opportunity for short sellers, who have superior information (Christophe, Ferri, and Angel, 2004), to trade (not trade) if they see an indication of prices overreacting to a positive (negative) NTP earnings announcement. Therefore, a positive (negative), non-trading period, earnings surprise may be accompanied by an increase (decrease) in opening-trade short sales for the stock, particularly if short sellers attempt to profit from an expected price reversal after a positive surprise from an NTP earnings announcement.

Blau and Pinegar (2010) find that short sellers are profitable when increasing *daily* short sales in response to positive earnings announcements. We look at *opening trade* short sales on days following positive and negative NTP earnings announcements to determine whether short volume during the opening trade is related to earnings surprises occurring in the non-trading period. We state the following hypothesis:

H4: A stock's short volume in the NYSE batch open or NASDAQ opening cross increases (decreases) with a positive (negative) surprise revealed in that stock's non-trading period earnings announcement that precedes the opening trade.

Option-expiration-day trading effects are documented by Stoll and Whaley (1990) who conclude that price changes on option-expiration days are likely due to non-informational trades, particularly program trading. Barclay, Hendershott, and Jones (2008) show that program trading on option-expiration days is a cause of increased buy-order pressure in the opening trade of some S&P 500 stocks and that this increased pressure results in temporary price changes. Stoll and Whaley (1991) find that on option-expiration Fridays, S&P 500 index stocks experience significant price reversals around the opening price. These price reversals may be due to the temporary price changes induced by expiration-day liquidity shocks documented by Barclay, Hendershott, and Jones (2008).

Diether, Lee, and Werner (2009) conclude that short sellers provide liquidity during periods of increased buy pressure and that informed short sellers target short-term overreaction in prices in order to profit from subsequent price declines. Based on these findings, we suggest that informed short sellers will increase short volume to provide liquidity for S&P 500 stocks with increased buy-order pressure during the opening trade on option-expiration days. Short sellers may trade as they predict that price increases will experience reversal during the trading day, allowing them to profit. Accordingly, for S&P 500 stocks, we examine whether short volume in the opening trade on option-expiration Fridays is related to price movements occurring during the period between Thursday's close and the opening trade on Friday. The hypothesis follows:

H5: On option-expiration Fridays, short volume in the NYSE batch open (NASDAQ opening cross) increases in overnight price changes for S&P 500 stocks.

II. DATA

We begin our sample formation by identifying ordinary common stocks that are listed on the NYSE or NASDAQ. We select stocks having a share code of 10 or 11 (ordinary, common shares) and having an exchange code of 1 or 3 (NYSE and NASDAQ firms, respectively) from the CRSP database. Then, by using TAQ, we restrict the selected NYSE and NASDAQ stocks to those that have at least one trade occurring before 10:30 AM EST on everyday of our sample period of January, 2005, to December, 2006. Our study focuses on short sales in the opening trade, so we think it necessary to restrict sample stocks to those having their first trade occur near the market's official open time of 9:30 AM EST. Lastly, we follow the convention of requiring a minimum share price for sample stocks (e.g., Diether, Lee, and Werner, 2009) by limiting our sample to those stocks having a CRSP opening or closing price of at least $5 on each sample day. Our selection method yields a sample of 1,072 NYSE firms and 688 NASDAQ firms. We test our hypotheses separately for the NYSE batch open and the NASDAQ opening cross as we examine short sale volume occurring as part of the opening trade.[5]

For each stock in our sample, we use the TAQ database to identify the first recorded trade occurring at or after 9:30 AM EST each day as the daily batch open or opening cross trade. We match the TAQ opening trade for each stock on each day to trades in the Regulation SHO short sales data by date and time. If a short sale occurs on the same date at the same time as the batch open or opening cross trade identified in the TAQ database, we consider the short sale to be

[5] Barclay, Hendershott, and Jones (2008) conclude that the NYSE batch open and the NASDAQ opening cross, started in 2004, function similarly in their price-setting ability.

traded in the opening trade of the day.[6] For each stock on each day, we calculate a normalized opening-trade short volume. Our normalized measure is calculated by dividing each stock-day, opening trade short volume by the mean daily opening trade short volume for the stock as measured over all sample days. Other daily observations taken from CRSP for each sample stock include: total volume, opening volume, common shares outstanding, and return.

We calculate several other variables for each sample stock. These include daily short volume, obtained by summing all shorted shares over each sample day; daily volume not in the batch open (opening cross) or intraday volume, which is daily volume less batch open (opening cross) volume; daily short volume not in the batch open (opening cross) or intraday short volume, which we calculate as daily short volume less short volume in the batch open (opening cross); overnight price change, the batch open (opening cross) price minus the previous day's close price; intraday price change, the close price minus the batch open (opening cross) price; the abnormal daily return, the CRSP daily return less the CRSP equally-weighted return for the day; and firm size, the CRSP shares outstanding value multiplied by the CRSP close price for the day.

Table 1 and Table 2 show summary statistics for our NYSE and NASDAQ samples, respectively.[7] We find short sales contribute 17% of daily volume on the NYSE and about 18% on NASDAQ over our entire sample, which is quantitatively similar to samples in other studies.[8] We focus on short sales during the opening trade, so we separate daily volume into opening trade volume and intraday volume. Intraday volume has roughly the same proportion of short selling as total volume with approximately 17% on the NYSE and 18% on NASDAQ. The batch open

[6] The data sometimes contains two trades that match date and time for a stock's TAQ opening trade because exempt and non-exempt short sales are reported in separate records. When this occurs, we sum the short sale volume for both records so that we account for all short sales that execute in the opening trade of the day.

[7] All Tables for Essay I are provided in the appendix to Essay I.

[8] Diether, Lee, and Werner (2009) find that short volume makes up 24% and 31% of total daily volume on the NYSE and NASDAQ, respectively; Blau, Van Ness, and Van Ness (2009) show that short sales, on average, make up slightly less than 20% of share volume; and Boehmer, Jones, and Zhang (2008) find short sales making up about 13% of volume on the NYSE SuperDOT system.

on the NYSE shows approximately 19% short volume; however, short sales make up 29% of the opening cross on NASDAQ.

The opening trade normally occurs quickly after the official market open time of 9:30 AM EST as the mean time for the batch open is 9:32 AM, and the mean time for the electronic opening cross is only ten seconds after trading opens. The first short sale normally occurs very close to 9:30 AM and only slightly later than the opening trade as we find the first short sale occurring at about 9:33 AM on both markets. Prices remain relatively flat during our sample period, both during the day and between days. The mean close price on the NYSE is equal to the mean batch open price of $37.97, and the mean opening cross and close prices on NASDAQ are separated by only two cents. The average abnormal daily return over our sample period is only one basis point on the NYSE and less than one basis point (+0.00%) on NASDAQ.

III. METHODS

In testing the first three hypotheses, we are interested in the relation between a stock's short volume in the day's opening trade and five other measures for the stock: 1) intraday short sales, denoted as *ISS* and defined as daily short volume less short volume in the opening trade; 2) overnight price change, denoted as *OvernightChg* and defined as the opening price minus the previous close price; 3) our first measure of the previous day's price change, denoted as *PrevCloClo* and defined as the close price lagged one day minus the close price lagged two days; 4) a second measure of the previous day's price change, denoted as *PrevOpenClo* and defined as the previous day's close price minus the previous day's opening price; and 5) intraday price change, denoted as *IntradayChg* and defined as the close price minus the opening price.

We begin our tests by dividing all stock-day observations into groups based on the normalized value of each stock's opening trade short volume on each trading day. We call this measure the stock's normal opening short volume and denote it as $NOSV_{i,t}$. $NOSV_{i,t}$ is calculated as the opening trade short volume for stock *i* on day *t*, divided by stock *i*'s mean opening trade short volume over all sample trading days. Group 1 contains observations with $NOSV_{i,t} >= 2$, indicating stock days when the opening-trade short volume is at least twice the normal amount. Group 2 observations are those where $1 <= NOSV_{i,t} < 2$, indicating the opening-trade short volume is at least the normal amount but less than twice the normal amount. Group 3 and Group 4 observations are those having $0.5 <= NOSV_{i,t} < 1$ and $0.0 < NOSV_{i,t} < 0.5$, respectively. Therefore, Group 3 observations have at least half the normal level but less than the normal amount of short sales in the opening trade; and Group 4 observations have some short selling in the opening trade but less than half the normal amount. Group 5 observations are those with no short sales in the opening trade, so $NOSV_{i,t} = 0$. Observations for a stock may appear in different groups since the groups are based on the normal opening short volume for each stock-day observation.

For each of these groups, we calculate mean levels of *ISS, OvernightChg, PrevCloClo, PrevOpenClo,* and *IntradayChg*. To determine whether there is a relation between levels of short selling in the opening trade and each of these measures, we perform t-tests for difference in means between the groups for each measure.

Next, we use regression analysis by estimating the following two OLS models:

$$NOSV_{i,t} = \alpha + \beta_1 ISS_{i,t} + \beta_2 SS_{i,t-1} + \beta_3 AbRet_{i,t-1} + \beta_4 ln(Size)_{i,t} + \gamma W + \delta Z + \varepsilon_{i,t} \quad (1)$$

$$NOSV_{i,t} = \alpha + \beta_1 PriceChange_{i,t} + \beta_2 SS_{i,t-1} + \beta_3 AbRet_{i,t-1} + \beta_4 ln(Size)_{i,t} + \gamma W + \delta Z + \varepsilon_{i,t} \quad (2)$$

In both models, the subscript *i,t* denotes values for the *i*th stock on the *t*th trading day of the sample. The dependent variable $NOSV_{i,t}$ is the normalized value of short volume in the opening trade for stock *i* on day *t*. In model 1, $ISS_{i,t}$ is intraday short volume for the *i*th stock on the sample's *t*th day, which is the independent variable of interest in testing the first hypothesis. In model 2, $PriceChange_{i,t}$ is the independent variable of interest when testing the second and third hypotheses. For Hypothesis 2, $PriceChange_{i,t}$ is either $OverightChg_{i,t}$, $PrevCloClo_{i,t}$, or $PrevOpenClo_{i,t}$. For testing Hypothesis 3, we use $IntradayChg_{i,t}$ as $PriceChange_{i,t}$.

In both models, we include several control variables related to short selling based on Diether, Lee, and Werner (2009). First, $SS_{i,t-1}$ is defined as total short volume for the stock on the previous trading day that is scaled by 10,000 (for reporting). We include $SS_{i,t-1}$ because short sales on a given day are correlated with those on the previous day. Next, $AbRet_{i,t-1}$ is the stock's abnormal daily return for the previous day, where $AbRet_{i,t}$ is the CRSP daily return for stock i on day t less the CRSP equally-weighted return for day t. We control for each stock's previous day's return because short sales increase (decrease) following positive (negative) returns. $Ln(Size)_{i,t}$ is the natural log of stock i's market cap on day t, calculated using the CRSP close price and outstanding common shares for the firm. The firm size measure is included because larger stocks are relatively easier to sell short.

In models 1 and 2, we include a matrix, W, containing five dummy variables. Each of these dummy variables corresponds to a day of the week and is equal to one if trading day t occurs on the corresponding day of the week and zero otherwise. Similarly, Z is a matrix of four dummy variables, corresponding to whether day t is a day when a macroeconomic announcement is made at 8:30 AM, is a day when a macroeconomic announcement is made at 10:30 AM, is the last trading day for a month, or is the last trading day for a quarter. We restrict the estimated coefficients of the matrix W variables so that they must sum to zero. Suits (1984) explains that restricting the estimation in this way allows us to interpret the unrestricted coefficient estimates within the model as averages over all days of the week, so that we avoid using an omitted day of the week, causing problematic interpretations by using the omitted day of the week as the base case for comparison.

Hypothesis 4 concerns a stock's opening trade short volume on days following non-trading period (NTP) earnings announcements, defined as a firm's normally scheduled earnings announcement that is announced outside of normal trading hours. The first opportunity for information in an NTP announcement to affect prices during normal trading hours is the next opening trade. Therefore, following Christophe, Ferri, and Angel (2004), we consider the trading day that begins with the opening trade after an NTP announcement to be the announcement day.

For tests of Hypothesis 4, we only use sample observations of firms for which we have data on all eight, normal, quarterly earnings releases during our two-year sample period. This requirement eliminates 4 NYSE firms and 5 NASDAQ firms, resulting in a restricted sample of 1,068 NYSE firms and 683 NASDAQ firms. For these firms, we obtain actual announcements and consensus estimates for quarterly earnings using IBES. We define a positive (negative) earnings announcement as one where actual earnings are greater than (less than) the consensus estimate for the announcement. In our restricted sample, 671 of 683 NASDAQ firms and 1,062 of 1,068 NYSE firms make at least one of eight earnings releases when trading is not open. There are 13,418 observations of stock earnings announcements with a total of 12,070 observations being NTP announcements. Therefore, it appears that during our sample period, firms prefer making earnings announcements during the non-trading period. Of the NTP announcements, 8,152 contain positive surprises, 3,656 contain negative surprises, and 262 announcements contain no surprise.

We use the following four OLS models as we test Hypothesis 4:

$$NOSV_{i,t} = \alpha + \beta_1 AnnDay_{i,t} + \beta_2 NTPAnn_{i,t} + \beta_3 SS_{i,t-1} + \beta_4 AbRet_{i,t-1} + \beta_5 ln(Size)_{i,t} + \gamma W + \delta Z + \varepsilon_{i,t} \tag{3}$$

$$NOSV_{i,t} = \alpha + \beta_1 NTPAnn_{i,t} + \beta_2 Sur_{i,t} + \beta_3 NTPAnn*Sur_{i,t} + \beta_4 SS_{i,t-1} + \beta_5 AbRet_{i,t-1} + \beta_6 ln(Size)_{i,t} + \gamma W + \delta Z + \varepsilon_{i,t} \tag{4}$$

$$NOSV_{i,t} = \alpha + \beta_1 NTPPos_{i,t} + \beta_2 NTPNeg_{i,t} + \beta_3 NTPPos*Sur_{i,t} + \beta_4 NTPNeg*Sur_{i,t} + \beta_5 SS_{i,t-1} + \beta_6 AbRet_{i,t-1} + \beta_7 ln(Size)_{i,t} + \gamma W + \delta Z + \varepsilon_{i,t} \tag{5}$$

$$NOSV_{i,t} = \alpha + \beta_1 NTPAnn_{i,t} + \beta_2 Sur_{i,t} + \beta_3 NTPPos_{i,t} + \beta_4 NTPNeg_{i,t} + \beta_5 NTPPos*Sur_{i,t} + \beta_6 NTPNeg*Sur_{i,t} + \beta_7 SS_{i,t-1} + \beta_8 AbRet_{i,t-1} + \beta_9 ln(Size)_{i,t} + \gamma W + \delta Z + \varepsilon_{i,t} \tag{6}$$

The dependent variable, $NOSV_{i,t}$, is our normalized measure of short volume in the opening trade used in models 1 and 2. Model 3 is estimated using all sample days whereas models 4, 5, and 6 are estimated using only a sample stock's earnings announcement days. Independent variables in the models include $Sur_{i,t}$, which is the surprise associated with stock *i*'s announcement on day *t* and also include a series of dummy variables indicating trading day characteristics by the appropriate variable equaling one when the characteristic exists for the day and zero otherwise. The dummy variables include $AnnDay_{i,t}$, denoting if day *t* is an earnings announcement day for stock *i*; $NTPAnn_{i,t}$, indicating if day *t* is one when stock *i*'s earnings announcement was made during the non-trading period preceding day *t*; $NTPPos_{i,t}$, marking whether an NTP announcement for stock *i* on day *t* is a positive surprise; and $NTPNeg_{i,t}$, denoting when an NTP announcement for stock *i* on day *t* contains a negative surprise. We also include interaction variables for variable $Sur_{i,t}$ with NTP announcement variables $NTPAnn_{i,t}$, $NTPPos_{i,t}$, and $NTPNeg_{i,t}$. The other variables in these models are controls as defined previously, and we continue to restrict estimated coefficients for day-of-week variables to sum to zero.

Hypothesis 5 examines whether there is a relation between *NOSV* and overnight price changes for S&P 500 stocks on option-expiration days. Therefore, we restrict the sample to only those firms that are part of the S&P 500 composite index over the entire sample period of January, 2005, to December, 2006. The resulting sample contains all observations from the main sample for the 367 firms that meet this requirement. We also include daily observations (obtained from DeltaNeutral.com) for total open interest and the put-call ratio for each of the 367 firms in the restricted sample. Because of the small number of restricted sample firms, we assume that S&P 500 stocks are similar regardless of trading market and do not separate the sample into NYSE and NASDAQ firms. We estimate the following OLS model:

$$NOSV_{i,t} = \alpha + \beta_1 OE_t + \beta_2 ON\_Chg_{i,t} + \beta_3 Rev_{i,t} + \beta_4 P/C_{i,t} + \beta_5 OI_{i,t} + \beta_6 OE*ON\_Chg_{i,t} + \beta_7 OE*Rev_{i,t} + \beta_8 OE*P/C_{i,t} + \beta_9 OE*OI_{i,t} + \beta_{10} SS_{i,t-1} + \beta_{11} AbRet_{i,t-1} + \beta_{12} ln(Size)_{i,t} + \gamma W + \delta Z + \varepsilon_{i,t} \quad (7)$$

In model 7, $NOSV_{i,t}$ continues to be our dependent variable, measuring the normalized value of short volume in the opening trade. Independent variables in model 7 include the following: $OE_{i,t}$, equaling one when trading day t is an option-expiration Friday and zero otherwise; $ON\_Chg_{i,t}$, the overnight price change for stock i on day t as defined in model 2; $P/C_{i,t}$, the put option volume divided by the call option volume for stock i on day t; and $OI_{i,t}$, the total open interest of option contracts for stock *i* on day *t*. We include $P/C_{i,t}$ and $OI_{i,t}$ to control for short sales in the opening trade that are related to option trading in the stock because Diether, Lee, and Werner (2009) show that put options trading for a stock are positively correlated with short selling in that stock. Additionally, Figlewski and Webb (1993) find that traded options provide completeness for a stock's market, facilitating short selling in that stock.

Stoll and Whaley (1991) show that S&P 500 stocks experience price reversals around the opening trade on option-expiration Fridays. In order to test whether short sellers attempt to trade on these known reversals, we include $Rev_{i,t}$ in model 7 as their calculation of stock *i*'s price movement around the opening trade on day *t*. As in Stoll and Whaley (1991), we begin calculating two different values of $Rev_{i,t}$ using the following:

$${}_{pre}R_{i,t} = [({}_{open}P_{i,t} - {}_{close}P_{i,t}) / {}_{close}P_{i,t}] \times 100 \quad (8)$$

$${}_{post}R_{i,t} = [({}_{open+30}P_{i,t} - {}_{open}P_{i,t}) / {}_{open}P_{i,t}] \times 100 \quad (9)$$

$${}_{post}R_{i,t} = [({}_{close}P_{i,t} - {}_{open}P_{i,t}) / {}_{open}P_{i,t}] \times 100 \quad (10)$$

In models 8, 9, and 10, ${}_{open+30}P_{i,t}$ is the first price for stock i occurring at or after 10:00 AM EST (i.e., 30 minutes after market opening); ${}_{open}P_{i,t}$ is the opening price for stock i on day t; and ${}_{close}P_{i,t}$ is the closing price of stock i on day t. Therefore, ${}_{pre}R_{i,t}$ is the return on stock i measured from the previous closing price to the opening price on day t, and ${}_{post}R_{i,t}$ is the return for stock i occurring between the opening trade and either 30 minutes after the market opens or market closing on trading day t. Accordingly, $Rev_{i,t}$ has two different values for each stock-day observation depending on whether the post-opening-trade return is calculated using the stock's closing price or the stock's price 30 minutes after the market opens. $Rev_{i,t}$ is valued according to the following rules:

$$Rev_{i,t} = {}_{post}R_{i,t} \text{ when } {}_{pre}R_{i,t} < 0 \quad (11)$$

$$Rev_{i,t} = (-1) \text{ X } {}_{post}R_{i,t} \text{ when } {}_{pre}R_{i,t} > 0 \quad (12)$$

A positive (negative) reversal is one where ${}_{post}R_{i,t}$ and ${}_{pre}R_{i,t}$ have opposite (the same) signs.

Other variables in model 7 include interaction terms for $OE_{i,t}$ with $ON\_Chg_{i,t}$, $Rev_{i,t}$, $P/C_{i,t}$, and $OI_{i,t}$ so that we can estimate the effect of these independent variables on option-expiration Fridays. We also include the two matrices, W and Z, containing control variables for day of week and trading day type, respectively, as described earlier. Model 7 is estimated using the Suits (1984) procedure of restricting the coefficients for day-of-week variables to sum to zero, as in our previous models.

IV. EMPIRICAL RESULTS

Table 3 and Table 4 show five groups of stock-day observations, divided according to each observation's level of normalized short selling in the opening trade, $NOSV_{i,t}$. In these tables, we present each group's mean values for each of our tested variables, and we show p-values for difference in the means between groups. We find support for our first and second hypotheses for NYSE stocks (Table 3). Our results suggest a positive, monotonic relation between batch open short sales and both intraday short selling and overnight price changes. Each group with successively higher levels of normalized batch open short volume also has significantly higher levels of intraday short sales and overnight price changes than the group with a lower level of opening trade short sales. However, our findings do not support the second part of Hypothesis 2, as we find no relation between previous day price changes and batch open short sales. Further, we do not find support for short sales in the batch open being negatively related to intraday price changes, as stated in Hypothesis 3.

When we view NASDAQ results in Table 4, we see limited support, at best, for a positive relation between opening cross short sale volume and intraday short sales, overnight price changes, or previous day price changes. However, for NASDAQ stocks, the results support a negative relation between opening-cross short sales and intraday price changes, as in our third hypothesis.

Table 5 shows regression results for tests of the first three hypotheses using our NYSE sample. We find support for Hypothesis 1, as batch open short volume is positively related to short selling over the remainder of the day when we control for other factors likely to affect the dependent variable. Hypothesis 2 is also supported as we find that batch open short volume is positively related to overnight price changes and price changes measured between the previous day's open and close. No support is found for Hypothesis 2 concerning the previous day close-to-close price change. Lastly, our results are opposite than expected for Hypothesis 3. We expect a negative relation between opening trade short sales and intraday price changes, but we find a positive relation.

For NASDAQ stocks, regression results support all of our first three hypotheses. Table 6 shows that there is a positive relation between opening cross short sales for a stock and short sales in that stock over the remainder of the day. Short sales also increase in the opening cross when there is positive price movement on the previous day according to both measures; however, there is no support for opening cross short sales increasing when the overnight price change is positive. We find evidence of a negative relation between short sales in the NASDAQ opening cross and price changes for the remainder of the day.

For our control variables in Table 5 and Table 6, we see that across all models and both markets, a stock's opening trade short volume tends to be positively related to both that stock's previous day's short selling and previous day's abnormal return. These results are consistent with previous work concerning daily short sales (e.g. Diether, Lee, and Werner, 2009). However, we show in Table 5 (Table 6) that firm size and opening trade short volume are negatively related (unrelated) on the NYSE (NASDAQ), whereas Diether, Lee, and Werner (2009) report that larger firms tend to be easier to short on a daily basis.

Other results provided in Table 5 and Table 6 indicate that across all models and both markets, short selling in the opening trade tends to decrease on days when a macroeconomic announcement is made at 8:30 AM, but it tends to increase on days with a 10:00 AM macroeconomic announcement. Also across all models and both markets, short sales tend to decrease in the opening trade on the last trading day of a month or quarter. Because we restrict the coefficients of the day of week variables to sum to zero, we interpret our results as averages across all days of the week, so we do not report coefficient estimates for these variables.[9] The Durbin-Watson statistic for the test of autocorrelated errors is presented for each model, and we conclude that autocorrelation is not a problem with the models presented in either Table 5 or Table 6. First-order autocorrelation ranges from 3.1% to 3.6% for NYSE observations (Table 5), and from 2.1% to 2.2% for NASDAQ observations (Table 6).

In Table 7 and Table 8, we present results from testing Hypothesis 4 for the NYSE and NASDAQ samples, respectively. We begin by estimating the first model using both announcement and non-announcement days to determine if there is any relation between a stock's opening-trade short sales for a day and that day being an earnings announcement day, in general, or an NTP earnings announcement day as opposed to non-announcement days. We find that, for both NYSE and NASDAQ, opening trade short volume in a stock increases on days the stock has an earnings announcement, with a larger increase occurring if the day is preceded by an NTP earnings announcement.

In the second model of Tables 7 and 8, we restrict the sample to only announcement days, so we remove the announcement day variable from the model but include the surprise from the announcement and an interaction variable for the surprise occurring with an NTP announcement. The results indicate that NTP earnings announcements are accompanied by increases in opening trade short volume on both markets as compared to days when the earnings announcement is

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[9] We do not report coefficient estimates for day of week variables in any of our results because all models restrict these coefficients to sum to zero for interpretation purposes.

made during trading. Earnings announcement surprises are not related to opening trade short sales on either market for announcement days, in general, or for NTP announcement days, specifically.

Next, in the third model, we again use only earnings announcement days from our samples. We use two dummy variables to separately test whether positive or negative earnings surprises affect opening trade short volume that follows an NTP announcement. We also include interaction variables for the earnings surprise with each dummy variable denoting whether the surprise is positive or negative for NTP announcements. Surprises may be neither positive nor negative, meaning a case of no surprise with an NTP announcement. The no surprise case is our base case for comparison.

Results indicate that NYSE stocks (Table 7) with positive earnings surprises have higher short volume occurring in the batch open that follows an NTP announcement than on days with no NTP earnings surprise, and there is greater short selling in the batch open with a larger positive surprise. However, there is no significant difference between NYSE stocks having negative NTP surprises and those with no NTP surprise. Therefore, in the NYSE sample, we find support for our fourth hypothesis concerning positive surprises but not for negative surprises. We find that NASDAQ stocks (Table 8) having either a positive or negative earnings surprise have higher levels of short sales in the opening cross following an NTP announcement than those stocks with no NTP surprise. However, the interaction of the direction of surprise indicator with the value of the NTP surprise is insignificant. Therefore, we consider the results for NASDAQ stocks to be that short volume in the opening cross following an NTP announcement is unrelated to earnings surprises. We find no support for Hypothesis 4 with the NASDAQ sample.

The fourth model in Tables 7 and 8 is estimated using announcement days and combines the third model with a variable for announcement surprise value and a variable indicating if the announcement is an NTP announcement. Here, we find that an NYSE stock (Table 7) experiences higher levels of short selling in its batch open following a positive NTP earnings announcement, and the larger the positive surprise, the higher the short sale volume in the batch open. We also find with this model that NYSE stocks' batch open short volume is unrelated to earnings surprises, in general; to the earnings announcement being made during the non-trading period; and to a negative NTP announcement surprise. Again, these results for the NYSE sample support Hypothesis 4 concerning positive NTP earnings announcements, but we find no support concerning negative announcements. Further, results indicate that NASDAQ opening cross short volume in a stock (Table 8) is unrelated to any of the variables concerning Hypothesis 4.

Results for control variables in the first model of Tables 7 and 8 are identical in direction and significance to the results for our models in Tables 5 and 6 (i.e., both NYSE and NASDAQ firms). However, when we study the results for our control variables in the other three models in Tables 7 and 8, the estimates for earnings announcement days differ from those for all trading days. We continue to find a positive relation between days with macroeconomic announcements at 10:00 AM and short selling in opening trades those days, in both markets. Additionally, NYSE firm size continues to be negatively related to batch open short volume in two of three models in Table 7, and NASDAQ firm size is negatively related to stocks' opening cross short volume on earnings announcement days in Table 8. All other control variables are insignificant for estimates using only earnings announcement days.

We also report the Durbin-Watson statistic from our tests for autocorrelation in the errors of our models and the coefficients of autocorrelation for the models in Tables 7 and 8. We believe that autocorrelation is not a problem in the first model where it is below three percent in both the NYSE and NASDAQ sample. It ranges from 5.9% in all models tested for the NASDAQ sample to 7.0% in one model tested for the NYSE sample when only announcement days are included. Because the announcement days occur quarterly, we do not consider the higher values problematic.

We present results from tests for a relation between an S&P 500 stock's opening trade short volume on option-expiration Fridays and that stock's price change between Thursday's close and Friday's opening trade in Table 9. We present two different models, each controlling for a different measure of price reversal around Friday's opening trade as in Stoll and Whaley (1991). The first model uses the stock's price thirty minutes after the markets open on Friday to calculate the day's reversal, and the second uses the close price for Friday in the calculation. Results show that opening trade short volume increases dramatically for S&P 500 stocks on option-expiration Fridays, and we find that opening trade short volume is positively related to overnight price changes, in general, which we previously show in our full sample of NYSE firms. More importantly, the interaction of overnight price change for a stock and the day being an option-expiration Friday is positively related to opening trade short volume. This result directly supports our fifth hypothesis that opening trade short sales in S&P 500 stocks are increasing in overnight price changes on option-expiration days.

Our models in Table 9 show that price reversals around the opening trade are negatively related to opening trade short volume for S&P 500 stocks, in general; but on option-expiration Fridays, the relation is positive. This result indicates that short sellers may trade based on known reversals for S&P 500 stocks on expiration days. Other new control variables include the put/call ratio and total open interest in options along with interaction variables for put/call ratio and total open interest with an indicator of whether the day is an option-expiration Friday. Results indicate that opening trade short selling is less when there is a higher number of puts per call, and the relation is more strongly negative on option-expiration Fridays. These results are not consistent with findings that put option trading and daily short selling are positively correlated (Diether, Lee, and Werner, 2009). The total open interest is unrelated to short volume in the opening trade on normal trading days; however on option-expiration days, we find a positive relation for total open interest. These results agree with results from Figlewski and Webb (1993) who conclude that traded options facilitate short selling.

Results for our standard control variables differ somewhat in this sample, which is restricted to only S&P 500 stocks. Differences include opening trade short volume increasing on days when an 8:30 AM macroeconomic announcement is made. Results from the full sample indicate a negative relation with 8:30 AM macroeconomic announcements for both NYSE and NASDAQ markets. Also, we find that a trading day being the last of the quarter is not related to opening trade short volume for a stock in the restricted sample. In the full sample, we find a negative relation for this variable on both markets.

The errors in the restricted sample of Table 9, show slightly more autocorrelation than the full sample. The restricted sample shows an autocorrelation coefficient of 5.1%. In the models for the full sample, errors show autocorrelation of about 2% for NASDAQ firms and about 3% for NYSE firms. Based on the Durbin-Watson statistic of 1.899 in Table 9, we do not consider a need to control for autocorrelation in the restricted sample.

V. SUMMARY AND CONCLUSIONS

This paper examines how a stock's short volume in the NYSE batch open or NASDAQ opening cross is related to market activity following and preceding the batch open or opening cross. We study the relation of short sales in the opening trade to the level of short sales and price changes occurring during the rest of the day, and we investigate the relation of opening trade short sales to four different preceding price changes: the overnight price change, the previous day's price change measured from the previous close to close and from the open to close, and overnight price changes for S&P 500 stocks related to option-expiration Fridays. We also study preceding activity in the relation of short sales in a stock's opening trade that follows a non-trading period earnings announcement to the earnings surprise in that announcement. Our results differ somewhat between NYSE and NASDAQ markets, depending on the relation tested.

We make three conclusions for both NYSE and NASDAQ firms. First, short volume in the batch open and opening cross is positively related to the short volume occurring over the remainder of the day. Second, a stock's short volume in the batch open and opening cross increases when the stock has a positive price change between the open and close on the previous day. These first two conclusions, taken together, are consistent with daily short sales increasing on days following positive returns and short selling in the open being predictive of increases in short volume over the entire day. Third, S&P 500 stocks trading on NYSE or NASDAQ have more short sales in their opening trade on option-expiration days when the opening price is higher than the previous close. We suggest that short sellers provide liquidity in the opening trade for S&P 500 stocks on expiration days in order to profit from known price reversals.

We make other conclusions for NYSE firms alone. First, batch open short volume not only increases for stocks that exhibit positive price changes in the previous day's open to close period but also increases for stocks exhibiting positive overnight price changes. Perhaps short sellers in the batch open consider price changes over the twenty-four hour period from open to open as they view pre-market indications of the batch open price. Second, many firms choose to release earnings when markets are closed. Short selling increases in the batch open on the next day for those firms with positive earnings surprises when markets are closed. However, there is no decrease in short selling in the batch open for firms who have earnings releases that reveal negative surprises when markets are closed. These results for earnings surprises during closed markets are consistent with informed short sellers acting quickly to trade around informational events in order to profit from their superior information.

Lastly, we are able to make two conclusions for NASDAQ firms that are not made for NYSE firms. First, short sales in the opening cross for a stock increase when the stock exhibits negative price movements during the trading day. Negative intraday price movements following increases in opening cross short volume indicate that short sellers in NASDAQ stocks may be able to predict returns during the trading day and not only across trading days. Second, opening-cross short volume increases for stocks that have positive price changes on the previous day when those changes are measured as close to close or open to close changes. However, short volume does not increase in the opening cross for stocks having positive overnight price changes.

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Appendix

Table 1: Summary Statistics – NYSE Firms

	Minimum	Maximum	Mean	Median
Volume in Batch Open	100	11,822,000	23,250.23	5,100
Short Volume in Batch Open	0	2,113,300	4,471.30	600
Normalized Short Volume in Batch Open	0	373.23	1.00	0.27
Batch Open Time	9:30:00 AM	10:29:46 AM	9:32:02 AM	9:31:21 AM
First Short Sale Time	9:30:00 AM	4:01:48 PM	9:33:43 AM	9:31:51 AM
Daily Volume	2,200	338,334,200	1,373,902.19	534,300
Daily Short Volume	100	45,390,100	231,455.72	101,200
Daily Volume not in Batch Open (Intraday)	2,100	337,248,600	1,350,651.95	526,100
Daily Short Volume not in Batch Open(Intraday)	0	45,390,100	226,984.42	99,100
Batch Open Price$_t$	5.07	555.50	37.97	34.13
Close Price$_t$	5.02	553.86	37.97	34.12
Close Price$_{t-1}$ – *Close Price*$_{t-2}$	-103.47	34.95	0.01	0.00
Close Price$_{t-1}$ – *Batch Open Price*$_{t-1}$	-21.55	32.59	+0.00	0.00
Overnight Price Chg	-103.54	31.76	0.01	0.00
Intraday Price Chg	-21.55	32.59	-0.00	0.00
Daily Return	-43.48%	52.51%	0.06%	0.00%
CRSP Equally-weighted Daily Return	-1.82%	2.45%	0.05%	0.12%
Abnormal Daily Return	-43.05%	51.97%	0.01%	-0.05%
Firm Size	83,524,050	459,191,780,240	9,707,849,704	2,547,998,765

The table presents summary statistics for NYSE firms in our sample used for analysis. The sample includes 1,072 NYSE common stocks with a CRSP share code of 10 or 11 that have at least one trade occurring before 10:30 AM EST on everyday of our sample period of January, 2005, to December, 2006, and that have either a batch open or closing price of $5 on each trading day. N*ormalized Short Volume in Batch Open* is a stock's daily short volume in the batch open divided by the stock's mean short volume in the batch open over the sample period. *Overnight Price Chg* is calculated as batch open price minus the previous day's close price. *Intraday Price Chg* is calculated as the day's close price minus the batch open price. *Daily Return* is the CRSP daily return for the stock, and *Abnormal Daily Return* is the CRSP daily return for the stock less the CRSP equally-weighted return for the day. *Firm size* is the daily market cap calculated from the CRSP shares outstanding value and the close price for the day. For indexing, *t* is the sample day.

Table 2: Summary Statistics – NASDAQ Firms

	Minimum	Maximum	Mean	Median
Volume in Open Cross	1	9,848,167	5,084.11	1,115
Short Volume in Open Cross	0	3,765,985	1,516.37	100
Normalized Short Volume in Open Cross	0	285.96	1.00	0.07
Open Cross Time	9:30:00 AM	10:29:23 AM	9:30:10 AM	9:30:02 AM
First Short Sale Time	9:30:00 AM	8:00:00 PM	9:33:04 AM	9:30:04 AM
Daily Volume	3,140	592,924,962	1,350,610.59	322,566
Daily Short Volume	100	100,018,527	249,614.11	56,935
Daily Volume not in Open Cross (Intraday)	2,718	592,918,262	1,345,526.47	319,113
Daily Short Volume not in Open Cross(Intraday)	0	100,015,427	248,097.68	56,018
Open Cross Price$_t$	4.94	153.97	27.11	24.02
Close Price$_t$	4.92	154.35	27.13	24.04
Close Price$_{t-1}$ – *Close Price*$_{t-2}$	-71.77	23.83	+0.00	0.00
Close Price$_{t-1}$ – *Open Cross Price*$_{t-1}$	-11.80	10.01	+0.00	0.00
Overnight Price Chg	-72.28	17.64	-0.00	0.00
Intraday Price Chg	-11.80	10.01	+0.00	0.00
Daily Return	-63.46%	48.21%	0.06%	0.00%
CRSP Equally-weighted Daily Return	-1.82%	2.45%	0.05%	0.12%
Abnormal Daily Return	-64.60%	48.09%	+0.00%	-0.08%
Firm Size	64,947,344	299,754,019,840	3,316,326,149	889,186,690

This table presents summary statistics for NASDAQ firms in our sample used for analysis. The sample includes 688 NASDAQ common stocks with a CRSP share code of 10 or 11 that have at least one trade occurring before 10:30 AM EST on everyday of our sample period of January, 2005, to December, 2006, and that have either an opening cross or closing price of $5 on each trading day. N*ormalized Short Volume in Open cross* is a stock's daily short volume in the opening cross divided by the stock's mean short volume in the opening cross over the sample period. *Overnight Price Chg* is calculated as opening cross price minus the previous day's close price. *Intraday Price Chg* is calculated as the day's close price minus the opening cross price. *Daily Return* is the CRSP daily return for the stock, and *Abnormal Daily Return* is the CRSP daily return for the stock less the CRSP equally-weighted return for the day. *Firm size* is the daily market cap calculated from the CRSP shares outstanding value and the close price for the day. For indexing, t is the sample day.

Table 3: Differences in Means between NYSE Batch Open Normalized Short Volume Groups

	Normalized Batch Open Short Volume			Means				
Group	Lower Bound	Upper Bound	Observations In Group	*ISS*	*OvernightChg*	*PrevCloClo*	*PrevOpenClo*	*IntradayChg*
G1	2<=*NOSV*		65,922	322,796	0.2281	0.0517	0.0414	0.00413
G2	1<=*NOSV*	*NOSV*<2	70,407	276,702	0.0753	0.0128	-0.0001	0.0102
G3	.5<=*NOSV*	*NOSV*<1	77,075	259,956	0.0221	0.0075	-0.0062	-0.0000
G4	0<*NOSV*	*NOSV*<0.5	141,308	221,030	-0.0350	-0.0104	-0.0180	-0.0030
G5	*NOSV*=0	*NOSV*=0	183,431	164,201	-0.0722	0.0043	0.0017	-0.0053
Difference Calculation				Differences in Means				
G1 – G2				46,094***	0.1527***	0.0389***	0.0415***	-0.0061
				(0.000)	(0.000)	(0.000)	(0.000)	(0.146)
G2 – G3				16,746***	0.0533***	0.0053	0.0062*	0.0102***
				(0.000)	(0.000)	(0.379)	(0.099)	(0.005)
G3 – G4				38,927***	0.0571***	0.0179***	0.0118***	0.0029
				(0.000)	(0.000)	(0.000)	(0.000)	(0.325)
G4 – G5				56,829***	0.0372***	-0.0147***	-0.0197***	0.0023
				(0.000)	(0.000)	(0.000)	(0.000)	(0.309)

In this table all stock-day observations in the sample are divided into groups based on level of normalized short volume in the batch open. The normalized measure, $NOSV_{i,t}$, is calculated as a stock's batch open short volume for a sample day divided by the stock's mean batch open short volume over the entire sample period. Daily stock observations are divided into groups. G1, G2, and G3 observations have at least twice the normal level, normal level to less than twice the normal level, and half the normal level to less than the normal level of short volume in the batch open, respectively, where the normal level is defined as normalized batch open short volume of 1.0. G4 observations range from more than zero to less than half the normal level of short volume in the batch open, and G5 observations have no short volume in the batch open. For each group, we present the mean value of tested measures in Hypotheses 1, 2, and 3, and the differences in means between the groups. $ISS_{i,t}$ is daily short sale volume less short sale volume in the batch open, $OvernightChg_{i,t}$ is the batch open price minus the previous close price, and $IntradayChg_{i,t}$ is the close price for the trading day minus the batch open price for the trading day. $PrevCloClo_{i,t}$ is close price lagged one day minus close price lagged two days. $PrevOpenClo_{i,t}$ is the previous day's close price minus open price. For index purposes, t is the sample day. P-values for statistical significance are reported in parentheses below the corresponding difference in means. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

Table 4: Differences in Means between NASDAQ Opening Cross Normalized Short Volume Groups

	Normalized Batch Open Short Volume			Means				
Group	Lower Bound	Upper Bound	Observations In Group	*ISS*	*OvernightChg*	*PrevCloClo*	*PrevOpenClo*	*IntradayChg*
G1	2<=*NOSV*		35,430	269,331	0.0260	0.0583	0.0492	-0.0195
G2	1<=*NOSV*	*NOSV*<2	28,853	221,774	0.0285	0.0141	0.0125	-0.0081
G3	.5<=*NOSV*	*NOSV*<1	33,762	235,087	0.0291	0.0070	0.0033	-0.0141
G4	0<*NOSV*	*NOSV*<0.5	81,657	381,536	0.0103	-0.0006	-0.0029	-0.0050
G5	*NOSV*=0	*NOSV*=0	164,973	184,756	-0.0241	-0.0087	-0.0031	0.0191
Difference Calculation				**Differences in Means**				
G1 – G2				47,557***	-0.0024	0.0442***	0.0367***	-0.0113**
				(0.000)	(0.6783)	(0.000)	(0.000)	(0.031)
G2 – G3				-13,313*	-0.0006	0.0071	0.0092*	0.0060
				(-0.066)	(0.894)	(0.369)	(0.067)	(0.229)
G3 – G4				-146,449***	0.0188***	0.0076	0.0062	-0.0091**
				(0.000)	(0.000)	(0.152)	(0.108)	(0.019)
G4 – G5				196,780***	0.0344***	0.0081**	0.0002	-0.0241***
				(0.000)	(0.000)	(0.014)	(0.949)	(0.000)

In this table all stock-day observations in the sample are divided into groups based on level of normalized short volume in the opening cross. The normalized measure, $NOSV_{i,t}$, is calculated as a stock's open cross short volume for a sample day divided by the stock's mean opening cross short volume over the entire sample period. Daily stock observations are divided into groups. G1, G2, and G3 observations have at least twice the normal level , normal level to less than twice the normal level, and half the normal level to less than the normal level of short volume in the opening cross, respectively, where the normal level is defined as normalized opening cross short volume of 1.0. G4 observations range from more than zero to less than half the normal level of short volume in the opening cross, and G5 observations have no short volume in the opening cross. For each group, we present the mean value of tested measures in Hypotheses 1, 2, and 3, and the differences in means between the groups. $ISS_{i,t}$ is daily short sale volume less short sale volume in the opening cross, $OvernightChg_{i,t}$ is the opening cross price minus the previous close price, and $IntradayChg_{i,t}$ is the close price for the trading day minus the opening cross price for the trading day. $PrevCloClo_{i,t}$ is close price lagged one day minus close price lagged two days. $PrevOpenClo_{i,t}$ is the previous day's close price minus the opening cross price. For index purposes, t is the sample day. P-values for statistical significance are reported in parentheses below the corresponding difference in means. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

Table 5: Regression Results for Hypotheses 1, 2, and 3 – NYSE Sample

	Model				
	(1)	(2)	(3)	(4)	(5)
Intercept	2.4739***	1.6559***	1.6558***	1.6544***	1.6508***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ISS_{i,t}$	0.0107***				
	(0.000)				
Overnight $Chg_{i,t}$		0.4149***			
		(0.000)			
Intraday $Chg_{i,t}$			0.0327***		
			(0.000)		
Close $Price_{i,t-1}$ – *Close* $Price_{i,t-2}$				-0.0007	
				(0.882)	
Close $Price_{i,t-1}$ – *Batch Open* $Price_{i,t-1}$					0.0178**
					(0.021)
$SS_{i,t-1}$	-0.0052***	0.0027***	0.0027***	0.0027***	0.0027***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Abdayret_{i,t-1}$	3.4108***	2.9012***	2.9550***	2.9598***	2.4682***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Lnfirmsize_{i,t}$	-0.0759***	-0.358***	-0.0358***	-0.0357***	-0.0355***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Macro $8{:}30_t$	-0.0956***	-0.0993***	-0.0930***	-0.0926***	-0.0928***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Macro $10{:}00_t$	1.1479***	1.1276***	1.1468***	1.1473***	1.1473***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Qtr End_t	-0.4736***	-0.4808***	-0.4826***	-0.4864***	-0.4881***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mo End_t	-0.2473***	-0.2323***	-0.2385***	-0.2355***	-0.2367***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R2	0.0377	0.0424	0.0301	0.0300	0.0300
DW Stat	1.928	1.936	1.937	1.937	1.936
1^{st} Order AutoCorr	0.036	0.032	0.032	0.031	0.032

This table presents regression results for five different models concerning Hypotheses 1, 2, and 3. The dependent variable in all models is the daily normalized short volume in the batch open, calculated as a stock's batch open short volume for the day divided by the stock's mean batch open short volume over the entire sample period. $ISS_{i,t}$ is a stock's sample day short sale volume less short sale volume in the batch open, *Overnight* $Chg_{i,t}$ is a stock's sample day batch open price minus the previous close price, and *Intraday* $Chg_{i,t}$ is a stock's close price for the trading day minus the batch open price. $SS_{i,t-1}$ is the stock's previous day's short sale volume scaled by 10,000, $Abdayret_{i,t-1}$ is the stock's previous day's abnormal return calculated as the stock's previous day's return minus the CRSP equally-weighted return for the day, and $Lnfirmzize_{i,t}$ is the natural log of the firm's sample-day market cap. *Macro* $8{:}30_t$ and *Macro* $10{:}00_t$ are dummy variables taking the value of 1 if a macroeconomic announcement was made at 8:30 AM or 10:00 AM on the trading day, respectively, and zero otherwise. *Qtr* End_t and *Mo* End_t take a value of 1 if the sample day is the last trading day of the quarter or month, respectively, and zero otherwise. DW stat is the Durbin-Watson statistic calculated to test for autocorrelation in our sample, and p-values for statistical significance are reported in parentheses below the corresponding coefficient estimates. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

Table 6: Regression Results for Hypotheses 1, 2, and 3 – NASDAQ Sample

	Model				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.9675***	0.8062***	0.7860***	0.8190***	0.8325***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ISS_{i,t}$	0.0010***				
	(0.000)				
Overnight $Chg_{i,t}$		0.0037			
		(0.762)			
Intraday $Chg_{i,t}$			-0.1036***		
			(0.000)		
Close $Price_{i,t-1}$ - *Close* $Price_{i,t-2}$				0.1202***	
				(0.000)	
Close $Price_{i,t-1}$ - *Open Cross* $Price_{i,t-1}$					0.2344***
					(0.000)
$SS_{i,t-1}$	-0.0006***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.000)	(0.007)	(0.009)	(0.005)	(0.008)
$Abdayret_{i,t-1}$	3.9674***	3.9571***	3.9443***	0.9441**	-0.3593
	(0.000)	(0.000)	(0.000)	(0.031)	(0.426)
$Lnfirmsize_{i,t}$	-0.0041	0.0039	0.0048	0.0033	0.0029
	(0.577)	(0.595)	(0.505)	(0.649)	(0.693)
Macro $8{:}30_t$	-0.2625***	-0.2631***	-0.2624***	-0.2632***	-0.2755***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Macro $10{:}00_t$	2.3011***	2.3067***	2.3076***	2.3007***	2.3020***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Qtr End_t	-1.0006***	-1.0165***	-1.0283***	-1.0124***	-1.0444***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mo End_t	-0.4301***	-0.4171***	-0.4098***	-0.4345***	-0.4272***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj. R2	0.0480	0.0479	0.0481	0.0481	0.0486
DW Stat	1.956	1.957	1.957	1.956	1.956
1st Order AutoCorr	0.022	0.022	0.021	0.022	0.022

This table presents regression results for five different models concerning Hypotheses 1, 2, and 3. The dependent variable in all models is the daily normalized short volume in the opening cross calculated as a stock's opening cross short volume for the day divided by the stock's mean opening cross short volume over the entire sample period. $ISS_{i,t}$ is a stock's sample day short sale volume less short sale volume in the opening cross, *Overnight* $Chg_{i,t}$ is a stock's sample day opening cross price minus the previous close price, and *Intraday* $Chg_{i,t}$ is a stock's close price for the trading day minus the opening cross price. $SS_{i,t-1}$ is the stock's previous day's short sale volume scaled by 10,000, $Abdayret_{i,t-1}$ is the stock's previous day's abnormal return calculated as the stock's previous day's return minus the CRSP equally-weighted return for the day, and $Lnfirmzize_{i,t}$ is the natural log of the firm's sample-day market cap. *Macro* $8{:}30_t$ and *Macro* $10{:}00_t$ are dummy variables taking the value of 1 if a macroeconomic announcement was made at 8:30 AM or 10:00 AM on the trading day, respectively, and zero otherwise. *Qtr* End_t and *Mo* End_t take a value of 1 if the sample day is the last trading day of the quarter or month, respectively, and zero otherwise. DW stat is the Durbin-Watson statistic calculated to test for autocorrelation in our sample, and p-values for statistical significance are reported in parentheses below the corresponding coefficient estimates. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

Table 7: Regression Results for Overnight Earnings Announcements – NYSE Sample

	Model			
	(1) All Trading Days	(2) Announcement Days	(3) Announcement Days	(4) Announcement Days
Intercept	1.5632***	2.1111	5.1474***	4.9615***
	(0.000)	(0.129)	(0.000)	(0.000)
Announce Day$_{i,t}$	1.2409***			
	(0.000)			
Overnight Ann$_{i,t}$	1.4096***	1.4451***		0.5597
	(0.000)	(0.000)		(0.358)
Surprise$_{i,t}$		0.9991		1.0145
		(0.201)		(0.192)
Overnight Ann$_{i,t}$ * *Surprise*$_{i,t}$		-0.8883		
		(0.263)		
ON Pos$_{i,t}$			1.8271***	1.3819**
			(0.000)	(0.015)
ON Neg$_{i,t}$			-0.3862	-0.8302
			(0.143)	(0.148)
ON Pos$_{i,t}$ * *Surprise*$_{i,t}$			4.3268***	3.3128***
			(0.000)	(0.001)
ON Neg$_{i,t}$ * *Surprise*$_{i,t}$			0.0212	-0.9933
			(0.694)	(0.203)
SS$_{i,t-1}$	0.0024***	-0.0021	-0.0008	-0.0008
	(0.000)	(0.255)	(0.677)	(0.664)
Abdayret $_{i,t-1}$	2.5119***	0.1302	-3.7131	-3.7491
	(0.000)	(0.975)	(0.359)	(0.354)
Lnfirmsize$_{i,t}$	-0.0330***	0.0042	-0.1298**	-0.1265**
	(0.000)	(0.947)	(0.040)	(0.045)
Macro 8:30$_t$	-0.0816***	-0.1422	-0.1430	-0.1371
	(0.000)	(0.423)	(0.413)	(0.433)
Macro 10:00$_t$	1.1079***	0.5307**	0.5775**	0.5759**
	(0.000)	(0.027)	(0.015)	(0.015)
Qtr End$_t$	-0.3898***	0.9388	1.2454	1.2576
	(0.000)	(0.511)	(0.376)	(0.371)
Mo End$_t$	-0.2725***	-0.3520	-0.3344	-0.3336
	(0.000)	(0.344)	(0.360)	(0.362)
Adj. R2	0.0419	0.0091	0.0420	0.0420
DW Stat	1.942	1.860	1.877	1.876
1st Order AutoCorr	0.029	0.070	0.062	0.062

This table presents regression results for four different models concerning Hypothesis 4. The dependent variable in all models is the daily normalized short volume in the batch open calculated as a stock's batch open short volume for the day divided by the stock's mean batch open short volume over the entire sample period. Model 1 is estimated using all sample day observations whereas models 2, 3, and 4 are estimated using only announcement day observations, defined as the actual day an announcement is made during trading or as the next trading day when an announcement is made outside of normal trading hours. *Announce Day*$_{i,t}$ is equal to 1 when the sample day is the day of a firm's regularly scheduled corporate earnings release and zero otherwise, while *Overnight Ann*$_{i,t}$ takes the value of 1 if a stock's regularly scheduled earnings release is announced outside of normal trading hours. *Surprise*$_{i,t}$ is calculated as a stock's actual announced earnings release less the consensus estimate for the announcement. *ON Pos*$_{i,t}$ (*ON Neg*$_{i,t}$) equals 1 when a stock's overnight announced earnings are higher (lower) than the consensus estimate for the stock's announced earnings. *SS*$_{i,t-1}$ is the stock's previous day's short sale volume scaled by 10,000, *Abdayret*$_{i,t-1}$ is the stock's previous day's abnormal return calculated as the stock's previous day's return minus the CRSP equally-weighted return for the day, and *Lnfirmzize*$_{i,t}$ is the natural log of the firm's sample-day market cap.

Macro 8:30$_t$ and *Macro 10:00*$_t$ are dummy variables taking the value of 1 if a macroeconomic announcement is made at 8:30 AM or 10:00 AM on the trading day, respectively, and zero otherwise. *Qtr End*$_t$ and *Mo End*$_t$ take a value of 1 if the sample day is the last trading day of the quarter or month, respectively, and zero otherwise. DW stat is the Durbin-Watson statistic calculated to test for autocorrelation in our sample, and p-values for statistical significance are reported in parentheses below the corresponding coefficient estimates. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

Table 8: Regression Results for Overnight Earnings Announcements – NASDAQ Sample

	Model			
	(1) All Trading Days	(2) Announcement Days	(3) Announcement Days	(4) Announcement Days
Intercept	0.7828***	4.1423***	4.2094***	4.0154***
	(0.000)	(0.003)	(0.002)	(0.004)
Announce Day$_{i,t}$	0.3331*			
	(0.062)			
Overnight Ann$_{i,t}$	0.8959***	0.9477***		0.5532
	(0.000)	(0.000)		(0.231)
Surprise$_{i,t}$		0.5445		0.5430
		(0.644)		(0.645)
Overnight Ann$_{i,t}$ * *Surprise*$_{i,t}$		-0.8380		
		(0.536)		
ON Pos$_{i,t}$			0.7564***	0.3049
			(0.000)	(0.479)
ON Neg$_{i,t}$			0.9247***	0.4735
			(0.000)	(0.284)
ON Pos$_{i,t}$ * *Surprise*$_{i,t}$			0.7775	0.2310
			(0.401)	(0.878)
ON Neg$_{i,t}$ * *Surprise*$_{i,t}$			-1.1285	-1.6749
			(0.331)	(0.312)
SS$_{i,t-1}$	0.0002**	-0.0005	-0.0005	-0.0005
	(0.039)	(0.356)	(0.369)	(0.357)
Abdayret $_{i,t-1}$	3.3137***	-1.7039	-1.4341	-1.5185
	(0.000)	(0.541)	(0.607)	(0.586)
Lnfirmsize$_{i,t}$	0.0046	-0.1373**	-0.1359**	-0.1312**
	(0.593)	(0.036)	(0.038)	(0.046)
Macro 8:30$_t$	-0.2568***	-0.2379	-0.2488	-0.2493
	(0.000)	(0.130)	(0.114)	(0.113)
Macro 10:00$_t$	2.2907***	0.3549*	0.3596*	0.3603*
	(0.000)	(0.099)	(0.095)	(0.094)
Qtr End$_t$	-0.9867***	-2.6664	-2.5549	-2.6073
	(0.000)	(0.141)	(0.159)	(0.151)
Mo End$_t$	-0.4260***	0.3808	0.4018	0.3947
	(0.000)	(0.257)	(0.231)	(0.240)
Adj. R2	0.0495	0.0216	0.0218	0.0217
DW Stat	1.958	1.881	1.881	1.881
1st Order AutoCorr	0.021	0.059	0.059	0.059

This table presents regression results for four different models concerning Hypothesis 4. The dependent variable in all models is the daily normalized short volume in the opening cross calculated as a stock's opening cross short volume for the day divided by the stock's mean opening cross short volume over the entire sample period. Model 1 is estimated using all sample day observations whereas models 2, 3, and 4 are estimated using only announcement day observations, defined as the actual day an announcement is made during trading or as the next trading day when an announcement is made outside of normal trading hours. *Announce Day*$_{i,t}$ is equal to 1 when the sample day is the day of a firm's regularly scheduled corporate earnings release and zero otherwise, while *Overnight Ann*$_{i,t}$ takes the value of 1 if a stock's regularly scheduled earnings release was announced outside of normal trading hours. *Surprise*$_{i,t}$ is calculated as a stock's actual announced earnings release less the consensus estimate for the announcement. *ON Pos*$_{i,t}$ (*ON Neg*$_{i,t}$) equals 1 when a stock's overnight announced earnings are higher (lower) than the consensus estimate for the stock's announced earnings. *SS*$_{i,t-1}$ is the stock's previous day's short sale volume scaled by 10,000, *Abdayret*$_{i,t-1}$ is the stock's previous day's abnormal return calculated as the stock's previous day's return minus the CRSP equally-weighted return for the day, and *Lnfirmzize*$_{i,t}$ is the natural log of the firm's sample-day market cap. *Macro 8:30*$_t$ and *Macro 10:00*$_t$ are dummy variables taking the value of 1 if a macroeconomic announcement is made at 8:30 AM or 10:00 AM on the trading day, respectively, and zero otherwise. *Qtr End*$_t$ and *Mo End*$_t$ take a value of 1 if the sample day is the last trading day of the quarter or month, respectively, and zero otherwise. DW stat is the Durbin-Watson statistic calculated to test for autocorrelation in our sample, and p-values for statistical significance are reported in parentheses below the corresponding coefficient estimates. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

Table 9: Regression Results for S&P 500 Stocks

	Model	
	(1)	(2)
Intercept	1.2193***	1.222***
	(0.000)	(0.000)
OE Day$_t$	3.8811***	3.8996***
	(0.000)	(0.000)
Overnight Chg$_{i,t}$	0.2370***	0.2368***
	(0.000)	(0.000)
Reversal_Open+30$_{i,t}$	-0.0483***	
	(0.000)	
Reversal_Close$_{i,t}$		-0.0214***
		(0.000)
Put / Call$_{i,t}$	-0.0011**	-0.0011**
	(0.041)	(0.041)
Open Interest$_{i,t}$	0.0000	0.0002
	(0.292)	(0.295)
OE Day$_t$ * *Overnight Chg*$_{i,t}$	0.3039***	0.3013***
	(0.000)	(0.000)
OE Day$_t$ * *Reversal_Open+30*$_{i,t}$	0.5115***	
	(0.000)	
OE Day$_t$ * *Reversal_Close*$_{i,t}$		0.3353***
		(0.000)
OE Day$_t$ * *Put / Call*$_{i,t}$	-0.0084***	-0.0083***
	(0.000)	(0.000)
OE Day$_t$ * *Open Interest*$_{i,t}$	0.0002***	0.0002***
	(0.001)	(0.000)
SS$_{i,t-1}$	0.0002***	0.0002***
	(0.005)	(0.005)
Abdayret $_{i,t-1}$	3.1632***	3.1034***
	(0.000)	(0.000)
Lnfirmsize $_{i,t}$	-0.0196**	-0.0197***
	(0.011)	(0.010)
Macro 8:30$_t$	0.0693***	0.0674***
	(0.000)	(0.000)
Macro 10:00$_t$	0.2209***	0.2283***
	(0.000)	(0.000)
Qtr End$_t$	0.0506	0.0516
	(0.440)	(0.431)
Mo End$_t$	-0.0683*	-0.0698*
	(0.069)	(0.063)
Adj. R2	0.1037	0.1039
DW Stat	1.899	1.899
1st Order AutoCorr	0.051	0.051

This table presents regression results for two different models concerning Hypothesis 5 that are estimated using a subsample containing only firms that are part of the S&P 500 composite index over the entire sample period from January, 2005, to December, 2006. The dependent variable in both models is the daily normalized short volume in the batch open (opening cross) calculated as a stock's batch open (opening cross) short volume for the day divided by the stock's mean batch open (opening cross) short volume over the entire sample period. Models 1 and 2 are estimated while controlling for a stock's price reversals around the opening trade calculated using prices 30 minutes after the first trade and prices at the close, respectively. *OE Day*$_t$ equals 1 when the trading day *t* is an option-expiration Friday and equals zero, otherwise. *Overnight Chg*$_{i,t}$ is a stock's sample day batch open (opening cross) price minus the previous close price. *Reversal_Open+30*$_{i,t}$ (*Reversal_Close*$_{i,t}$) is price reversals calculated as the difference between a stock's price change measured from the batch open / opening cross to 30 minutes after the open (closing) and *Overnight Chg*$_{i,t}$. Reversals are positive when the movement of the price change after the batch open / opening cross is in the opposite direction of the *Overnight Chg*$_{i,t}$. *Put / Call*$_{i,t}$ is the ratio of put volume to call volume for a firm's options trading on the sample day, and *Open Interest*$_{i,t}$ is the total open interest in a stock's options trading on the sample day. *SS*$_{i,t-1}$ is the stock's previous day's short sale volume scaled by 10,000, *Abdayret*$_{i,t-1}$ is the stock's previous day's abnormal return calculated as the stock's previous day's return minus the CRSP equally-weighted return for the day, and *Lnfirmzize*$_{i,t}$ is the natural log of the firm's sample-day market cap. *Macro 8:30*$_t$ and *Macro 10:00*$_t$ are dummy variables taking the value of 1 if a macroeconomic announcement is made at 8:30 AM or 10:00 AM on the trading day, respectively, and zero otherwise. *Qtr End*$_t$ and *Mo End*$_t$ take a value of 1 if the sample day is the last trading day of the quarter or month, respectively, and zero otherwise. DW stat is the Durbin-Watson statistic calculated to test for autocorrelation in our sample, and p-values for statistical significance are reported in parentheses below the corresponding coefficient estimates. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

ESSAY II: SHORT SALES AROUND OPEN-MARKET REPURCHASE ANNOUNCEMENTS

Open-market repurchase (OMR) programs are the most popular method for firms to repurchase stock according to Billett and Xue (2007) and Stephens and Weisbach (2000). In fact, any type of stock repurchase is preferred to dividends as a method for delivering cash into the hands of stockholders as Grullon and Michaely (2002) show total repurchase values to be 113% of dividend values in their sample. A number of studies document the reaction of stock prices to OMR announcements,[10] but we consider short sales occurring around these announcements to document the trading behavior of short sellers during the days immediately following an OMR announcement and to perhaps offer new findings concerning OMR announcements.

Chan, Ikenberry, Lee, and Wang (2010) consider the quality of OMR announcements as indications of inside information. They highlight the potential for firms to take advantage of the normally-positive, OMR announcement effect in order to intentionally mislead investors by using an OMR announcement to falsely indicate firm quality. Chan, et al. (2010) suggest that these firms have suspect intent to repurchase stock but show that these OMR-announcing firms continue to see increased prices at announcement. As previous studies view short sellers as

[10]Examples include Chan, Ikenberry, and Lee (2007); Chan, Ikenberry, and Lee (2004); and Ikenberry, Lakonishok, and Vermaelen (1995).

informed investors,[11] we believe that short volume will increase following OMR announcements by firms with limited intentions of repurchasing stock.

Comment and Jarrell (1991) and Stephens and Weisbach (1998) position the announced size of an OMR program as a managerial signal of firm quality, saying that larger programs are stronger signals of firm quality. However, Chan, et al. (2010) question the reliability and credibility of OMR program size as a signal of firm quality. Because of the question raised by Chan, et al. (2010), we use short sale volume occurring after OMR announcements as a test of whether OMR program size serves as a signal of firm quality. Kadiyala and Vetsuypens (2002) suggest that short sales decrease in the positive signaling strength of a corporate event. Therefore, we examine short selling in a firm's stock following an OMR announcement to determine whether program size serves as a signal of firm quality.

One important aspect of studying short sales around OMR announcements is that positive abnormal returns tend to occur during OMR announcement periods (Chan, et al., 2010), and Blau and Wade (2009) state that it is important to study short selling around positive information events in order to have a complete analysis of whether or not short sellers possess superior information. According to Blau and Pinegar (2010), it is an open question of whether short sellers are superiorly informed before announcements as they find that short sales are more reactive to than predictive of earnings announcements and that short sales do not increase before positive or negative earnings announcements.[12]

The most common explanation for firms making an OMR announcement is to signal undervaluation (e.g., Ikenberry and Vermaelen, 1996). Further, short sellers tend to be active

[11]See Diether, Lee, and Werner (2009); Boehmer, Jones, and Zhang (2008); Dechow, Hutton, Meulbroek, and Sloan (2001); and Diamond and Verrecchia (1987).
[12] These results are inconsistent with Christophe, Ferri, and Angel (2004) who find short sales to be predictive of negative earnings announcements as short volume increases prior to negative announcements being made.

when prices are above their fundamental value (Diether, Lee, and Werner, 2009). However, we believe short sellers are likely to be active in OMR stocks for two reasons. First, Christophe, Ferri, and Angel (2004) expect some level of short selling in a stock at any given time and say that informed short sales should decrease prior to positive earnings news. They define positive earnings news as announcements resulting in abnormal price increases during the announcement period, a description that also applies to OMR announcements (e.g., Chan, Ikenberry, and Lee, 2004). Second, according to Jagannathan, Stephens, and Weisbach (2000), firms tend to make OMR announcements after periods of poor price performance, and Christophe, Ferri, and Hsieh (2010) suggest that short selling may be related to stock price momentum as stocks with declining values are aggressively shorted.

The contribution of this study is to document the behavior of short sellers after OMR announcements. We examine short selling following OMR announcements to determine whether short sellers are able to distinguish between firms that have suspect intent to repurchase, whereas Chan, et al., (2010) find that the market as a whole does not make a distinction between these firms and others. Then, because the question is open as to whether OMR program size serves as a signal of firm quality, we examine whether post-announcement short volume is related to OMR program size as a test of the signaling power of the announced size. Lastly, we determine whether short sales are predictive of repurchasing behavior following an OMR announcement by examining whether post-announcement short sales decrease when firms engage in actual repurchases following their OMR announcement. We study the relation between short sales that immediately follow an OMR announcement and the estimated repurchases made during the year that follows the announcement. Firms tend to either complete a program or repurchase practically no shares (Stephens and Weisbach, 1998), and the majority of repurchase activity for a firm takes place within one year after the OMR announcement (Chan, Ikenberry, and Lee, 2007).

I. LITERATURE REVIEW

Although an open-market repurchase (OMR) announcement indicates that the board of directors gives the firm's management the permission to repurchase shares, the announcement does not serve as a firm commitment to do so (Ikenberry and Vermaelen, 1996). However, OMR announcements are generally considered favorable news by investors as Vermaelen (1981) suggests that firms use OMRs to signal undervaluation. According to Dittmar (2000), the positive price reaction for a firm's stock in response to an OMR announcement is partially because the market responds to an OMR program as a signal of undervaluation. Other results document OMR announcement-period and post-announcement returns. Chan, Ikenberry, and Lee (2007) report firms that repurchase stock during the first year after their OMR announcement outperform matched firms in each of the four years after announcement, but firms that do not repurchase stock during the first year show flat returns after the first year. Chan, Ikenberry, and Lee (2004) find abnormal announcement-period returns of 2.2% and excess performance of 6.7% (including the announcement effect) in the first year after an OMR announcement. Chan, Ikenberry, Lee, and Wang (2010) show 2% abnormal returns during the announcement period of OMRs.

Chan, Ikenberry, and Lee (2004) state that an interesting question is whether or not perceived mispricing related to OMR announcements is due to public or private information, and Dittmar (2000) reports that managers engage in stock repurchases because information asymmetry between insiders and shareholders results in stocks being incorrectly priced.

However, information asymmetry is likely lower between insiders and short sellers than between insiders and other public traders as Christophe, Ferri, and Angel (2004) conclude that short sellers are informed and rely on private information more heavily than public information to make trading decisions. Chan, et al., (2010) question whether the market distinguishes between OMR-announcing firms based on firm earnings quality as measured by discretionary accruals, a public information item. They find that the market response of 2% abnormal returns during the OMR announcement period is the same for firms across different levels of earnings quality. However, short sellers who possess superior information (e.g., Christophe, Ferri, and Angel, 2004) and who can determine whether managers are falsely signaling with OMR announcements should increase short sales when firms use OMRs as false signals. Oded (2005) shows that firms that falsely signal with an OMR bear costs by earning lower post-announcement returns. Therefore, by increasing short sales as the market responds positively to OMR announcements by false-signal firms, short sellers can profit from the lower future returns of these firms.

Stephens and Weisbach (1998) argue that the market's positive response to the undervaluation signal of an OMR announcement is related to the announced target ratio because it proxies for the signaling strength of management's inside information. Comment and Jarrell (1991) suggest that the target ratio of an OMR serves as a particularly strong signal versus the target ratios of other repurchases methods because the target ratio serves as management's only choice variable in an OMR. They find that post-announcement returns monotonically increase in OMR target ratios. However, Chan, et al., (2010) argue against OMR program size as a reliable and credible signal. They say some managers not intending to repurchase stock use OMRs to mislead investors about the quality of the firm, leaving the target ratio as a questionable signal of firm quality.

Dittmar (2000) explains that repurchases are a method for a firm to distribute excess cash to shareholders when capital exceeds that needed for the firm's investment opportunities. She says OMRs are preferable to dividends because the firm does not have to commit to the repurchase. Rationally-functioning managers should only repurchase shares if they believe the shares are currently undervalued (Ikenberry and Vermaelen, 1996). Stephens and Weisbach (1998) and Jagannathan, Stephens, and Weisbach (2000) document that a significant number of firms that announce a buyback do not complete the repurchase. They find that 74%-82% and 53%-72% of shares, respectively, announced as part of an OMR are subsequently bought back as part of the OMR.[13] Stephens and Weisbach (1998) show that firms tend to repurchase either all shares targeted in the announcement or practically none. They find that 24% of firms repurchase 100% or more of announced shares (complete the program) but that 70% repurchase less than 20% of announced shares. Of those firms repurchasing less than 20% of announced shares, 21% repurchase less than 5% of announced shares, and 16% repurchase less than 1% of announced shares.

Chan, Ikenberry, and Lee (2007) find that managers have the ability to time the market with both the announcement and execution of an OMR, meaning managers may use their OMR announcement for its positive price effect and only begin repurchasing stock if the price stays below their valuation. Oded (2005) suggests announcing firms base their decisions to make post-announcement repurchases on realized values, so firms that complete an OMR program may be those whose stock price remains below managerial valuation after the announcement.

[13] Stephens and Weisbach (1998) and Jagannathan, Stephens, and Weisbach (2000) rely on estimates of the aggregate amount of shares repurchased as part of an announced program because the information is not directly observable. Their estimates are reported as lower and upper bounds. Jagannathan, Stephens, and Weisbach (2000) report that their 53%-72% result likely underestimates the actual completion rates for announcements in their sample period because the last two years of their sample accounted for 35% of the announced shares to be repurchased, and they did not track shares repurchased after the end of their sample period. Therefore, they suggest a better estimate would likely agree with Stephens and Weisbach (1998), meaning a 74% - 82% completion rate.

Chan, Ikenberry, and Lee (2004) suggest that post-OMR-announcement price drift is contingent on whether the stock is actually repurchased, an idea supported by Chan, Ikenberry, and Lee (2007) who separate their sample of OMR-announcing firms into three groups according to how much outstanding equity the firm repurchases in the year after announcement. Their sample is divided into firms that repurchase no stock, those repurchasing less than 4%, and those repurchasing more than 4%. Their results show that all groups have significant and positive abnormal returns in the first year after announcement, but firms repurchasing shares during the first year after announcement show continuing positive drift in years two through four after announcement. However, firms repurchasing no stock in the first year do not show significant drift after the first year.

II. HYPOTHESES

Chan, Ikenberry, Lee, and Wang (2010) suggest that some managers, experiencing pressure to boost stock prices, take advantage of the market's positive response to OMR announcements and announce an OMR program to mislead investors about the quality of the firm. Using a firm's level of discretionary accruals as a proxy for managerial intent of repurchasing, they consider higher levels of discretionary accruals to be an indication of lower managerial intent to repurchase shares.[14] Chan, et al. (2010) argue that discretionary accruals lower earnings quality because discretionary accruals inflate earnings. They define firms with higher levels of discretionary accruals as firms with lower earnings quality, but they find that the abnormal return for both groups is about 2% during the OMR announcement period. However, Chan, et al. (2010) find that announcing firms with high levels of discretionary accruals do not have long-run positive returns, whereas firms with low levels of discretionary accruals do.

We examine whether short sellers react to a firm's OMR announcement according to a firm's discretionary accrual usage. If discretionary accruals serve as an indication of management's intended purpose for an OMR (Chan, et al., 2010), reactionary short sellers (Blau and Pinegar, 2010) should respond to OMR announcements by adjusting their short volume according to the firm's use of discretionary accruals. Short sales increase due to short-term overreaction in prices (Diether, Lee, and Werner, 2009). Since Chan, et al. (2010) find that

[14] Chan, Ikenberry, Lee, and Wang (2010) report that managers have some discretion in the amount of accruals of a firm. They estimate the part of accruals over which managers have discretion and term that part as discretionary accruals.

OMR announcement period returns are positive for firms with high discretionary accruals but that these firms do not show the same long-term positive returns as other OMR-announcing firms, short sellers may interpret the positive reaction for high-discretionary-accrual firms as a short-term overreaction, resulting in an increase in short volume.

Our study offers insight into the discussion of whether OMRs serve as tools used to mislead investors (e.g., Oded, 2005, and Chan, et al., 2010) as we examine whether short sellers react differently to OMRs based on a firm's discretionary accrual level, which serves as a proxy for managerial intent and a measure of firm quality at the time of announcement. We test the relation between a firm's level of discretionary accruals at the time of an OMR announcement and short volume in its stock following the announcement. If short sellers' reactions to OMR announcements are related to a firm's discretionary accrual usage, it is an indication that informed investors are able to determine whether firm management has limited intentions to complete the announced OMR, whereas Chan, et al., (2010) conclude that the market, as a whole, does not possess this ability. We expect to find a positive relation between short sales and discretionary accruals used by firms at the time of announcement. We test the following hypothesis:

H1: Post-OMR-announcement short volume is positively related to a firm's level of discretionary accruals at the time of the OMR announcement.

A larger OMR program, indicated by a higher percentage of outstanding shares being targeted for repurchase, may or may not serve as a stronger positive signal than a smaller program. Comment and Jarrell (1991) show that abnormal returns after an OMR announcement are positively related to the announced target ratio for a repurchase, and they conclude the target ratio is a particularly important signal of undervaluation in the context of an OMR because it is the only choice variable to serve as a signal. Additionally, Stephens and Weisbach (1998) argue that the size of the repurchase target proxies for the quality of the announcement's information content and therefore serves as a signal of undervaluation. According to Comment and Jarrell (1991) and Stephens and Weisbach (1998), larger target ratios serve as stronger signals of firm quality, in the context of an OMR. However, Chan et al., (2010) question the use of OMR program size as an indication of managerial information and argue that program size is difficult to interpret as a reliable and credible signal.

Kadiyala and Vetsuypens (2002) advocate the use of decreased short sales following a corporate announcement as an indication of the event's positive signal. They explain that post-announcement returns are ambiguous as an indicator of signaling strength when the announced behavior increases liquidity. Price increases following an OMR announcement may be due to liquidity effects and not necessarily due to an informational signal. Cook, Krigman, and Leach (2004) find that a firm's repurchase of shares increases liquidity in the firm's stock. Therefore, the explanation of Kadiyala and Vetsuypens (2002) indicates positive returns following an OMR announcement are ambiguous indicators of whether larger programs are stronger signals.

Since Chan, et al. (2010) question OMR program size as a reliable and credible signal, we examine whether OMR program size is interpreted as a positive signal by examining the reaction of short sellers to announced OMR target ratios. If we find that post-announcement short sales do not decrease in program size, then evidence exists that larger target ratios are not reliable and credible as stronger positive signals than smaller programs. This finding would support the contention of Chan, et al. (2010) that program size is a questionable signal. We state our hypothesis as follows:

H2: Post-OMR-announcement, abnormal short selling does not decrease as OMR program size increases.

OMRs are a means by which undervalued firms stand ready to repurchase shares, but a significant number of firms do not complete their announced OMR program because they repurchase few or no shares (Jagannathan, Stephens, and Weisbach, 2000). Abnormal returns are generally positive in the five days surrounding an OMR announcement (e.g., Chan, et al., 2010), and the market's reaction to an OMR announcement largely determines whether a firm's stock will actually be repurchased because Oded (2005) indicates that an OMR-announcing firm bases its decision to repurchase or not on realized returns, only beginning to repurchase if the price remains below inside valuation. According to Bhattacharya and Dittmar (2009) and Oded (2005), OMR-announcing firms that do not subsequently complete their OMR program bear costs for non-completion in the form of increased, unwanted scrutiny by investors and lower returns, respectively. These findings are consistent with an undervalued firm announcing an OMR, foregoing actual repurchase activity if the market's reaction to the OMR corrects the undervaluation, and suffering lower returns later as it does not complete its repurchase program when it does not repurchase shares because it is no longer undervalued.

Short sellers who have superior information about the true price of a stock (Christophe, Ferri, and Angel, 2004) have an opportunity to profit by shorting OMR stocks that are overvalued after announcement. An OMR stock that is overvalued following the announcement will likely not be repurchased because it is irrational to repurchase a stock that is not undervalued (Ikenberry and Vermaelen, 1996), so the firm is at risk of not completing its repurchase program and subsequently earning lower returns. Firms experiencing lower returns due to non-completion are likely those firms that limit actual repurchases during the first year after the OMR is announced because Stephens and Weisbach (1998) find that firms that complete repurchases typically do so within one year of announcement and since Chan, Ikenberry, and Lee (2007) show that only firms repurchasing stock during the first year of an OMR program have positive long-run abnormal returns.

OMR stocks that should not be repurchased by the firm because they are not undervalued after the OMR announcement are attractive targets to short sellers either because they are overvalued or because they will suffer lower returns if they are not subsequently repurchased. Holden and Subrahmanyam (1992) indicate that informed traders will aggressively and rapidly trade around information events in order to profit from their information, so we believe that short sales will immediately increase following an OMR-announcement that results in an overvalued stock. In turn, this increase in short sales should be predictive of limited repurchasing behavior for the firm during the year following the OMR announcement because the stock is overvalued after its announcement. Stocks remaining undervalued after an OMR announcement will likely have decreased short volume and will likely be repurchased by the firm because they remain undervalued. In either case, abnormal short selling following an OMR announcement should be negatively related to repurchasing activity that follows the announcement. We state the following hypothesis:

H3: Abnormal short selling immediately after a firm announces an OMR is negatively related to the firm's actual repurchase activity during the year following the OMR announcement.

III. SAMPLE FORMATION

Our sample of OMR-announcing firms is taken from the SDC acquisitions database and contains firms making announcements from February 14, 2005, through December 19, 2006. The original number of firms identified in the SDC database as OMR firms during our sample period is 1,214. We eliminate 337 firms for which we are not able to obtain a measure of the number of shares or dollar amount of stock targeted in the OMR, and we exclude 184 firms that make more than one OMR announcement during our sample period, attempting to avoid effects that may be attributable to a firm making multiple OMR announcements. These two eliminations leave 693 potential firms for our sample. We take closing price and outstanding shares data from CRSP for each trading day from 25 days before the announcement to 2 days after the announcement for each of these stocks, and we identify the SIC code and obtain the following yearly data items from Compustat: current assets; total assets; cash; current liabilities; debt in current liabilities; depreciation and amortization; net property, plant, and equipment; sales; and taxes payable. Short sales are taken from the REG SHO data and are aggregated to the daily level so that we obtain an observation for daily short volume for each OMR stock on each day during our sample period. We eliminate OMR-announcing stocks that do not have all data items available in CRSP and Compustat, that are not ordinary common shares trading on either the NYSE or NASDAQ, that have an announcement-day, CRSP closing price of less than five dollars, and that do not have an identifiable daily short volume on each day over the interval of 10 days before to 5 after the OMR announcement. These four requirements remove another 279 stocks from the sample. Our final sample consists of 414 OMR-announcing firms. Of these, 226 are NYSE stocks and 188 are NASDAQ stocks.[15]

[15] The full sample is used for univariate analysis, but the sample tested in most of our regressions has 391 observations because of missing data for independent variables. Of these 391 observations, 218 (173) are NYSE (NASDAQ) stocks.

IV. METHODS

We are partly motivated in our study from previous findings of abnormal returns during OMR announcement periods; therefore, we check whether stocks in our sample exhibit positive, abnormal holding period returns (AHPRs) during the announcement window.[16] We calculate the AHPRs for each sample stock during the five-day announcement period surrounding the OMR-announcement day (t=0). The AHPR is the holding period return for the stock over the interval (t-2, t+2) less the holding period return for the CRSP value-weighted index over the same time.

Our short selling measure, *SS,* is calculated as the percentage of outstanding shares sold short for each sample stock on each day. Then we calculate abnormal short selling, *ABSS*, for each stock-day observation by subtracting the median value for *SS* over the entire sample period from the stock-day observation of SS. The median value of SS serves as our measure of normal short selling volume for each sample stock following the trading-pattern approach used by Christophe, Ferri, and Hsieh (2010). We also calculate a separate measure of abnormal short selling, *ABSS_weekday*, in which we subtract the day-of-the-week median as our measure of normal short selling.

We check our sample for similarity with samples in other studies by two different approaches that measure abnormal short selling during the pre-announcement period. As in Blau and Pinegar (2010), we examine changes in the level of abnormal short sales that occur in the 10 days before the announcement day *t*. We do this by comparing the daily mean of abnormal short

[16] Since our sample consists of different firms in different time periods than the samples of previous studies, we make no direct comparisons between our sample and previous samples. We only check for similarity.

sales during the interval (t-10, t-6) with the daily mean of abnormal short sales during 5 days, 3 days, and 1 day before the announcement is made. As in Christophe, et al. (2004), we then use abnormal short sales in the 5 day pre-announcement period as our dependent variable using the following OLS regression model:

$$ABSS_{(t-5,t-1)} = \alpha + \beta_1 AHPR_{(t-2,t+2)} + \beta_2 AHPR_{(t-25,t-1)} + \beta_3 lnPrice_{(t-5,t-1)} + \varepsilon \qquad (1)$$

Model 1 is similar to models in Christophe, et al. (2004) in that our independent variables include contemporaneous and future returns, but lagged returns and contemporaneous prices are also included in our independent variables. The dependent variable $ABSS_{(t-5,t-1)}$ is the sum of abnormal short selling for each day during the five days prior to the OMR announcement day t. $AHPR_{(t-2,t+2)}$ is the abnormal holding period return measured two days before to two days after the OMR announcement. We include $lnPrice_{(t-5,t-1)}$, the natural log of the mean daily close price during the five days before announcement to control for abnormal pre-announcement short selling related to current price. $AHPR_{(t-25,t-1)}$, the abnormal holding period return for twenty-five days before announcement is included to control for previous and contemporaneous returns because Christophe, Ferri, and Hsieh (2010) explain that stocks experiencing extended periods of low returns may be aggressively shorted, and most OMR-announcement stocks have seen recent periods of low returns (Peyer and Vermaelen, 2009).

In testing our first hypothesis (H1), we estimate each firm's discretionary accruals at the time of the OMR announcement as a measure of its earnings quality. Based on the work of Chan, Ikenberry, Lee, and Wang (2010), we calculate a firm's total accruals before the OMR announcement by using Compustat annual items for the firm. The following equation is used for the calculation:

$$Accruals = (\Delta CA - \Delta CASH) - (\Delta CL - \Delta STD - \Delta TP) - DEP \qquad (2)$$

ΔCA is change in current assets; $\Delta CASH$ is change in cash; ΔCL is change in current liabilities; ΔSTD *is* change in the debt portion of current liabilities; ΔTP *is* change in taxes payable; and *DEP is* depreciation and amortization expense at the end of the previous year. The changes are measured between the beginning and end of the sample firm's fiscal year, for the fiscal year ending before the OMR announcement is made.

We are interested in the discretionary component of accruals, which we call discretionary accruals (DA), as a proxy for the firm's earnings quality, as in Chan, et al. (2010). To estimate DA, we first run the following regression model for all NYSE and NASDAQ stocks at the end of their fiscal years that occur during the two years of our sample period:

$$(Accruals/TA) = \alpha_0\,(1/TA) + \alpha_1\,(\Delta Sales/TA) + \alpha_2\,(PPE/TA) + \varepsilon \qquad (3)$$

TA is total assets at the end of the fiscal year; $\Delta Sales$ is the change in sales over the fiscal year; and *PPE* is net property, plant, and equipment at fiscal-year end. We separate the NYSE and NASDAQ stocks by SIC number into the 48 Fama-French industries (Fama and French, 1997) and estimate model 3 for each industry. After estimation, we compute non-discretionary accruals and discretionary accruals for our sample firms as follows:

$$NDA = (\hat{a}_0 + \hat{a}_1 \Delta Sales + \hat{a}_2 PPE) \,/\, TA \qquad (4)$$

$$DA = (Accruals \,/\, TA) - NDA \qquad (5)$$

NDA is non-discretionary accruals for each sample firm computed as a fitted value using the estimated, industry-specific coefficients from model 3. *DA*, our measure of discretionary accruals for each sample firm, is calculated as the difference between the firm's total accruals, scaled by its total assets, minus the sample firm's non-discretionary accruals.

We also use a relative measure of discretionary accruals in order to control for whether our sample stocks' levels of discretionary accruals are uniformly distributed over DA levels for all NYSE and NASDAQ firms. Following Chan, et al. (2010), we form quintiles, by sample year, of all NYSE and NASDAQ stocks based on their estimated discretionary accruals. A sample firms that is grouped into the quintile with the highest (lowest) levels of discretionary accruals among all NYSE and NASDAQ firms for the year is classified as a HDA (LDA) firm as a measure of its use of discretionary accruals relative to other firms.

We use the following OLS model in our regression analysis of H1:

$$
\begin{aligned}
ABSS_{(t+1,t+5)} &= \alpha + \beta_1 AHPR_{(t-2,t+2)} + \beta_2 AHPR_{(t-25,t-1)} + \beta_3 DA_{(t=0)} \\
&+ \beta_4 HDA + \beta_5 LDA + \beta_6 Earn\_Surprise_{(t=0)} + \beta_7 Earn\_Ann_{(t-2,t+2)} \\
&+ \beta_8 \text{ Earn}\_Surprise_{(t=0)} * Earn\_Ann_{(t-2,t+2)} + \varepsilon
\end{aligned} \tag{6}
$$

The dependent variable $ABSS_{(t+1,t+5)}$ is the sum of daily abnormal short sales occurring over the five day, post-OMR-announcement period. *HDA* (*LDA*) takes the value of 1 when the announcing stock is part of the highest (lowest) discretionary accrual quintile formed from all NYSE and NASDAQ stocks, and 0 otherwise. We are particularly interested in the estimates of β_3, β_4, and β_5 as tests of the relation between abnormal short selling and an announcing firm's use of discretionary accruals. We expect β_3, the coefficient for the level of discretionary accruals of the firm, to be positive since we believe abnormal, post-announcement short sales increase in use of discretionary accruals. We do not have a primary interest in the estimates of the coefficients for HDA and LDA, individually, but we are interested in the difference between the two coefficients. We offer no prediction for the sign of β_5's estimate, but we expect it to be less than the estimate for β_4 because we expect abnormal short selling to be relatively higher for *HDA* firms than for *LDA* firms. Even though not related to a stated hypothesis, the estimated coefficient for $AHPR_{(t-2,t+2)}$ serves as a test of how short sellers react to OMR announcement-period returns, in general. Any prediction for this estimate is ambiguous since Kadiyala and

Vetsuypens (2002) indicate a negative relation, but the results of Blau and Pinegar (2010) show that short sales increase in reaction to both negative and positive announcements.

We also control for effects to post-announcement abnormal short selling when an earnings announcement is made during the 5-day announcement period of an OMR. $Earn\_Surprise_{(t=0)}$ is the surprise contained in the most recent regular, quarterly earnings announcement occurring as of OMR-announcement day. The surprise is calculated as actual earnings minus the consensus estimate for the announcement, both taken from IBES. $Earn\_Ann_{(t-2,t+2)}$ is equal to 1 if an earnings announcement occurs during the OMR-announcement interval of (t-2, t+2) and 0 otherwise. We believe it is important to control for the earnings announcement effects because 98 of our 414 sample firms also announce earnings during the 5 days surrounding their OMR announcement. To control for the size of earnings surprises made during the OMR announcement window, we include the interaction term between the size of the surprise and the variable indicating the announcement is made during the OMR announcement window.

The second hypothesis (H2) deals with the relation of post-announcement, abnormal short sales to OMR program size. As in Comment and Jarrell (1991), we separate our sample stocks into three groups based on the announced percentage of outstanding shares targeted by the OMR program (also called program size). The high target group (HTG) contains firms targeting more than 10%; the mid target group (MTG) contains firms targeting 5% to 10%; and the low target group (LTG) contains firms targeting less than 5%. To test H2, we use OLS to estimate the following regression model:

$$ABSS_{(t+1,t+5)} = \alpha + \beta_1 AHPR_{(t-2,t+2)} + \beta_2 AHPR_{(t-25,t-1)} + \beta_3 Target_{(t=0)} + \beta_4 HTG + \beta_5 LTG + \beta_6 Earn\_Surprise_{(t=0)} + \beta_7 Earn\_Ann_{(t-2,t+2)} + \beta_8 \, \mathrm{Earn}\_Surprise_{(t=0)} * Earn\_Ann_{(t-2,t+2)} + \varepsilon \qquad (7)$$

In model 7 the dependent variable is our abnormal short sales measure calculated for post-announcement days 1 through 5. The variables of interest for H2 are *Target*, *HTG*, and *LTG*. *Target* is the target ratio calculated as the number of shares announced as being potentially repurchased during the OMR program divided by the number of outstanding shares at the time of announcement. *HTG* (*LTG*) is valued at 1 when the announcing stock is classified in the high target group (low target group) based on the firm seeking to repurchase greater than 10% (less than 5%) of outstanding shares, and valued at 0 otherwise. The mid target group, MTG, serves as the omitted class such that the group of firms with a repurchase target of 5% - 10% of outstanding shares serves as the base case for comparison. According to H2, abnormal, post-announcement short selling does not decrease as OMR program size increases. Therefore, we expect the estimate for the coefficient of $Target_{(t=0)}$ to be greater than or equal to zero. The other variables in model 7 are the same as previously described and are included in the regression model for the same reasons stated earlier.

Stephens and Weisbach (1998) find that a firm that repurchases stock during the three years after its OMR announcement makes the majority of its repurchases during the first year, and they find that firms tend to either complete OMR programs by repurchasing at least the announced target amount or not complete them by repurchasing less than 5% of the target. We estimate the number of shares repurchased during the first year after announcement by totaling the day to day decreases in each firm's CRSP daily outstanding shares value. The estimation is calculated for the 252 trading days following the OMR announcement, but we delete those days whose shares outstanding changed due to splits and stock dividends as indicated by CRSP distribution codes. This estimation process closely follows Stephens and Weisbach (1998), except that we use daily observations for decreases in outstanding shares rather than monthly decreases. From our estimate for actual repurchase activity, we label sample firms repurchasing at least 100% (less than 5%) of their targeted amount of shares in the first year as firms that complete (do not complete) their OMR program.

Using an OLS regression model, we test if post-announcement repurchase activity and post-announcement abnormal short selling are related using the following model:

$$ABSS_{(t+1,t+5)} = \alpha + \beta_1 AHPR_{(t-2,t+2)} + \beta_2 AHPR_{(t-25,t-1)} + \beta_3 Repurchase_{(t+1,t+252)} + \beta_4 Complete + \beta_5 NonComplete + \beta_6 Earn\_Surprise_{(t=0)} + \beta_7 Earn\_Ann_{(t-2,t+2)} + \beta_8 \text{ Earn}\_Surprise_{(t=0)} * Earn\_Ann_{(t-2,t+2)} + \varepsilon \quad (8)$$

We believe that informed short sellers who view the price response to an OMR announcement are able to predict the announcing firm's actual repurchasing behavior because a stock that is undervalued (overvalued) after the announcement should be repurchased (not repurchased) by the firm (Ikenberry and Vermaelen, 1996). According to Holden and Subrahmanyam (1992), informed traders will quickly trade around information events in order to profit from their information, so we believe that short sales will immediately increase (decrease) for stock that is overvalued (undervalued) following an OMR announcement. In model 8, abnormal short sales occurring during the first five days following a sample firm's OMR announcement is the dependent variable. The independent variables used to test our third hypothesis (H3) are $Repurchase_{(t+1,t+252)}$, *Complete,* and *NonComplete*. $Repurchase_{(t+1,t+252)}$ is the proportion of announcement-day, CRSP shares outstanding that we estimate to be actually repurchased during the 252 trading days following the OMR announcement. *Complete* (*NonComplete*) has a value of 1 when the sample firm is part of the completing (non-completing) group of sample firms and a value of 0 if not.[17]

[17] We use an independent variable that occurs up to a period of one year in the future, relative to our dependent variable, as in Dechow, et al. (2001). Their model includes the change in the level of short interest as the dependent variable and price changes occurring over the next year as an independent variable. These two variables are

We expect the estimated coefficient for the direct measure of repurchase activity to show a negative relation between repurchasing and abnormal short sales in the days following the OMR announcement. Further, we expect completing (non-completing) firms to have lower (higher) levels of short selling following an OMR announcement.

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analogous to our use of abnormal short selling as the dependent variable and estimated repurchase activity occurring up to one year in the future as an independent variable.

V. EMPIRICAL RESULTS

We present summary statistics for our sample in Table 1.[18] While we do not directly compare our sample with previous ones, we find some consistency with prior studies (e.g. Chan, et. al, 2004). Our sample firms experience positive abnormal returns during a 5-day announcement window, centered on announcement day. NYSE firms in our sample experience a mean announcement-period AHPR of 0.66%, while NASDAQ firms have a mean AHPR of 1.27% during the announcement window. Chan, et al. (2004) find AHPRs of approximately 2% during the 5-day announcement period, but they say that these returns are decreasing over time as the impact of an OMR announcement is weakening. Mean target size for OMR programs in our sample is 8.09% (8.07%) for NYSE (NASDAQ) firms. Chan et al., (2004) find mean target size to be 6.9%. Across both NYSE and NASDAQ firms, we find that 26% of our sample repurchases at least 100% of targeted shares within one year after the OMR announcement, and 13%, 4%, and 7% of our sample firms repurchase between 5% and 20%, between 1% and 5%, and less than 1% of targeted shares, respectively. Stephens and Weisbach (1998) find that 24% of firms repurchase at least 100% of their announced target, that 11% repurchase between 5% and 20% of targeted shares, 5% repurchase between 1% and 5% of targeted shares, and 16% of OMR firms repurchase less than 1% of their target in the first year after the OMR announcement is made. In Table 1, we also see that within each market, the results for *ABSS* and *ABSS_weekday* in the pre- and post-announcement periods are similar.

[18] All tables for Essay II are presented in the appendix to Essay II.

In Table 2, we present findings for means of and differences in means of abnormal short selling during the ten trading days preceding a firm's OMR announcement. Here, we see that NYSE firms tend to have higher one-day, abnormal short selling, on average, in the 5-day, 3-day, and 1-day period before an announcement is made, as opposed to the interval of (t-10, t-6). The difference appears greater one day before the announcement is made. NASDAQ firms show no significant difference in abnormal short selling over the 10 days before an OMR announcement is made. Table 2 presents results for both of our measures of abnormal short selling. All results for differences in means are nearly identical for the two measures. For the remainder of the tests, we use only *ABSS* as our measure of abnormal short selling.

In Table 3, we present regression results as we check the relation between abnormal short selling in the 5-day period before an OMR announcement and the abnormal returns occurring in the 5 days surrounding the announcement. We find that neither NYSE nor NASDAQ firms have announcement period returns that are significantly related to abnormal short selling in the 5 days before making an OMR announcement. This result is consistent with Blau and Pinegar (2010) who find that short selling does not increase before positive earnings announcements.

Table 4 presents OLS regression results and shows that a firm's level of discretionary accruals at the time of its OMR announcement is not related to abnormal short selling that occurs in the 5 days after the announcement. Therefore, our results do not support our first hypothesis (H1), which states that post-announcement short selling increases in a firm's use of discretionary accruals at the time of an OMR announcement. The coefficient estimate for $DA_{(t=0)}$ is insignificant in both NYSE and NASDAQ samples. The variables *HDA* and *LDA* are also insignificant for both samples, indicating that short sellers do not appear to adjust short selling in the tested post-announcement period for NYSE or NASADAQ firms that have discretionary accrual levels in the highest or lowest quintiles formed for all NYSE and NASDAQ firms during the year of the sample firm's OMR announcement. However, two other independent variables in the regression model are significantly related to post-announcement short selling.

Abnormal short sales in the 5 days following an OMR announcement tend to decrease as both NYSE and NASDAQ announcing firms show higher announcement-period returns. This negative relation between post-announcement short sales and announcement-period returns indicates that short sellers react to the price response of an OMR announcement, decreasing short sales in stocks with positive price moves. Additionally, abnormal short sales increase in earnings-announcement surprises that occur during the 5 day OMR announcement period. Post-OMR-announcement short sales are not related to the most recent earnings announcement surprise for a firm, in general, and they are not related to whether a firm makes an earnings announcement during the same period as the OMR announcement. The post-announcement short sales are related to the surprise contained in an earnings announcement when it is made during the same window as the OMR announcement.

In Table 5, results for NYSE and NASDAQ firms that announce an OMR program are consistent with our second hypothesis (H2) that abnormal short selling that occurs during the five days following the OMR announcement does not decrease as the amount of shares announced as part of the OMR program increases. Post-announcement, abnormal short selling is not related to an NYSE firm's announced target being in the largest or smallest third of all sample programs. We find that short sales in the 5 days following a NASDAQ firm's OMR announcement are not related to whether the OMR program size is part of the highest or lowest third of program sizes sampled. However, the larger the target of the repurchase, the higher the degree of short selling occurring in NASDAQ stocks during the post-announcement period. Kadiyala and Vetsuypens

(2002) suggest that short selling should decrease when a positive corporate announcement is made, and Comment and Jarrell (1991) find that the size of an OMR program is a positive signal. However, Chan, et al. (2010) question OMR program size as a positive signal. Our work supports the contention that larger OMR size announcements are not stronger positive signals than smaller size announcements.

As in the previous model, the results in Table 5 show that post-announcement, abnormal short sales for both NYSE and NASDAQ firms are negatively related to announcement-period returns and positively related to earnings-announcement surprises that are made specifically during the 5-day window surrounding OMR announcements. We also find, in this model, a negative relation between short sales for NYSE firms and their abnormal returns during the 25 days before the OMR announcement.

Our third hypothesis (H3) purports that abnormal short sales following an OMR announcement should decrease in the actual repurchasing of stock by the firm. The results we present in Table 6 do not support H3. We find a significant relation between estimated repurchase activity in the year following the announcement and short selling in the five days after the announcement for NYSE and NASDAQ firms. However, the sign of the relation is opposite of that predicted by H3. We find that short sales after an OMR announcement increase in estimated repurchasing that occurs during the year after the OMR is announced.

We also test whether post-announcement short sales are related to whether a firm completes its repurchase during the first year of its program or whether it is likely not to complete its program because it repurchases less than 5% of its target during the first year. The results in Table 6 show that abnormal short selling in the post-announcement period is unrelated to whether a firm is a completing or likely to be a non-completing firm, based on first-year estimated repurchases. We continue to see a negative (positive) relation between post-announcement short selling and OMR-announcement-period returns (earnings-announcement surprises during the OMR announcement window) for NYSE and NASDAQ firms, and we find that NYSE firms show a negative relation between short selling after an OMR announcement and the abnormal returns the firm experiences in the 25 days before the OMR announcement. These two findings are consistent with our Table 5.

VI. SUMMARY AND CONCLUSIONS

Our empirical results support only one of our three hypotheses. Comment and Jarrell (1991) present OMR program size as an effective, positive signal; however, Chan, et al. (2010) question OMR program size as an effective, credible signal. Relying on Kadiyala and Vetsuypens (2002), we use post-announcement short sales to test our second hypothesis that states that there is no decrease in post-announcement abnormal short selling as OMR program sizes increase. Results indicate that there is no relation between OMR program size and post-announcement short selling for NYSE firms, and NASDAQ firms show higher levels of short selling after higher OMR targets are announced. If larger OMR targets were considered stronger positive signals, we would find short sales decreasing after higher targets are announced. Therefore, we conclude that OMR program size is not an effective signal for firms to use as short sellers do not reduce short sales in response to larger programs.

We find no evidence that short sellers make trading decisions based on an announcing firm's level of discretionary accruals at the time an OMR is announced as stated in our first hypothesis. Chan, et al. (2010) suggest that firms may use an OMR to falsely signal positive news to the market in order to get a short-term price increase. Their tests show that the market response to an OMR announcement is not related to a firm's level of discretionary accruals, meaning firms may be able to mislead investors with an OMR announcement. If short sellers have superior information (e.g., Christophe, Ferri, and Angel, 2004) they should be able to parse the differences in high-quality and low-quality firms related to their use of discretionary accruals and adjust their activity following an OMR announcement accordingly. Our results indicate that short sales after an OMR announcement do not change with the announcing firm's use of discretionary accruals, so we conclude that short sellers respond no differently to an OMR-announcing firm's accrual quality than the market, in general, and that managers may be able to mislead even normally-informed investors by announcing an OMR.

We also have no findings to support our third hypothesis which suggests that abnormal short sales in the days following an OMR announcement are negatively related to the firm's repurchasing activity during the year following the announcement. However, our results show that short sales following an OMR announcement increase in actual repurchase activity for both NYSE and NASDAQ firms. Our third hypothesis indicates that post-announcement short sales will increase for firms that do not complete the OMR program as informed short sellers can predict repurchasing behavior. Our results show no relation between short sales following an OMR announcement and whether or not a firm completes its OMR program during the first year. If short sellers could predict repurchasing behavior, they should decrease short selling for repurchasing firms, which are shown to have positive price drift up to three years after the OMR announcement (e.g., Chan, Ikenberry, and Lee, 2004). As a result of our tests, we conclude that short sellers are not able to predict the repurchasing behavior of firms that announce an OMR.

Lastly, our results indicate that short sales in both NYSE and NASDAQ stocks decrease following positive, OMR announcement-period returns, but that they increase following positive earnings surprises that occur during the same period as the OMR announcement. Blau and Pinegar (2010) show that reactive short sellers increase activity following positive earnings announcements. Our results agree with theirs concerning earnings announcements, but our results indicate that short sellers react differently to positive, OMR announcements. Also, short sellers are shown to be contrarian in contemporaneous returns (e.g., Diether, Lee, and Werner, 2009). However, our results indicate that around OMR announcements, short sales decrease in positive returns. Therefore, we conclude that short sellers may consider open market repurchase announcements to be different than other positive corporate announcements.

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Appendix

Table 1: Summary Statistics

Panel A: NYSE	Mean	Median	Minimum	Maximum
$AHPR_{(t=0)}$	0.3805	0.5521	-22.2608	10.3109
$AHPR_{(t-2,t+2)}$	0.6625	1.1637	-23.4109	12.8881
$Price_{(t=0)}$	38.57	34.90	5.57	145.47
$MktCap_{(t=0)}$	11,861,174	3,482,550	91,650	214,881,442
$DA_{(t=0)}$	0.3100	0.0181	-2.2726	33.4801
$Target_{(t=0)}$	8.0891	6.4168	0.1757	51.2325
$Repurchase_{(t+1,t+252)}$	5.0606	3.8584	0.0000	36.2102
$Repurchase\_Tgt_{(t+1,t+252)}$	76.5769	66.2401	0.0000	719.1120
$ABSS_{(t-5,t-1)}$	0.2915	0.0717	-0.9505	3.6694
$ABSS\_weekday_{(t-5,t-1)}$	0.2892	0.0739	-0.9650	3.6425
$ABSS_{(t+1,t+5)}$	0.3466	0.1557	-1.1809	7.7573
$ABSS\_weekday_{(t+1,t+5)}$	0.3447	0.1521	-1.2380	7.7539

Panel B: NASDAQ	Mean	Median	Minimum	Maximum
$AHPR_{(t=0)}$	0.6858	0.5953	-39.5815	20.3317
$AHPR_{(t-2,t+2)}$	1.2664	1.2627	-33.2216	21.5718
$Price_{(t=0)}$	24.22	20.42	5.01	128.87
$MktCap_{(t=0)}$	5,015,970	642,453	34,651	229,916,700
$DA_{(t=0)}$	0.1939	0.0312	-22.8896	13.6919
$Target_{(t=0)}$	8.0693	6.6436	1.3152	43.5456
$Repurchase_{(t+1,t+252)}$	5.9367	4.0890	0.0000	57.5132
$Repurchase\_Tgt_{(t+1,t+252)}$	84.7601	52.2639	0.0000	631.5658
$ABSS_{(t-5,t-1)}$	0.4983	0.1220	-1.8893	18.7866
$ABSS\_weekday_{(t-5,t-1)}$	0.4945	0.1227	-1.8827	18.8560
$ABSS_{(t+1,t+5)}$	0.7511	0.2461	-2.0237	18.6092
$ABSS\_weekday_{(t+1,t+5)}$	0.7476	0.2337	-2.0171	18.6006

This table presents summary statistics for our sample which includes 226 NYSE common stocks and 188 NASDAQ common stocks with a CRSP share code of 10 or 11 that made an open-market repurchase announcement during the period of Feb. 14, 2005, to December 19, 2006, and that had a closing price of at least $5 on announcement day. Panel A includes statistics for NYSE firms in our sample, and Panel B contains the statistics for NASDAQ sample firms. *AHPR* is the percentage abnormal holding period return calculated as the daily return from close to close less the same-day return on the CRSP value-weighted portfolio; *Price* is the CRSP closing price for the stock; *MktCap* is calculated by multiplying *Price* by same-day outstanding shares found in CRSP; *DA* is the estimated, announcement year discretionary accruals scaled by total assets; *Target* is the proportion of outstanding shares announced as part of the repurchase program, reported here as a percent; *Repurchase* is the estimated proportion of announcement-day outstanding shares that are actually repurchased, reported as a percent; *Repurchase_Tgt* is the estimated proportion of targeted shares actually repurchased, reported as a percent; *ABSS* is abnormal short sales calculated as the proportion of daily outstanding shares sold short less the median value of daily outstanding shares sold short for the sample period; and *ABSS_weekday* is a measure of abnormal short sales calculated as *ABSS* but by subtracting the median for the corresponding weekday. For indexing purposes, *t=0* is the day of the repurchase announcement.

Table 2: Mean Short Selling in the Pre-announcement Period

	NYSE		NASDAQ	
Day	*ABSS*	*ABSS_weekday*	*ABSS*	*ABSS_weekday*
t-10	0.0493	0.0479	0.0808	0.0787
t-9	0.0505	0.0495	0.0864	0.0850
t-8	0.0426	0.0421	0.0980	0.0974
t-7	0.0358	0.0364	0.0571	0.0584
t-6	0.0318	0.0319	0.0732	0.0728
t-5	0.0459	0.0452	0.1017	0.0991
t-4	0.0578	0.0563	0.0810	0.0804
t-3	0.0598	0.0593	0.0845	0.0837
t-2	0.0479	0.0487	0.1337	0.1345
t-1	0.0801	0.0798	0.0974	0.0968
Difference				
$\overline{(t-10, t-6)} - \overline{(t-5, t-1)}$	-0.0160*	-0.0160*	-0.0210	-0.0200
	(0.099)	(0.099)	(0.394)	(0.397)
$\overline{(t-10, t-6)} - \overline{(t-3, t-1)}$	-0.0210	-0.0210*	-0.0260	-.0270
	(0.102)	(0.096)	(0.306)	(0.297)
$\overline{(t-10, t-6)} - (t-1)$	-0.0380**	-0.0380**	-0.0180	-0.0180
	(0.035)	(0.034)	(0.490)	(0.483)

Here we present the mean daily short sales occurring for sample stocks over the interval of (t-10, t-1) where t = 0 is the open-market repurchase announcement day. *ABSS* is abnormal short sales calculated as the proportion of daily outstanding shares sold short less the median value of daily outstanding shares sold short for the sample period; and *ABSS_weekday* is another measure of abnormal short sales calculated as *ABSS* but by subtracting the median for the corresponding weekday. Differences in means are shown as the average abnormal short sales occurring over the (t-10, t-1) interval minus average abnormal short sales occurring over intervals (t-5, t-1) and (t-3,t-1) and minus the abnormal short sales occurring on day t-1. Results for NYSE (N = 226) and NASDAQ (N = 188) firms are presented in separate columns. Located in parentheses below each difference in means is the p-value for statistical significance. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

Table 3: Regression Results for Pre-announcement Abnormal Short Selling and Announcement Period Return

	NYSE	NASDAQ
Intercept	-0.0018	-0.0067
	(0.547)	(0.304)
$AHPR_{(t-2,t+2)}$	-0.0125	-0.0224
	(0.186)	(0.213)
$AHPR_{(t-25,t-1)}$	-0.0047	-0.0222**
	(0.260)	(0.025)
$lnPrice_{(t-5,t-1)}$	0.0014	0.0036*
	(0.103)	(0.081)
Adj. R^2	0.013	0.040
F Value	2.00	3.59**
Observations	226	188

In the OLS model, $ABSS_{(t-5,t-1)}$ serves as the dependent variable and is the sum of daily abnormal short selling during the 5-day pre-OMR-announcement period. $AHPR_{(t-2, t+2)}$ is the abnormal holding period return during the 5-day period centered on announcement day $t = 0$, $AHPR_{(t-25,t-1)}$ is the abnormal holding period return during the 25 trading days occurring before announcement day. $lnPrice_{(t-5,t-1)}$ is the natural log of the mean daily closing price during the 5 days before the OMR announcement. Estimated coefficients for our NYSE and NASDAQ sample are listed for the tested model with p-values for statistical significance given in parentheses below the estimate. ** or * indicate significance at the 5% or 10% level, respectively.

Table 4: Regression Results for Hypothesis 1

	NYSE	NASDAQ
Intercept	0.0033***	0.0050***
	(0.000)	(0.004)
$AHPR_{(t-2,t+2)}$	-0.0562***	-0.0383**
	(0.000)	(0.012)
$AHPR_{(t-25,t-1)}$	-0.0074	-0.0099
	(0.109)	(0.224)
$DA_{(t=0)}$	0.0000	0.0010
	(0.862)	(0.150)
HDA	-0.0020	-0.0005
	(0.175)	(0.854)
LDA	0.0020	0.0039
	(0.223)	(0.186)
$Earn\_Surprise_{(t=0)}$	0.0018	0.0035
	(0.765)	(0.779)
$Earn\_Ann_{(t-2,t+2)}$	0.0019	0.0017
	(0.129)	(0.491)
$Earn\_Surprise_{(t=0)} * Earn\_Ann_{(t-2,t+2)}$	0.0355***	0.1921***
	(0.009)	(0.000)
Adj. R^2	0.162	0.097
F Value	6.22***	3.32***
Observations†	218	173

In the OLS model, $ABSS_{(t+1,t+5)}$ serves as the dependent variable and is the sum of daily abnormal short selling during the 5-day, post-OMR-announcement period. $AHPR_{(t-2,\, t+2)}$ is the abnormal holding period return during the 5-day period centered on announcement day $t = 0$, $AHPR_{(t-25,t-1)}$ is the abnormal holding period return during the 25 trading days occurring before the announcement day. $DA_{(t=0)}$ is the yearly, announcement day estimated discretionary accruals, scaled by assets; *HDA* (*LDA*) is equal to 1 if $DA_{(t=0)}$ is in the quintile of highest (lowest) estimated discretionary accruals formed for all NYSE and NASDAQ stocks in the announcement year and is equal to 0, otherwise. $Earn\_Surprise_{(t=0)}$ is the surprise contained in the most recent regular, quarterly earnings announcement occurring as of announcement day; $Earn\_Ann_{(t-2,t+2)}$ is equal to 1 if the earnings announcement occurs during the OMR-announcement interval of (t-2, t+2) and 0 otherwise. Estimated coefficients for our NYSE and NASDAQ sample are listed for the tested model with p-values for statistical significance given in parentheses below the estimate. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.
†We lose eight (fifteen) observations in the regression for our NYSE (NASDAQ) sample due to missing data for independent variables.

Table 5: Regression Results for Hypothesis 2

	NYSE	NASDAQ
Intercept	0.0033**	0.0012
	(0.017)	(0.645)
$AHPR_{(t-2,t+2)}$	-0.0551***	-0.0471***
	(0.000)	(0.003)
$AHPR_{(t-25,t-1)}$	-0.0079*	-0.0069
	(0.085)	(0.398)
$Target_{(t=0)}$	0.0173	0.0478*
	(0.201)	(0.068)
HTG	-0.0024	-0.0009
	(0.139)	(0.790)
LTG	-0.0022	0.0036
	(0.105)	(0.166)
$Earn\_Surprise_{(t=0)}$	0.0007	0.0085
	(0.910)	(0.497)
$Earn\_Ann_{(t-2,t+2)}$	0.0015	0.0025
	(0.220)	(0.311)
$Earn\_Surprise_{(t=0)}$ $*Earn\_Ann_{(t-2,t+2)}$	0.0361***	0.1469***
	(0.008)	(0.009)
Adj. R^2	0.174	0.104
F Value	6.73***	3.51***
Observations†	218	173

In the OLS model, $ABSS_{(t+1,t+5)}$ serves as the dependent variable and is the sum of daily abnormal short selling during the 5-day post-OMR-announcement period. $AHPR_{(t-2,\ t+2)}$ is the abnormal holding period return during the 5-day period centered on announcement day $t = 0$, $AHPR_{(t-25,t-1)}$ is the abnormal holding period return during the 25 trading days occurring before announcement day. $Target_{(t=0)}$ is the proportion of announcement-day outstanding shares that are target in the repurchase; *HTG* (*LTG*) is equal to 1 if $Target_{(t=0)}$ is in the tercile of highest (lowest) $Target_{(t=0)}$ for all sample firms and is equal to 0, otherwise. $Earn\_Surprise_{(t=0)}$ is the surprise contained in the most recent regular, quarterly earnings announcement occurring as of announcement day; $Earn\_Ann_{(t-2,t+2)}$ is equal to 1 if the earnings announcement occurs during the OMR-announcement interval of (t-2, t+2) and 0 otherwise. Estimated coefficients for our NYSE and NASDAQ sample are listed for the tested model with p-values for statistical significance given in parentheses below the estimate. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.

†We lose eight (fifteen) observations in the regression for our NYSE (NASDAQ) sample due to missing data for independent variables.

Table 6: Regression Results for Hypothesis 3

	NYSE	NASDAQ
Intercept	0.0024***	0.0053***
	(0.008)	(0.002)
$AHPR_{(t-2,t+2)}$	-0.0549***	-0.0414***
	(0.000)	(0.007)
$AHPR_{(t-25,t-1)}$	-0.0083*	-0.0062
	(0.072)	(0.439)
$Repurchase_{(t+1,t+252)}$	0.0210*	0.0341**
	(0.060)	(0.034)
Complete	-0.0013	-0.0033
	(0.307)	(0.234)
NonComplete	-0.0003	0.0036
	(0.885)	(0.269)
$Earn\_Surprise_{(t=0)}$	0.0043	0.0043
	(0.480)	(0.726)
$Earn\_Ann_{(t-2,t+2)}$	0.0018	0.0019
	(0.146)	(0.439)
$Earn\_Surprise_{(t=0)}$ *$Earn\_Ann_{(t-2,t+2)}$	0.0327**	0.1789***
	(0.015)	(0.001)
Adj. R^2	0.161	0.117
F Value	6.20***	3.86***
Observations†	218	173

In the OLS model, $ABSS_{(t+1,t+5)}$ serves as the dependent variable and is the sum of daily abnormal short selling during the 5-day post-OMR-announcement period. $AHPR_{(t-2, t+2)}$ is the abnormal holding period return during the 5-day period centered on announcement day, $AHPR_{(t-25,t-1)}$ is the abnormal holding period return during the 25 trading days occurring before announcement day. $Repurchase_{(t+1,t+252)}$ is the estimated proportion of announcement-day, outstanding shares that are actually repurchased over the 252 trading days following the OMR announcement; *Complete* (*NonComplete*) is equal to 1 if the estimated proportion of announced targeted shares is greater than or equal to 100% (less than 5%) and is equal to 0, otherwise. $Earn\_Surprise_{(t=0)}$ is the surprise contained in the most recent regular, quarterly earnings announcement occurring as of announcement day; $Earn\_Ann_{(t-2,t+2)}$ is equal to 1 if the earnings announcement occurs during the OMR-announcement interval of (t-2, t+2) and 0 otherwise. Estimated coefficients for our NYSE and NASDAQ sample are listed for the tested model with p-values for statistical significance given in parentheses below the estimate. ***, **, or * indicate significance at the 1%, 5%, or 10% level, respectively.
†We lose eight (fifteen) observations in the regression for our NYSE (NASDAQ) sample due to missing data for independent variables.

ESSAY III: PROFIT EFFICIENCY AND BIG BANK PRESENCE IN RURAL MARKETS

When large banks compete in rural banking markets where one-market banks operate, concerns arise for a variety of reasons including how these large banks might affect competition, profitability, and profit efficiency within the market. Pilloff (1999) concludes that big-bank presence in rural markets lowers competition within the market since banking operations in those markets enjoy higher returns on assets. In rural markets where one-market banks operate, we investigate whether higher returns are due to market power or if big bank presence helps improve profit efficiency, and we also examine whether small-market competition from multiple big banks changes performance for one-market banks in rural markets. One important consideration in this study is how to define a big bank. We follow Pilloff (1999) by defining a rural-market (non-MSA), big bank to be one of the 25 largest banks the United States, based on total deposits, holding at least 10% of a state's total deposits and operating in a non-MSA county where at least one single-market banks operates.

There are several reasons big banks might want to operate in rural markets. Perhaps big banks operate in small markets because they can compete more efficiently due to economies of scale or improved product delivery systems, or big banks may have a presence in small markets because there is plenty of profit to be made due to lower competition among banking institutions, possibly creating higher loan prices or lower deposit rates in the local market. In other words, we investigate if big banks are maintaining a presence in markets to extract rents or if they compete in markets where they have a competitive advantage due to improved operating efficiencies, or both.

Previous studies consider the effect of big-bank presence on the profitability of small banks operating in the same rural or urban market, but have only examined profit efficiency effects of large bank presence in urban markets. Pilloff (1999) argues that big bank presence reduces competition levels, allowing competing banks that operate only in one rural market to enjoy higher ROA. Pilloff concludes that one reason big banks lower competition is there may be weak incentives for big banks to aggressively compete in these markets, which suggests they may operate at lower efficiency levels in these markets if competing one-market banks are operating at lower levels of efficiency. Hannan and Prager (2009) show similar results in a sample of both rural and urban banking markets as they test the effects of large and small, multi-market bank competition on small, single-market banks. They demonstrate that the presence of a large bank that operates primarily outside a small, single-market bank's market has a significant effect on both the ROA and ROE of small, single-market banks within a rural market, but they find no such relation in urban markets, suggesting that big bank presence significantly affects profitability of one-market banks only in rural locations. Berger, Dick, Goldberg, and White (2009) study both profitability and profit efficiency of small, single market banks as they relate to competing bank size and market share in MSA markets and conclude that large, multiple-market banks compete more efficiently than small, single market banks located in urban markets.

We extend this previous research by answering the open question of the effect of large bank presence on the profit efficiency of rural, one-market banks. Additionally, our work offers insight as to whether large banks operating in these markets compete on efficiency to earn higher in-market returns or if they may be earning higher in-market returns without competing through operating efficiency in these markets. We do not analyze the efficiency of large banks in the local market, but we consider the efficiency of the competing small, one-market banks within the market as an indication of what level of efficiency is necessary for big banks within the market. We focus on profit efficiency of one-market banks in rural markets because banks having accounting profitability affected by the presence of large, competing banks (Hannan and Prager, 2009) may also experience efficiency effects from the presence of a big bank within the market.

Our contribution is fourfold: First, we test whether rural, single-market bank profit efficiency is decreased by the presence of one competing large bank. If the profit efficiency of a small bank is lower when a single big bank is present than when there is no large bank operating in the same market, then big banks choosing to be in the market may be able to generate sufficient returns without having to operate efficiently to do so. Intuitively, markets where banks enjoy market power and rent extraction without highly efficient competitors are where you would expect big banks to desire a presence. Second, we test whether the presence of more than one competing big bank has an effect on profit efficiency within rural markets where a one-market bank operates. The profit efficiency differences for one-market, rural banks that compete against multiple big banks indicate whether the presence of competing big banks induces banks in the market to compete on efficiency. Third, we modify the profit efficiency model and use a two-stage Heckman (1979) correction for data selection bias because big banks may choose to only be present in those markets having a propensity to be highly profitable. Previous studies finding increased returns for single-market banks in rural markets might not be driven by big banks affecting the profitability of the banks within these markets, but by big banks choosing to operate in highly profitable rural markets where single-market banks are located. Pilloff (1999) suggests that big banks do not target profitable rural markets but that large bank entry into these markets is normally a byproduct of larger merger activity. We agree with his assertion and suggest that a big bank's continued presence in a rural market after entry is likely a conscious decision made by management. Therefore, we do not specifically consider why a big bank enters a rural market, only that the big bank is present in that market. Lastly, we examine whether higher returns to rural, one-market banks competing against a big bank are the result of higher loan income. Banks with some degree of market power due to lower levels of intra-market competition may earn higher returns through non-competitive deposit- and loan-related rates and fees. Other studies have investigated deposit-related interest rates (e.g., Hannan and Prager, 2004, and Park and Pennacchi, 2009) and fees (e.g., Hannan, 2006) for small banks facing big bank competition, so we focus on loan income as the source of higher returns to one-market banks competing with a big bank in a rural market.

I. LITERATURE REVIEW

Big banks maintain a presence in rural markets for a variety of reasons. Here, we review the literature for four of those reasons as we consider the effects of big bank presence on the competition, profitability, and efficiency of one-market banks operating in rural markets. Big banks may choose to operate in rural markets because of rate-setting advantage from market power, unmet demand for lending, above-average returns without competing through efficiency, and access to relatively more core deposits.

Market power exists when banks can charge higher loan prices and offer lower deposit rates due to a lack of competition. Market power studies have conflicting findings about the relation between prices and market concentration. Berger and Hannan (1998) find increased market power where banks in more concentrated markets charge higher loan rates and pay lower deposit rates. Conversely, Simons and Stavins (1998) find some deposit rates rose and some fell depending on the level of concentration when comparing market prices before and after merger activity. Hannan (1991) finds evidence that market power is very low in a 1984 sample. Akhavein, Berger, and Humphrey (1997) find little in the way price changes within a market, after a merger.

Santomero (1999) asserts that market power may have declined over time. The decline in market power is likely true because of technological advancements. Empirical findings on market power through deposit and loan prices are mixed with some finding support, such as Cyrnak and Hannan (1998), and others finding no support such as Radecki (1998). Neumark and

Sharpe (1992) find market power for deposits where banks in concentrated markets are slower to raise deposit rates and quicker to lower them with changes in market interest rates. In contrast, Sapienza (2002) finds that in-market mergers result in a substantial decline in loan rates for business borrowers.

In summary, the results for market power are mixed with some finding market power, and others not. The results depend on sample period, whether or not mergers and acquisitions are considered, and other measurement issues. In the case of large bank presence in rural markets, these prior results indicate that market power could exist and that big banks desire to maintain a presence in those markets with the highest likelihood of market power. Delis and Tsionas (2009) perform a joint estimation of market power and cost efficiency for individual banks and conclude there is a negative relation between market power and efficiency. This finding agrees with our conjecture that big banks may maintain a presence in rural markets with a likelihood of market power in order to earn higher returns without competing on efficiency.

Large banks may also maintain a presence in small rural markets due to a lack of competition for business lending. Many studies find evidence that smaller banks tend to make more relationship-oriented loans. If small banks make more of these loans due to less competition, this lack of competitors could increase the likelihood that big banks will maintain a presence in these markets to lend to customers who have limited access to loans because of fewer lenders in the market. Even though big banks are not typically considered small business lenders, they are likely to be competitive for small business loans that are more transaction based and do not rely on relationships.

Studies of relationship lending typically investigate small-bank loan quantities and prices to small businesses as compared to large-institution lending to small businesses. Petersen and

Rajan (1994) use survey data from the SBA and find multiple bank relationships reduce quantities and increase loan prices for borrowers. Berlin and Mester (1998) hypothesize that customers with bank relationships will have loan rates smoothed in response to credit and interest rate shocks, but find evidence that banks smooth only in response to interest rate shocks. Berlin and Mester's results indicate banks avoid using market power to extract rents from small businesses. Detragiache, Garella, and Guiso (2000) provide theory that multiple banks can reduce adverse selection and early project liquidation, and find empirical evidence that better economic conditions increase the likelihood of a single lender. Survey evidence from Cyree and Wansley (2009) finds that 85% of bank founders indicate their motivation for starting a bank in their market is due to the business market being underserved. Together, these empirical findings indicate that big banks are more likely to want a presence in rural markets where fewer relationship lenders and competing big banks exist.

An additional reason for big bank presence in a rural market is to compete with less efficient banks in the market. It follows that big banks are more likely to remain in a market if the competitors in that market are comparatively less efficient. Put another way, big banks are likely to find it desirable to operate in a less efficient market because they can still make attractive returns with average intra-bank levels of efficiency.

Pilloff (1999) suggests that big banks are normally present in rural markets due to merger activity, so we turn to studies of efficiency after takeovers for possible motivations of a big bank's continued presence in a rural market. First, we consider studies that show little cost-efficiency difference after M&A activity. For example, Berger and Humphrey (1992) find in over half of large mergers in the 1980s, the acquirer was more efficient than the target; however, cost efficiency improvements were not very successful, on average. Peristiani (1997) finds acquirers do not improve cost efficiency after a merger for a sample of takeovers from 1980 to 1990. Rhoades (1998) investigates nine case studies of mergers involving large banks, most occurring in the early 90s, which seemed likely to make efficiency gains and finds that only four out of the nine were successful in improving cost efficiency.

More recently, researchers have focused on profit efficiency since this specification allows for inefficiency in both inputs and outputs. Akhavein et al. (1997) find a 16% increase in relative profit efficiency after a merger, largely due to increasing revenues by banks shifting output towards loans. Berger (1998) finds higher profit efficiency after takeovers and that improvement is in part due to better risk diversification. However, Berger et al. (2009) find lower profit efficiency for small, single market banks competing against large multiple-market banks in urban markets.

In total, efficiency studies suggest that substantial improvements in efficiency are possible, but not likely as banks get larger and expand products into new markets. While results are mixed, they tend to indicate no significant difference in efficiency with increases in size and scope regardless of merger activity in the market. As an extension to big bank presence in rural markets, it is unclear that inefficiency would be a main reason for market presence, but conventional wisdom suggests that big banks would wish to compete in markets that are less efficient so that they are not required to compete on efficiency within the market.

Big banks may enter rural markets to obtain relatively cheap core deposits. Core deposits are defined as retail deposits consisting of checking, savings, small CDs, and money market accounts. DeLong and DeYoung (2007) find that post-merger banks have improved core deposits-to-assets ratios and say that customers providing core deposits are likely to purchase additional products from the bank. Therefore, core deposits not only provide cheaper sources of funds but also likely provide increased revenues from the same customers. We account for the effects of low cost deposits and increased revenue through using profitability measures, which include revenue from loans and securities as well as the costs from deposit interest.

As shown by Cyree (2010), acquiring banks are willing to pay higher prices for banks with large amounts of deposits. Since many big banks enter rural markets through acquisitions, it could be the case that big banks desire a presence in these markets to provide access to inexpensive sources of funding through core deposits. Our study looks specifically at big bank effects on rural markets. Big banks that desire funding through core deposits likely find rural banks a particularly attractive target since DeYoung, Hunter, and Udell (2004) find that core deposits account for 67% of total deposits in rural banks and that core depositors are unlikely to leave the bank in the short run.

II. HYPOTHESES

Pilloff (1999) shows increased profitability for rural, single-market banks when at least one big bank is competing within the market. We test whether our sample confirms previous results concerning profitability in order to establish that we have a similar sample and that our results generalize. Our focus, however, is on differences in profit efficiency between rural markets where one-market banks compete against big banks and those where they do not. We believe that big banks are likely to operate in rural markets where they can enjoy higher in-market returns without having to compete on efficiency, which would demonstrate some degree of market power. Not having to compete on efficiency can be demonstrated by relative inefficiencies of competing one-market banks. The results of Berger et al. (2009) show that the presence of large, multiple-market banks in urban markets significantly decrease the profit efficiency of small, single-market banks operating in the same urban market. We investigate whether or not the same is true in rural markets as we consider the presence of big banks affecting the profit efficiency of rural, one-market banks. Our first hypothesis is stated as follows:

H1: When a big bank is present in a rural market, banks operating only in that market have lower levels of profit efficiency.

Pilloff (1999) suggests that big banks may have limited motivation to act aggressively in rural markets as they compete against single-market banks, thus lowering intra-market competition levels and allowing all banks in the market to earn higher returns. Pilloff also concludes that all banks in these markets continue to earn higher returns whether there is one competing big bank or multiple big banks. We hypothesize that if there are multiple big banks in the market, big banks are required to compete on efficiency, at least with one another, in order to earn higher intra-market returns. If this is true, then single-market banks would likely operate with comparable profit efficiency in order to be competitive with the big banks in the market. The result is that rural, single market banks would have less reduction in profit efficiency when competing against more than one big bank. Therefore, we state our second hypothesis as follows:

H2: When multiple big banks are present in a rural market, banks operating in that market have higher levels of profit efficiency than when only one big bank is present in the market.

Further, we consider whether previous results concerning performance differences of small, rural banks are driven by the presence of competing big banks or whether big banks exercise choice in maintaining their presence in certain rural markets. Our market power hypothesis predicts that big banks are present in markets where they can be highly profitable without having to compete on efficiency. Previous work with the profitability of rural, one-market banks has not considered the issue of banks choosing to remain in highly profitable markets, so we consider the level and efficiency of rural, small bank profitability as it relates to the likelihood that a competing big bank is present in the same market, stating our third hypothesis as follows:

H3: The probability of big bank presence in a rural market is related to the profitability of one-market banks operating in that market.

Lastly, we investigate the source of higher returns to small, rural banks competing against big banks. Pilloff (1999) suggests the higher profitability to small banks competing with big banks in rural markets is due to big banks having limited motivation to compete within the market, thus lowering competition and increasing returns. Returns may be increasing as lower levels of intra-market competition endow banks with market power, allowing them to either charge higher loan rates and fees, pay (charge) lower (higher) deposit-related rates (fees), or both. Hannan and Prager (2004) and Hannan (2006) document that multimarket banks tend to pay lower deposit rates and charge higher deposit-related fees, respectively, than one-market banks competing within the same market. These findings suggest that deposit-related rates and fees are not likely the source of higher returns to a rural, one market bank competing with a big bank. To investigate whether loan income offers higher returns, we examine the relation between the ratio of interest and fee income from loans to total loans for rural, one-market banks and big bank competition in the market. Park and Pennacchi (2009) indicate that big banks tend to set loan rates over a wide geographical area, whereas small banks operating in one market likely set rates according to the competitive environment within their market. Big-bank loan rates across many markets that are higher than necessary to compete with one-market banks in their respective rural markets may result in rural, one-market banks being able to charge higher loan rates when competing with a big bank. However, Park and Pennacchi (2009) find that as big-bank presence increases within a market, intra-market loan rates decrease due to competition, suggesting that multiple big banks within the rural market may limit loan-rate profitability. Therefore, we also examine the ratio of interest and fee income from loans to total loans and whether or not multiple big banks are competing within the market. We offer the following two hypotheses:

H4: When a big bank is present in a rural market, banks operating only in that market have higher levels of loan income.

H5: When multiple big banks are present in a rural market, banks operating in that market have lower levels of loan income than if they were competing against one big bank.

III. DATA AND METHODS

Our sample contains individual banks (savings and loan institutions are excluded) that operate in one rural county as of June 30 each year according to the Summary of Deposits (SOD) and contains information on the individual county in which the sample bank operated. The sample period is 1996 through 2007. We end our sample period in 2007 to avoid effects of the financial crisis beginning after 2007. Following Pilloff (1999), a sample bank must meet the following three criteria: 1) the bank's offices are located in one county, 2) the county has to be in a non-metropolitan statistical area (non MSA), and 3) at least two other banks must operate in the same rural county. This sampling technique results in an unbalanced panel of data since banks do not necessarily appear in the sample from year to year. Table 1 presents a breakdown of the number of sample banks by year; the unbalanced panel consists of 26,299 observations over twelve years, from 1996 through 2007.[19] The sample contains a mean of 2,192 sample banks per year and shows that banks meeting our sample criteria are decreasing over time. Reasons that a bank may not meet sampling criteria include the bank opening offices in another market and fewer than three banks operating in its one-county market in a sample year. We also include an indicator variable for whether a big bank operates within the sample bank's one-county market.

Based on Pilloff (1999), a big bank meets two criteria: 1) the bank is one of the 25 largest banks or bank holding companies in the United States, not including savings and loan institutions, as determined by total deposits as of June 30 in each year, and 2) the bank holds at

[19] All Tables for Essay III are presented in the appendix to Essay III.

least 10% of total deposits in a state.[20] For example, if in a sample year, a bank that is one of the 25 largest banks in the nation holds 12% of total state deposits in Florida and 8% of total state deposits in Colorado, the bank is considered a big bank in all counties where it operates within Florida in that sample year. However, the bank is not considered a big bank in any of the counties where it operates in Colorado during that sample year. In Table 1, there are 5,039 observations in which banks compete with at least one big bank in their markets and a total of 1,167 observations in which banks have multiple big banks operating in their markets during the sample period. The yearly mean is 420 and 97 sample banks that compete with at least one big bank and with more than one big bank, respectively, during each sample year.

We examine the performance of one-market, rural banks as it relates to competition with big banks by using two different performance measures: return on assets (ROA) and profit efficiency (PROF_EFF). Then, we investigate how income from loan rates and fees (INT_FEE_INC) of sample banks are related to big bank competition. Observations for ROA, PROF_EFF, and INT_FEE_INC are calculated using information found in each sample bank's fourth-quarter Call Report for each sample year.

We estimate the efficient profit frontier using all banks for every year, not just rural banks, so that each estimate is a proportion of the frontier using all banks and not just those in our sample. We measure profit efficiency as a combination of the model of DeYoung and Hasan (1998) and Berger and Mester (1997). This model is chosen since it allows banks to have negative profits and still remain in the sample, which is particularly important in small, rural markets where the numbers of competitors are usually low. The outputs chosen for this method allow some power over output quantities rather than the standard output prices. Profit efficiency also allows for inefficiency in outputs and inputs (see Berger, Hancock, and Humphrey, 1993).

[20] We consider bank holding companies to be banks unless otherwise stated.

Our model uses a Fourier-flexible form similar to DeYoung and Hasan (1998) and Berger and Mester (1997) and includes trigonometric terms to account for banks that are far from the sample means for dependent variables. This ability is also important for small banks, including those competing with big banks in the rural areas contained in our sample. For input prices, we estimate averages across geographic areas in MSAs or rural counties as in DeYoung and Hasan (1998). The outputs for each year vary at the bank-specific level and our estimation for only one year avoids the problem of technological change and inter-temporal differences. The dependent variable is operating profit less loan-loss reserves, and we add a constant that varies for each year and equals the absolute value of the minimum profit plus one added to each firm so that profit is positive.[21] There are three outputs at the bank-level: total loans, securities, and fee-based financial services measured as non-interest income minus service charges on deposit accounts.[22] The input price vector is measured at the MSA or county level for the cost of borrowed funds, the price of physical capital, and the wage rate of labor. Z is a conditioning vector that includes a Herfindahl index for each geographic area, the average non-performing loan ratio in the geographic area, and bank-specific equity capital. The Fourier terms are the trigonometric terms that provide a global approximation of the profit function when values of Y are far from the sample mean. The nine X variables are Y, Z, and W variables transformed so they fall on the interval of the domain of trigonometric functions.[23]

The error terms are separated into two parts as in Jondrow, Lovell, Materov, and Schmidt (1982), DeYoung and Hasan (1998), and Berger and DeYoung (1997) with *u* representing profit

[21] See Berger and Mester (1997) page 917 for details.
[22] Note that we use securities as an output as in Berger and Mester (1997) rather than transactions deposits as in DeYoung and Hasan (1998).
[23] We use the transformation of the variables such that they lie in the interval from [$0.1*2\pi$, $0.9*2\pi$] as in footnote three of Berger, Leusner, and Mingo (1997). Also, we use only the transformed variables for the outputs as discussed in DeYoung and Hasan (1998) footnote 15 as well as Berger and Mester (1997) footnote 29.

inefficiency and v representing a normal random error. We transform the errors such that the inefficiency is stated as a proportion of actual profits as compared to the predicted profits if the bank were on the stochastic frontier for a particular year, net of random error, while subtracting out the constant in each year as in Berger and Mester (1997):

$$Alt\ \pi\ EFF^b = \frac{\hat{\pi}_b}{\hat{\pi}_{\max}} = \frac{\exp[f(Y^b, W^b, Z^b, v^b) \times \exp(\ln \hat{u}_\pi^b) - \theta}{\exp[f(Y^b, W^b, Z^b, v^b) \times \exp(\ln \hat{u}_\pi^{\max}) - \theta} \qquad (1)$$

For example, a bank that has profit efficiency of 0.80 is operating at 80 percent efficiency, or 20 percent inefficiency, for a particular year as compared to the most efficient bank, regardless of location.

For our study, we use a two-stage Heckman (1979) correction procedure to control for sample selection bias since a competing big bank may choose to only maintain a presence in markets that tend to be more profitable. In the first stage, we use a Probit model to estimate the probability that a big bank is present in a sample market. In the second stage, the inverse Mills ratio from the Probit analysis is used to control for the probability that a big bank operates in the sample bank's market. The following first-stage Probit model is used:

BIG = f (MKT_ROA, LNPOP, POPGROWTH, HHIADJ, MBB, NUMBER_BANKS) (2)

BIG is a binary dependent variable taking the value of one if a big bank is present in the sample bank's local market and zero otherwise. *MKT_ROA* is the mean return on assets of sample banks within the market. *LNPOP* in the natural log of the population for the county according to US Census Bureau estimates. *POPGROWTH* is the year-over-year growth rate for the county population estimate. *HHIADJ* is the adjusted Herfindahl-Hirschman Index (*HHI*) for the local market, calculated using percent of county deposits held by each bank as the market share to find the *HHI*, then dividing by 1000 for adjustment. *MBB* is a dummy variable equal to one if there is more than one big bank present in the local market and zero otherwise. Lastly, *NUMBER_BANKS* is the total number of banks operating in the market. We include these variables in our model because big banks may only choose to maintain operations in sample markets that have more profitable small banks or those that are larger, are experiencing growth, are less competitive, are free from other competing large banks, or are markets having fewer competing banks. We also include a series of dummy variables indicating in what sample year the observation occurred in order to control for yearly fixed effects. The Probit model is estimated using the yearly dummy variable for 1996 as the omitted group, and so sample year 1996 serves as the comparison case.

The regression model used in the second stage of the Heckman (1979) procedure to estimate the effect of a competing big bank's presence on the profitability of sample banks is as follows:

$$\begin{aligned} PERF = {} & \alpha + \beta_1 BIG + \beta_2 LNPOP + \beta_3 POPGROWTH + \beta_4 HHIADJ \\ & + \beta_5 LNASSETS + \beta_6 LOANAST + \beta_7 MBB + \beta_8 NUMBER\_BANKS \\ & + \beta_9 LAMBDA + \gamma Q + \varepsilon \end{aligned} \tag{3}$$

The dependent variable *PERF* is one of our two measures of performance—either *ROA*, defined as the sample bank's net income for the sample year divided by its reported assets on the fourth-quarter Call Report; or *PROF_EFF*, defined as the sample bank's ratio of profit as compared to the best practice bank located on the efficient frontier for the year, given the bank's inputs and outputs. *LNASSETS* is the natural log of the sample bank's reported assets on the fourth-quarter Call Report. To control for risk-levels of sample banks, we use *LOANAST* which is the ratio of total loans to assets. *LAMBDA* is the inverse Mills ratio from the first-stage Probit model that controls for the probability that a big bank operates in a sample market, and *epsilon* is the error term which is assumed to be normally distributed. All other variables are as defined earlier. The second-stage regression model is estimated using ordinary least squares, and we include a matrix, *Q*, of yearly dummy variables for year 1996 through 2007 which are used to control for yearly fixed effects. We restrict the OLS model such that the coefficient estimates for the yearly dummy variables must sum to zero. Suits (1984) explains that this restriction over a class of dummy variables allows interpretation of estimated coefficients as averages over the class of dummy variables instead of relying on an omitted variable to serve as the base case for comparison.

To investigate any effect big bank presence has on loan income to sample banks, we use the following second-stage, OLS model:

$$\begin{aligned} INT\_FEE\_INC = {} & \alpha + \beta_1 BIG + \beta_2 LNPOP + \beta_3 POPGROWTH + \beta_4 HHIADJ \\ & + \beta_5 LNASSETS + \beta_6 LOANAST + \beta_7 MBB + \beta_8 NUMBER\_BANKS \\ & + \beta_9 LAMBDA + \gamma Q + \varepsilon \end{aligned} \tag{4}$$

The dependent variable *INT_FEE_INC* is interest and fee income from loans from the yearly income statement divided by total loans reported on the fourth-quarter Call Report, and it serves as our measure of loan income. All other variables are as previously described. Again, we restrict the model by requiring coefficient estimates for the yearly dummy variables in matrix, *Q*, to sum to zero.

IV. RESULTS

Table 2 contains summary statistics comparing the means of sample variables for rural banks competing with at least one big bank versus those not competing with any big bank. *ROA* between the groups is virtually identical and the difference between markets with and without a competing big bank is not significant. In contrast to *ROA*, sample banks located in big-bank markets have a mean profit efficiency that is significantly lower than those sample banks in non-big-bank markets. Previous research has shown that it is difficult to draw conclusions about differences in *ROA* between bank groups using simple mean analysis, and our results are just as problematic. However, our results for profit efficiency support the hypothesis that banks operating in rural markets where big banks choose to operate are not as profit efficient as those who do not compete against big banks. Additionally, the results indicate big banks operating in our sample markets may not find it necessary to compete on efficiency since the small bank competitors in the market tend to be less efficient in these markets.

The results from our sample for mean *HHI* show that non-big-bank markets tend to be more concentrated than those without a big bank, whereas as Pilloff (1999) concludes that big-bank markets tend to be less competitive than non-big-bank markets. Sample banks competing with a big bank earn higher levels of loan income, as hypothesized, and in fact earn lower levels of interest and fee income from loans than those not competing with a big bank. The differences in means for the other sample variables are largely as expected. First, sample banks in big-bank markets are significantly larger than those in non-big-bank markets as measured by total assets.

Second, big banks operate in markets that are significantly larger in population and have a significantly faster population growth than markets without a big bank. Next, the total number of banks located in rural markets where a big bank operates is significantly higher than in non-big-bank markets. Lastly, sample banks competing with a big bank lend at a significantly higher ratio of total loans-to-assets than do sample banks not competing against a big bank.

The sample contains a total of 5,039 observations for banks that compete with at least one big bank over the sample period and 21,260 observations for sample banks operating in markets without a big bank. Table 3 presents results from the first-stage Probit model and indicates factors that affect the probability that a big bank is located in a sample-bank market. As market population increases and as market population grows at a faster rate, there is a significant increase in the probability that a big bank will be located in the sample market. Big banks are less likely to operate in markets that have more individual banks since the estimate for the *NUMBER_BANKS* variable is negative and significant; additionally, if one of those individual banks located in a sample market is another big bank, it does not affect the probability that a big bank will be present in the market as the estimate for multiple big banks in the market is insignificant.

Estimates for market-level *ROA* indicate that big banks are significantly more likely to be located in those markets that are more profitable, an important result since we hypothesize that big banks choose to maintain operations in rural markets that are profitable. However, the estimate for *HHI* shows that big banks are less likely to be in markets that are more concentrated. The results for these two variables show mixed support for our market power hypothesis that big banks operate in rural markets where profitability is high but that are less competitive, so they may have exercisable market power in these markets, and they may not. We do not present marginal effects for the explanatory variables in the Probit model since they are not necessary for our analysis; however, the inverse Mills ratio from the first-stage regression is included as the independent variable *LAMBDA* in the second-stage OLS regressions for the dependent variables of *ROA*, *PROF_EFF*, and *INT_FEE_INC* in order to control for possible sample selection bias.

We report the results of the performance regressions to investigate the hypothesis that big bank presence is related to differential market performance. The first column of coefficient estimates in Table 4 contains the results for regressions using *ROA* as the dependent variable. Several important results stand out. First, the variable of most importance to this analysis is the *BIG* indicator for large-bank presence in local markets. After controlling for the probability that a big bank will be present in a sample market, we find that the average *ROA* for sample banks is significantly higher when a big bank is present. In contrast to previous studies, however, we find the effect of multiple big bank presence is significant and negative concerning *ROA*. These estimates imply that a single big bank operating within the rural market is associated with increased profitability as measured by *ROA*, but as more big banks operate in local markets return on assets is lower for sample banks. Lower *ROA* for sample banks in markets with multiple big banks suggests that when more than one big bank is in a local rural market, the big banks choose to compete with one another, thereby increasing competition within the local market. So, any perceived big-bank behavior of extracting rents in local rural markets seems to be constrained by the presence of other competing big banks. The estimate for *HHIADJ* is insignificant indicating that as the local market becomes less competitive, *ROA* does not necessarily increase. Intuitively, we would expect less competition within the market to result in higher returns due to pricing power. Finally, *LAMBDA* included from the first-stage is significant indicating the control for probability of big bank presence in a sample market is necessary. In total, coefficient estimates indicate that *ROA* increases for rural, one market banks when a big bank is present in the same market, and higher probabilities of big bank presence are associated with higher levels of *ROA* for competing small banks. These results are consistent with previous findings that higher returns for rural, small banks are associated with those banks competing with a large bank, but we also show the necessity of controlling for a big bank's choice to operate in profitable markets.

Markets with higher populations have a significantly negative effect on *ROA* while there is no significant relation between population growth rate and sample-bank *ROA*. The result that larger sample banks earn significantly higher returns on their assets agrees with conventional banking wisdom that larger banks make more profit. When a sample bank lends proportionally more, returns are significantly higher as shown by the loans-to-assets coefficient. The number of banks within a local rural market is significantly related to *ROA*.

Table 4 provides regression results for the model containing *PROF_EFF* as the independent variable. Focusing on results for the variables *BIG* and *MBB* allows insight into how big bank presence affects market profit efficiency. When a big bank is present in a sample market, profit efficiency for small banks is significantly lower. Conversely, multiple big bank presence in a market appears to improve efficiency, all else constant, since the estimate for the multiple-big-bank variable is significantly positive. Combined with the results for *ROA*, these results suggest that big banks may be able to extract rents in profitable, rural markets while operating relatively inefficient when there is not a competing big bank, but if more than one big bank is present, it appears that all banks must compete on efficiency. Similar to results using *ROA* as the performance measure, *LAMBDA* from the first-stage Probit model significantly affects profit efficiency, indicating that controlling for probability of a competing big-bank is necessary. A puzzling result is that more concentrated markets have higher levels of profit efficiency, which is counter-intuitive as less competitive markets should allow for lower levels of intra-market efficiency. The number of competing banks within the market is associated with higher profit efficiency in sample banks, consistent with higher levels of efficiency being necessary to compete with a larger number of banks.

Control variables also provide evidence for the effects of big bank presence on market performance. When profit efficiency is used as the dependent variable in the second-stage OLS model, there are some distinct differences when compared to results for *ROA*. Markets with large populations have significantly higher profit efficiency while a faster growing population significantly decreases profit efficiency. Larger sample banks are associated with lower profit efficiency. However, sample banks lending at a higher loan-to-asset ratios are associated with significantly higher levels of profit efficiency, which is consistent with the results for *ROA*.

So far, our results indicate that when sample banks compete with one big bank, they are able to earn higher returns at lower levels of efficiency, but the presence of more than one big bank in the market results in lower returns and higher levels of efficiency for sample banks. The results in Table 4 concerning the independent variable *INT_FEE_INC* offer some explanation for higher returns to small banks competing against one big bank. The coefficient estimate for big bank presence shows that sample banks competing with a big bank have higher loan income in the form of interest and fees, but when a small bank competes with multiple big banks, it earns lower levels of interest and fee income from loans. Even though there is an insignificant relation between sample-bank *ROA* and *HHIADJ*, we find that higher *HHIADJ* corresponds to sample banks earning higher interest and fee income from loans. Taken together, these results suggest that the source for higher returns to small banks in competition with a single big bank is the ability to charge higher loan rates and fees in a market that is less competitive and less efficient. However, it appears that when a small bank competes with multiple big banks it earns lower returns as it charges lower loan rates and fees in a more efficient market.

Other results concerning loan income include that sample banks earn more interest and fee income from loans in markets with a higher population and those growing at a faster rate. However, larger banks, those with higher proportions of lending, and banks with more competitors within their market earn less income from loans in the form of interest and fees. *LAMBA* continues to be significantly related to the independent variable, so controlling for sample selection bias is an important part of our analysis.

V. ROBUSTNESS TESTING

For robustness, we again estimate our second-stage regressions to compare markets that do not contain a big bank to markets where one big bank is present and, separately, non-big-bank markets to those with multiple big banks present. That is, we use two restricted samples. The first restricted sample includes non-big-bank markets and markets with one big bank, and the second restricted sample includes non-big-bank markets and markets with multiple big banks. In Table 5, results for the first restricted sample confirm our previous findings that when a sample bank competes with one big bank, the small bank earns higher *ROA*, performs less efficiently, and earns higher loan income from interest and fees. However, in the restricted sample, sample banks exhibit higher *ROA* in more concentrated markets. In tests for the whole sample, *HHIADJ* is insignificant, but the result in the restricted sample is intuitive. We expect banks in more concentrated markets to earn higher returns.

Table 6 indicates that small banks competing with multiple big banks have higher *ROA*, lower profit efficiency, and higher interest and fee income from loans than those sample banks competing with no big banks. These results are the same as the results for the whole sample and the first restricted sample. However, the small-bank increase in *ROA*, decrease in profit efficiency, and increase in loan income are smaller in magnitude than those for sample banks competing in one-big-bank markets.

There are other differences in results for the second restricted sample compared to the whole sample. In the second restricted sample, *ROA* for small banks is unrelated to the total number of banks competing in the market, but profit efficiency for small banks is positively related to the total number of banks in the market. Also, in the second restricted sample, interest and fee income from loans is negatively related to the size of the market, measured by population.

In sum, from our robustness tests, it appears that when a sample bank competes with one or more big banks, it earns higher *ROA*, operates less efficiently, and earns more interest and fee income from loans. However, because of the magnitude of the estimates, it appears that sample banks competing with multiple big banks have a smaller increase in *ROA*, a smaller decrease in profit efficiency, and a smaller increase in loan income from interest and fees than small banks competing with only one big bank. We verify the smaller magnitudes between market types by running our regressions on a third restricted sample that contains only markets where sample banks compete against big banks.

Table 7 gives the results of our regression analysis on the restricted sample comparing sample banks competing against one big bank to sample banks competing against multiple big banks. Our previous findings are verified. In markets where one big bank operates, sample banks exhibit higher *ROA*, less profit efficiency, and higher interest and fee income from loans, as compared to markets where sample banks compete against multiple big banks. *LAMBDA* continues to be a significant variable in all of our robustness tests, verifying the need to control for a big bank's choice to operate in more profitable markets.

VI. CONCLUSIONS

In this paper, we analyze the effects of big-bank presence on the performance of banks that operate exclusively in one rural market. Our performance measures include both return on assets and profit efficiency. We confirm previous findings that big-bank presence within a rural market has a positive effect on profitability of one-market banks in the same market, but our findings also show that when multiple big banks are competing in rural markets, single-market banks in the same market have a smaller increase in return on assets than when competing with only one big bank. We also contribute new findings concerning the effect of competing big banks on the profit efficiency of rural, single-market banks. Supporting our first hypothesis, we find that when a big bank is present in a rural market, a one-market bank in that market has lower levels of profit efficiency. However, we also find support for our second hypothesis. When multiple big banks are in a rural market, a one-market bank in that market has higher profit efficiency than when competing with one big bank. That is, a one-county bank operates less efficiently when competing against at least one big bank, but when competing against more than one big bank, there is a smaller decrease in efficiency.

We hypothesize that big banks have a higher probability of being located in rural markets that are more profitable, so we use a two-stage regression model to control for possible selection bias, following Heckman (1979). Results from the first-stage Probit model support our third hypotheses. We find a positive relation between the rural market's average level of return on assets and the probability that a big bank is present in the market. Results from the second-stage models show that controlling for the probability that a big bank is present in a market is necessary.

Lastly, we find support for our fourth and fifth hypotheses as we try to explain the increased returns to small banks competing against a big bank. Our results indicate that rural, one-market banks competing against only one big bank earn more income from loan interest and loan fees. One-market banks competing against more than one big bank also earn higher levels of income from loan interest and fees, but the increase is smaller than when the one-market bank competes against only one big bank.

We draw several conclusions from our results. First, when at least one big bank competes in a local rural market, single-market banks in the market earn higher returns that are not explained by selection bias, and these returns are not due to increased profit efficiency. Higher returns appear to be the result of banks being able to charge higher loan rates and fees in a less competitive, less efficient market. However, the presence of more than one competing big bank affects market performance differently. When more than one big bank competes within a rural market, one-market banks competing in the same market operate less efficiently and with higher returns. However, the decrease in efficiency and the increase in returns are both smaller in magnitude than when only one big bank operates within the market. In other words, in multiple-big-bank markets, accounting profit is more difficult to obtain, and banks appear to be competing on price since interest income from loans and fees also increases by a smaller amount than it does in one-big-bank markets. Probit analysis indicates that big banks are more likely to be in more profitable rural markets that contain a one-market bank, and controlling for the probability of big-bank presence in the market is important.

We consider that the performance of one-market banks in rural markets is an indicator of the performance level by competing big banks within the same market. We conclude that big banks choose to maintain a presence in higher-profit markets where they find it unnecessary to compete on efficiency to earn higher in-market returns, which suggests some degree of exercisable market power. However, this market power is reduced if there is more than one big bank operating in the market because big banks earn lower returns and must operate more efficiently. Implications of this study include that regulators and other stakeholders must use caution when one big bank enters a rural banking market as big banks attempt to extract rents from these small markets when no other large competitor is present.

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Appendix

Table 1: Number of Banks in the Sample by Year

Sample Year	Number of Banks	Big-Bank Markets	Multiple-Big-Bank Markets
1996	3,036	350	67
1997	2,833	362	47
1998	2,627	327	67
1999	2,440	328	66
2000	2,309	467	78
2001	2,178	424	83
2002	2,083	501	123
2003	1,900	411	121
2004	1,803	472	125
2005	1,835	518	151
2006	1,736	460	127
2007	1,519	419	112
Total	26,299	5,039	1,167
Yearly Mean	2,192	420	97

Table 1 presents the number of banks in the sample for each year of the sample period 1996 – 2007. To be included as a sample bank, all of the following criteria must be met: 1) the bank must operate exclusively in one county, 2) the county in which the bank operates must be a non metropolitan statistical area (non MSA), and 3) there must be at least two other banks (whether they are considered big or not) operating in the same county. A big bank is one that meets both of the following criteria: 1) one of the 25 largest banking institutions in the United States as measured by total deposits in the sample year and 2) holds at least 10% of the deposits within an individual state in the sample year. A market is defined as the county in which a sample bank operates. Big-bank (multiple-big-bank) markets have at least one (more than one) big bank operating in the market.

Table 2: Means and Differences in Means between Market Types

	Full Sample	Big-Bank Markets	Non-Big-Bank Markets	Difference in Means	p-value for Difference
ROA (%)	1.11	1.11	1.12	-0.01	0.359
PROF_EFF (%)	53.01	51.54	53.36	-1.82***	0.000
ASSETS (1,000)	71,935	87,256	68,304	18,952***	0.000
LOAN_AST (%)	57.74	61.00	56.97	4.03***	0.000
INT_FEE_LI (%)	8.30	7.99	8.37	-0.38***	0.000
POP	28,600	45,212	24,663	20,549***	0.000
POPGROWTH (%)	.07	0.46	-0.02	0.48***	0.000
HHI	2,525	2,201	2,602	-402***	0.000
NUMBER_BANKS	7.01	8.33	6.70	1.63***	0.000
MKT_ROA (%)	1.12	1.11	1.12	-0.01	0.215

Table 2 contains means for the entire sample and for individual market types, difference in means calculated as the mean for big-bank markets minus the mean for non-big-bank markets, and p-values for significant difference between the means of the two market types. The sample period is 1996 – 2007. The full sample contains 26,299 bank-year observations—5,039 (1,167) are big-bank (multiple-big-bank) market observations. A big-bank (multiple-big-bank) market has at least one (more than one) big bank operating in the market. Sample bank variables include the following: *ROA* is yearly net income divided by assets; *PROF_EFF* is yearly profit efficiency; *ASSETS* is the value of assets on each bank's fourth quarter call report; *LOAN_AST* is the ratio of total loans to assets; and *INT_FEE_LI* is the ratio of interest and fee income from loans to total loans. Market-description variables include the following: *POP* is the estimated county population; *POPGROWTH* is the calculated yearly population growth rate; *HHI* is the Herfindahl-Hirschman Index, calculated using market share as the percentage of total deposits a sample bank has for the sample market; *NUMBER_BANKS* is the number of banks (not offices, but separate FDIC certificate numbers) that operate in the local market; and *MKT_ROA* is the mean *ROA* for all banks in the local market. *** indicates significant difference in means at the 1% level for big-bank markets vs. non-big-bank markets.

Table 3: Results for First-stage Probit Model

Independent Variable: *BIG*		
Dependent Variables	Coefficient Estimate	p-value
Intercept	-7.5416***	0.000
MKT_ROA	5.5523***	0.005
LNPOP	0.6212***	0.000
POPGROWTH	4.9239***	0.000
HHIADJ	-0.0407***	0.002
MBB	7.5144	0.996
NUMBER_BANKS	-0.0137***	0.004
Y97	0.1229***	0.010
Y98	0.0844*	0.086
Y99	0.1374***	0.000
Y00	0.4605***	0.000
Y01	0.4364***	0.000
Y02	0.5682***	0.000
Y03	0.4291***	0.000
Y04	0.6060***	0.000
Y05	0.6775***	0.000
Y06	0.6217***	0.000
Y07	0.6531***	0.000

Table 3 presents results for the first-stage Probit model. The sample period is 1996 – 2007. For our 26,299 bank-year observations, the Probit model estimates the probability that a big bank operates in a sample bank's county of operation in the sample year. *BIG* is the indicator variable for the presence of a big bank in the sample market, equal to one when a big bank is present in the local market and equal to zero when a big bank is not present. *LNPOP* is the natural log of market population; *POPGROWTH* is the calculated yearly population growth rate; *HHIADJ* is the Herfindahl-Hirschman Index for the market divided by 1000; *MBB* is an indicator equal to one if there is more than one big bank in the market and zero otherwise; *NUMBER_BANKS* is the total number of banks operating in the market; *Y97 – Y07* are dummy variables indicating the sample year, used to control for yearly fixed effects with 1996 serving as the omitted year. * and *** indicate significance at the 10% and 1% levels, respectively.

Table 4: Results for Second-stage OLS Models

	Independent Variables		
	ROA	*PROF_EFF*	*INT_FEE_INC*
	Coefficient Estimate		
Dependent Variables	(p-value)		
Intercept	-0.0091***	0.3734***	0.1268***
	(0.000)	(0.000)	(0.000)
BIG	0.0079***	-0.0605***	0.0104***
	(0.000)	(0.000)	(0.000)
LNPOP	-0.0019***	0.0169***	0.0004*
	(0.000)	(0.000)	(0.084)
POPGROWTH	-0.0001	-0.1901***	0.0348***
	(0.969)	(0.002)	(0.000)
HHIADJ	0.0001	0.0045***	0.0005***
	(0.112)	(0.000)	(0.000)
LNASSETS	0.0020***	-0.0047***	-0.0024***
	(0.000)	(0.000)	(0.000)
LOANAST	0.0016***	0.0983***	-0.0089***
	(0.000)	(0.000)	(0.000)
MBB	-0.0063***	0.0328***	-0.0081***
	(0.000)	(0.001)	(0.000)
NUMBER_BANKS	0.0001***	0.0005	-0.0007***
	(0.002)	(0.214)	(0.000)
LAMDA	-0.0044***	0.0329***	-0.0056***
	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.058	0.451	0.333

Table 4 presents results for three separate, second-stage OLS models with *ROA*, *PROF_EFF*, or *INT_FEE_INC* serving as the independent variable. The sample period is 1996 – 2007. *ROA* is return on assets, calculated as yearly net income from the income statement divided by the firm's assets reported on the fourth quarter balance sheet. *PROF_EFF* is a bank's yearly profit efficiency, calculated relation to the year's best practice bank having a profit efficiency of 1 or 100%. *INT_FEE_INC* is our measure of loan income, calculated as the ratio of the bank's yearly interest and fee income from loans to the bank's total loans from the fourth quarter call report. *BIG* is an indicator variable for the presence of a big bank in the sample bank's one-county market; *LNPOP* is the natural log of market population; *POPGROWTH* is the market's calculated yearly population growth rate; *HHIADJ* is the Herfindahl-Hirschman Index for the market divided by 1000; *LNASSETS* is the natural log of a sample bank's asset value reported on the fourth quarter call report; *LOANAST* is a sample bank's yearly ratio of total loans to assets; *MBB* is an indicator equal to one if there is more than one big bank in the market and zero otherwise; *NUMBER_BANKS* is the number of banks operating in the market; and *LAMDA* is the inverse Mills ratio from the first-stage Probit model. Yearly dummy variables were included to control for yearly fixed effects and are not reported because we restricted the model so that coefficient estimates for these variables must sum to one. The sample tested has a total of 26,299 observations, consisting of 5,039 observations for sample banks in markets with at least one big bank (1,167 have more than one big bank) and 21,260 observations for sample banks in markets without a big bank present. * and *** indicate significance at the 10% and 1% levels, respectively, and p-values are provided in parentheses below corresponding coefficient estimates.

Table 5: Robustness Results for One-big-bank Markets versus Non-big-bank Markets

	Independent Variables		
	ROA	*PROF_EFF*	*INT_FEE_INC*
	Coefficient Estimate		
Dependent Variables	(p-value)		
Intercept	-0.0085***	0.3880***	0.1249***
	(0.000)	(0.000)	(0.000)
BIG	0.0074***	-0.0601***	0.0086***
	(0.000)	(0.000)	(0.000)
LNPOP	-0.0018***	0.0160***	0.0007***
	(0.000)	(0.000)	(0.003)
POPGROWTH	0.0005	-0.1690***	0.0400***
	(0.890)	(0.008)	(0.000)
HHIADJ	0.0001*	0.0046***	0.0005***
	(0.056)	(0.000)	(0.000)
LNASSETS	0.0019***	-0.0051***	-0.0025***
	(0.000)	(0.000)	(0.000)
LOANAST	0.0018***	0.0970***	-0.0085***
	(0.000)	(0.000)	(0.000)
NUMBER_BANKS	0.0001***	0.0008**	-0.0007***
	(0.010)	(0.037)	(0.000)
LAMDA	-0.0042***	0.0327***	-0.0047***
	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.054	0.451	0.326

Table 5 presents results for three separate, second-stage OLS models with *ROA*, *PROF_EFF*, or *INT_FEE_INC* serving as the independent variable. The sample period is 1996 – 2007. *ROA* is return on assets, calculated as yearly net income from the income statement divided by the firm's assets reported on the fourth quarter balance sheet. *PROF_EFF* is a bank's yearly profit efficiency, calculated relation to the year's best practice bank having a profit efficiency of 1 or 100%. *INT_FEE_INC* is our measure of loan income, calculated as the ratio of the bank's yearly interest and fee income from loans to the bank's total loans from the fourth quarter call report. *BIG* is an indicator variable for the presence of a big bank in the sample bank's one-county market; *LNPOP* is the natural log of market population; *POPGROWTH* is the market's calculated yearly population growth rate; *HHIADJ* is the Herfindahl-Hirschman Index for the market divided by 1000; *LNASSETS* is the natural log of a sample bank's asset value reported on the fourth quarter call report; *LOANAST* is a sample bank's yearly ratio of total loans to assets; *NUMBER_BANKS* is the number of banks operating in the market; and *LAMDA* is the inverse Mills ratio from the first-stage Probit model. Yearly dummy variables were included to control for yearly fixed effects and are not reported because we restricted the model so that coefficient estimates for these variables must sum to one. The sample tested has a total of 25,132 observations, consisting of 3,872 observations for sample banks in markets with one big bank 21,260 observations for sample banks in markets without a big bank present. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, and p-values are provided in parentheses below corresponding coefficient estimates.

Table 6: Robustness Results for Multiple-big-bank Markets versus Non-big-bank Markets

	Independent Variables		
	ROA	*PROF_EFF*	*INT_FEE_INC*
	Coefficient Estimate (p-value)		
Dependent Variables			
Intercept	0.0002	0.2902***	0.1409***
	(0.912)	(0.000)	(0.000)
MBB	0.0049***	-0.0546***	0.0065***
	(0.000)	(0.000)	(0.000)
LNPOP	-0.0030***	0.0246***	-0.0008***
	(0.000)	(0.000)	(0.008)
POPGROWTH	-0.0016	-0.1605**	0.0273***
	(0.702)	(0.017)	(0.000)
HHIADJ	0.0001	0.0060***	0.0006***
	(0.103)	(0.000)	(0.000)
LNASSETS	0.0020***	-0.0041***	-0.0026***
	(0.000)	(0.000)	(0.000)
LOANAST	0.0021***	0.0999***	-0.0095***
	(0.000)	(0.000)	(0.000)
NUMBER_BANKS	0.0000	0.0015***	-0.0007***
	(0.191)	(0.000)	(0.000)
LAMDA	-0.0119***	0.0917***	-0.0146***
	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.067	0.452	0.379

Table 6 presents results for three separate, second-stage OLS models with *ROA*, *PROF_EFF*, or *INT_FEE_INC* serving as the independent variable. The sample period is 1996 – 2007. *ROA* is return on assets, calculated as yearly net income from the income statement divided by the firm's assets reported on the fourth quarter balance sheet. *PROF_EFF* is a bank's yearly profit efficiency, calculated relation to the year's best practice bank having a profit efficiency of 1 or 100%. *INT_FEE_INC* is our measure of loan income, calculated as the ratio of the bank's yearly interest and fee income from loans to the bank's total loans from the fourth quarter call report. *MBB* is an indicator equal to one if there is more than one big bank in the sample market and zero otherwise; *LNPOP* is the natural log of market population; *POPGROWTH* is the market's calculated yearly population growth rate; *HHIADJ* is the Herfindahl-Hirschman Index for the market divided by 1000; *LNASSETS* is the natural log of a sample bank's asset value reported on the fourth quarter call report; *LOANAST* is a sample bank's yearly ratio of total loans to assets; *NUMBER_BANKS* is the number of banks operating in the market; and *LAMDA* is the inverse Mills ratio from the first-stage Probit model. Yearly dummy variables were included to control for yearly fixed effects and are not reported because we restricted the model so that coefficient estimates for these variables must sum to one. The sample tested has a total of 22,427 observations, consisting of 1,167 observations for sample banks in markets with multiple big banks and 21,260 observations for sample banks in markets without a big bank present. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, and p-values are provided in parentheses below corresponding coefficient estimates.

Table 7: Robustness Results for One-big-bank Markets versus Multiple-big-bank Markets

	Independent Variables		
	ROA	*PROF_EFF*	*INT_FEE_INC*
	Coefficient Estimate		
Dependent Variables	(p-value)		
Intercept	0.0199***	0.1226*	0.1590***
	(0.000)	(0.070)	(0.000)
ONE_BIG	0.0100***	-0.0511***	0.0139***
	(0.000)	(0.000)	(0.000)
LNPOP	-0.0057***	0.0420***	-0.0047***
	(0.000)	(0.000)	(0.000)
POPGROWTH	-0.0428***	-0.0258	-0.0119
	(0.000)	(0.862)	(0.610)
HHIADJ	0.0002	0.0004	0.0004
	(0.264)	(0.828)	(0.213)
LNASSETS	0.0028***	-0.0053**	-0.0011***
	(0.000)	(0.013)	(0.001)
LOANAST	-0.0016**	0.1019***	-0.0083***
	(0.039)	(0.000)	(0.000)
NUMBER_BANKS	0.0003***	-0.0037***	-0.0003***
	(0.000)	(0.000)	(0.003)
LAMDA	-0.0086***	0.0546***	-0.0116***
	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.087	0.458	0.231

Table 7 presents results for three separate, second-stage OLS models with *ROA*, *PROF_EFF*, or *INT_FEE_INC* serving as the independent variable. The sample period is 1996 – 2007. *ROA* is return on assets, calculated as yearly net income from the income statement divided by the firm's assets reported on the fourth quarter balance sheet. *PROF_EFF* is a bank's yearly profit efficiency, calculated relation to the year's best practice bank having a profit efficiency of 1 or 100%. *INT_FEE_INC* is our measure of loan income, calculated as the ratio of the bank's yearly interest and fee income from loans to the bank's total loans from the fourth quarter call report. *ONE_BIG* is an indicator variable, equaling one when one big bank is present in a sample bank's one-county market and zero otherwise; *LNPOP* is the natural log of market population; *POPGROWTH* is the market's calculated yearly population growth rate; *HHIADJ* is the Herfindahl-Hirschman Index for the market divided by 1000; *LNASSETS* is the natural log of a sample bank's asset value reported on the fourth quarter call report; *LOANAST* is a sample bank's yearly ratio of total loans to assets; *NUMBER_BANKS* is the number of banks operating in the market; and *LAMDA* is the inverse Mills ratio from the first-stage Probit model. Yearly dummy variables were included to control for yearly fixed effects and are not reported because we restricted the model so that coefficient estimates for these variables must sum to one. The sample tested has a total of 5,039 observations, consisting of 3,872 observations for sample banks in markets where one big bank is present and 1,167 observations for sample banks in markets with multiple big banks. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, and p-values are provided in parentheses below corresponding coefficient estimates.

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