INSIDER TRADING PATTERNS DURING THE COVID PERIOD

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ABSTRACT

Insider transactions have captured the attention of scholars, regulators, and investors. In this paper, we investigate the patterns of insider trading activities during the pandemic. Our analysis uncovers distinctive trends of insider purchases and sales throughout this specific period. By examining the overall market performance and the surging uncertainty, we discover potential correlations with insider trading behaviors. Empirical evidence from our regressions indicates that insiders acted as contrarian traders during the pandemic. Moreover, we find the pronounced predictive power of insider trading activities in forecasting future firm returns during this period. By carefully excluding routine transactions, our study concludes that opportunistic insider dealings not only maintained their contrarian patterns but also retained their potency in predicting future returns. This underscores the informative value of insider trades, particularly in the face of heightened market unpredictability.

JEL Classifications: G10; G14

Keywords: Insider trading; Pandemic period; Market performance; Market uncertainty; Routine and opportunistic trades.

I. INTRODUCTION

The COVID pandemic, which began in early 2020, expanded to an unparalleled global crisis, profoundly affecting economies, societies, and financial markets worldwide. This unprecedented period witnessed drastic fluctuations in market indices, wide-scale economic contractions, intermittent lockdowns, and profound uncertainties, thereby leading to chaotic reactions in stock markets. Such extreme market conditions offer fertile ground for examining unique financial behaviors. Specifically, insider trading, a phenomenon that traditionally serves as a barometer for a firm's potential future prospects, becomes particularly attractive in this setting. The pandemic-induced market volatility, combined with limited visibility into companies' operations due to widespread disruptions, may have influenced insiders' decisions in novel ways. With significant information asymmetries arising due to the pandemic's unforeseen challenges, insiders might possess distinct insights into their firms' future performance.

In the unique context of the COVID pandemic, understanding insider trading dynamics becomes especially critical due to unprecedented market volatility and economic uncertainty. The literature posits that insiders may trade differently during the pandemic period. Anginer et al. (2020) find that in the early months of the Covid period, insiders notably bought shares following the stock market decline. Sanz (2021) finds that insiders with business ties to China sold their company shares earlier and more frequently, during the early COVID months. Henry et al. (2022) claim that insiders at firms connected to China made more profitable sales than those without such connections, especially with non-preplanned trades, suggesting they had a public information advantage due to their geographic ties, which also predicted market returns during this period. Mason and Elkassabgi (2022) observe that, before public announcements of COVID vaccine developments for Pfizer and Moderna, there were notable increases in trade volatilities and higher stock returns, suggesting potential information leaks and possible insider trading among investors. Hoang et al. (2023) document that after the initial COVID outbreak, corporate insiders in 25 countries consistently sold shares, with less selling in countries with stronger disclosure, enforcement, judiciary, and investor protection. In this study, we concentrate on the U.S. market to examine insider trading activities during the pandemic period, assessing potential correlations between market performance, market uncertainty, and insider trading behaviors. Such a focus not only offers insights into the dynamics of insider decision-making under extreme conditions but also provides a lens to understand the broader financial market reactions during global crises.

Insiders have informational and timing advantages as they are informed more about the company's fundamentals. Kyle (1985) provides evidence that insider profits increase with their information advantage. Gespa (2008) mentions that insiders as the end-user of the information, they can determine the rate at which the market learns this information. Because of this advantage, insider may buy or sell securities before a significant announcement that is expected to impact the stock price. Cziraki et al. (2021) find that net insider purchase increases prior to open market share repurchase announcements.

Literature has investigated the determinants driving insider transactions and the informational value inherent in insider trades. Rozeff and Zaman (1998), Lakonishok and Lee (2001), and Cziraki et al. (2021) suggest that insiders' transactions stem from their perception of stock mis-valuation, often acting contrarian by buying undervalued stocks and selling overvalued ones, with various studies highlighting differences such as the influence of firm size on this behavior and insiders trading based on beliefs about firm fundamentals and the duration of mispricing. Givoly and Palmon (1985), Seyhun (1988), Lakonishok and Lee (2001), Kahle (2000), Piotroski and Roulstone (2005), and Jiang and Zaman (2010) examine insider trading activities and find that insider transactions can predict future stock returns, with various studies confirming that insiders' trades are informed by superior knowledge about a firm's fundamentals and are closely correlated with future firm-specific financial outcomes, including earnings performance and cash-flow news. Moreover, research by Kahle (2000), Ali et al. (2011), and Chen et al. (2014) suggest that insiders adjust their trading behavior in response to pivotal events that might influence a company's valuation, including instances like convertible debt offerings, stock fire sales, and share repurchase declarations.

In this study, we answer the questions of whether insiders got more involved during the pandemic, what the determinants of these insider transactions are during the pandemic, and whether these insider transactions are implicitly informative and have predictive power. Firstly, we commence our analysis by analyzing the overarching trend of insider transactions in 2020, juxtaposed with market performance and uncertainty. Secondly, we assess the underlying determinants of insider transactions during the COVID period, utilizing regressions of insider trading activities on past returns. Thirdly, we explore the informational value inherent in insider trading during this period and evaluate its predictive capability regarding future stock returns.

Our analysis begins by examining the insider trading activities throughout 2020. We employ three specific metrics to dissect these activities: the dollar volume of insider transactions, the number of insider transactions, and the number of insiders engaged in transactions. We find a notable surge in insider purchase transactions from the end of February to the start of April. Conversely, the patterns for sell transactions stand out: throughout 2020, we observe a fourfold increase in both the frequency and scale of insider sell transactions. Compared to these three metrics of insider transactions for the past 5 years, 2015-2019, those of 2020 demonstrate different characteristics, which proves that 2020 insider transaction activities are special. Additionally, we employ the S&P 500 as a proxy for market performance and the VIX as an indicator of market uncertainty to investigate the potential correlation between insider transactions and both market performance and uncertainty.

Next, we examine the determinants of insider transactions during the pandemic period by running regressions of insider trading activities on past returns. Following Lakonishok and Lee (2001), we calculate the Net Purchase Ratio (NPR) as our measure for insider trading activities. For a thorough analysis, we incorporate instantaneous returns, past day returns, past week returns, and past month returns into our regression analysis. Across all these time frames, we identify pronounced negative correlations between insider trading activities and firms' past returns. These findings underscore that insiders adopted a clear contrarian trading stance during the pandemic. Specifically, they executed purchase transactions during periods of lower returns and sale transactions when returns were elevated. We posit that a firm's past performance served as the primary determinant for insider transactions throughout the pandemic period.

Additionally, we explore the informational value inherent in insider trading during the COVID period and assess its predictive capability for future firm returns within that timeframe. Utilizing measures such as the next month, next quarter, next 6-month, and next year's returns, our regression analysis examines the relations between the firm's future returns and insider trading activities. Across all considered future return periods, we identify robust positive correlations between insider trading activities and subsequent returns. These findings emphasize that during the COVID period, insider transactions conveyed substantial insights regarding future firm returns, affirming the potent predictive power of such insider activities during this distinctive period.

Furthermore, following Cohen et al. (2012), we analyze the trading behaviors of both routine and opportunistic insider transactions. Analyzing the trading patterns of these insider transaction types, we notice that opportunistic insider transactions mirror the broader trend observed in overall insider transactions, both for purchases and sales. In contrast, routine transactions exhibit more consistent, average patterns throughout 2020. These observations lead us to conclude that the primary drivers of insider trading activities during the COVID period were opportunistic rather than routine transactions. To further validate our initial findings, we revisit our regression analysis, focusing on the relationships between insider trading activities and both past and future firm returns by using opportunistic and routine insider trading samples, respectively. The results remain consistent with our prior sections: insiders clearly acted as contrarian traders during the pandemic, and their opportunistic trades demonstrated a compelling predictive strength for future firm returns within that period.

The rest of the paper is structured as follows. Section II presents data and methodology. Section III discusses the empirical results. Section IV concludes the paper.

II. DATA AND METHODOLOGY

A. Data

Our primary dataset for this analysis is sourced from the Thomson Financial Insider Trading database, which offers comprehensive data on insider transactions, including company name, transaction date, price, type, and insider position codes. Our insider trading sample includes all executive officers' open market transactions from January 2020 to December 2020. We restrict our focus to transactions bearing the codes "P" or "S", where "P" signifies open market purchases and "S" indicates open market sales by corporate executives. Furthermore, we limit our selection to insider transactions that score the highest on the dataset's cleanse indicator. We sourced data on firms' returns and characteristic information from the CRSP stock database.

It's noteworthy that among these insider open market transactions, there are significant sell transactions that could be misconstrued. Upon closer scrutiny, we determine that these were executed by the former CEO of Amazon, Jeff Bezos. The proceeds from these stock sales were channeled into financing ventures like Blue Origin, a rocket company, and the "Bezos Earth Fund", a commitment of over $10 billion aimed at mitigating climate change effects. In November 2020, Blue Origin achieved a significant milestone by successfully launching its space tourism rocket to the edge of Earth's atmosphere. Moreover, Bezos allocated $2 billion to the Day 1 Fund, which backs homeless services and early childhood education. These ventures were predominantly financed through the sale of Amazon stocks. Given that these insider transactions do not provide insights into the future performance of firms or market uncertainty, we have decided to exclude them from our sample. The raw insider transaction data figures are presented in the Appendix Section. Our final sample of insider trades consists of 48,348 insider sell transactions and 6,813 insider purchase transactions.

B. Methodology

a) Methodology of Variables Constructions

Our primary variables to examine insider trading activities include the dollar volume of insider transactions, the number of insider transactions, and the number of insiders engaged in trading.

Specifically, we calculate the dollar volume of insider transactions by using the number of shares traded times the price of shares traded. After that, we aggregate the dollar volume of insider transactions for each trading day. For every day within our sample timeframe, we compute these metrics individually for both purchase and sell transactions.

To explore the connection between insider trading activities and prospective returns, we introduced the variable 'Net Purchase Ratio' (NPR), inspired by the methodology of Lakonishok and Lee (2015). This metric is derived from the Thomson Financial Insider Trading database and is designed to measure the balance of insider purchases to sales within our specified sample interval. The process of computing NPR involves two primary steps: firstly, we calculate the net purchase share volume. This is achieved by subtracting the total share volume of insider sales from the cumulative share volume of insider purchases. Secondly, to determine the NPR, the net purchase share volume is divided by the collective share volume of all insider transactions that took place over the period. The inherent utility of the NPR lies in its capacity to offer a ratio reflecting the magnitude of insider purchases in relation to the entirety of insider trading activities. This aids in capturing the prevailing sentiment and tendencies among insiders.

b) Classification of Insider Trades (Routine vs. Opportunistic Trades)

To examine whether insider transactions uniformly followed a similar trend during the pandemic, we divide our sample of insider transactions into two categories: routine and opportunistic trades. Following Cohen, Malloy, and Pomorski (2012), we establish a criterion wherein an executive officer must have recorded at least one transaction yearly over three successive years. The measure we choose permits an insider to be associated with both routine and opportunistic trades. Specifically, if an executive officer conducts trades during the same months across at least three consecutive years, we define the subsequent trades in these particular months—including the transactions during the initial two years—as routine trades. Any transactions executed in alternate months are tagged as opportunistic trades.

C. Summary statistics

Table 1 displays the descriptive statistics of all variables included in our analysis. Specifically, the summary statistics provided by this table consist of three sections: insider trading activities, performance, and control variables. Panel A presents the statistics for insider transactions. Based on the transaction types, we categorize insider transactions into purchase transactions and sell transactions. Based on variables such as dollar volume, share volume, the count of insider transactions, and the number of insiders participating in these trades, we observe that insiders executed a significantly higher number of sell transactions compared to purchase transactions during the pandemic period. It can also reflect that insiders may have obtained the relevant information in advance and conducted sell transactions to preserve their interests. We further categorize insider transactions into routine transactions and opportunistic transactions. We can find that compared to routine transactions, there are more opportunistic insiders engaged in insider transactions and more insider transactions are defined as opportunistic transactions, accompanied by higher dollar volume and shares volume. Panel B presents the mean and median of various performances by daily data. The mean of the daily net purchase ratio (NPR) is -0.684, suggesting that there was a greater volume of insider selling compared to insider purchasing. This observation aligns with the outcomes obtained in panel A of our study. The current day's return, the previous day's return, the previous 7 days' cumulative return, and the previous 30 days' cumulative return are 0.006, 0.004, 0.015, and 0.065, respectively.

Panel C presents the mean and median of various performances by monthly data. The mean of the monthly net purchase ratio (NPR) is -0.626, suggesting that there was a greater volume of insider selling compared to insider purchasing. This observation aligns with the outcomes obtained in panel A and panel B of our study. The current month's return, the previous month's return, the previous 3 months' cumulative return, the previous 6 months' cumulative return, the next month's return, the next 3 months' return, the next 6 months' return, and the next 12 months' return are 0.032, 0.049, 0.107, 0.187, 0.033, 0.158, 0.310, and 0.555 respectively. Panel D and Panel E show the mean values and median values of control variables. Size is defined as the firm's market capitalization at the end of each year. The book-to-market ratio is defined as the log of firm's book value divided by its market cap at the end of each year. Illiquidity is defined as the daily ratio of absolute stock return to dollar volume. Idiosyncratic volatility is calculated by estimating the common volatility component using the Fama and French (1993) three-factor model, and then subtracting it from the total volatility of individual assets. Using daily data, on average, our sample firms have a size of 19,160,676.75, the log of book-to-market ratio of -1.304, an illiquidity measure of 0.218, and an idiosyncratic volatility measure of 0.030. Using monthly data, on average, our sample firms have a size of 17,890,942.82, the log of a book-to-market ratio of -1.207, an illiquidity measure of 0.173, and an idiosyncratic volatility measure of 0.029.

Table 1: Summary statistics

Panel A presents insider transaction characteristics in our sample. Based on the transaction types, we categorize insider transactions into purchase transactions and sell transactions. Using trade-level classification, we separate the insider transactions into routine transactions and opportunistic transactions. Panel B presents the characteristics of performance by daily data. Panel C presents the characteristics of performance by monthly data. NPR can be calculated by dividing the net share volume of insider transactions by the total aggregate share volume of insider transactions. Panel D and Panel E present the characteristics of the control variables for daily data and monthly data separately. The sample period is from January 1, 2020 to December 31, 2020.

Panel A: Insider Transactions		
	Mean	
	Purchase Transactions	Sell transactions
Dollar Volume	10,148,276.64	201,734,211.00
#of Shares	1,284,243.61	3,091,610.64
#of Insider Transactions	61.86	264.98
#of Insiders traded	45.35	130.43
Dollar Volume for Routine	195,605.97	29,600,917.77
Dollar Volume for Opportunistic	1,761,569.10	53,630,938.28
#of Shares for Routine	45,781.13	277,649.26
#of Shares for Opportunistic	230,376.14	697,074.87
#of Routine Insider Transactions	3.43	37.35
#of Opportunistic Insider Transactions	8.60	62.86
#of Insiders Traded, Routine	2.38	15.23
#of Insiders Traded, Opportunistic	5.84	32.60
Panel B: Performance (daily data), in percentage		
	Mean	Median
Net purchase ratio	-0.684	-1.000
RET_d	0.006	0.005
RET_{d-1}	0.004	0.004
$RET_{d-7,d}$	0.015	0.014

	Mean	Median
$RET_{d-30,d}$	0.065	0.055
Panel C: Performance (monthly data), in percentage		
	Mean	Median
Net purchase ratio	-0.626	-1.000
RET_{m}	0.032	0.024
RET_{m-1}	0.049	0.026
$RET_{m-3,m}$	0.107	0.054
$RET_{m-6,m}$	0.187	0.069
RET_{m+1}	0.033	0.017
$RET_{m,m+3}$	0.158	0.103
$RET_{m,m+6}$	0.310	0.209
$RET_{m,m+12}$	0.555	0.368
Panel D: Control Variables (daily data)		
	Mean	Median
Size	19,160,676.75	3,190,191.40
Log Book to Market	-1.304	-1.233
Illiquidity	0.218	0.001
Idiosyncratic Volatility	0.030	0.023
Panel E: Control Variables (monthly data)		
	Mean	Median
Size	17,890,942.820	2,802,225.060
Log Book to Market	-1.207	-1.131
Illiquidity	0.173	0.001
Idiosyncratic Volatility	0.029	0.022

III. EMPIRICAL ANALYSIS

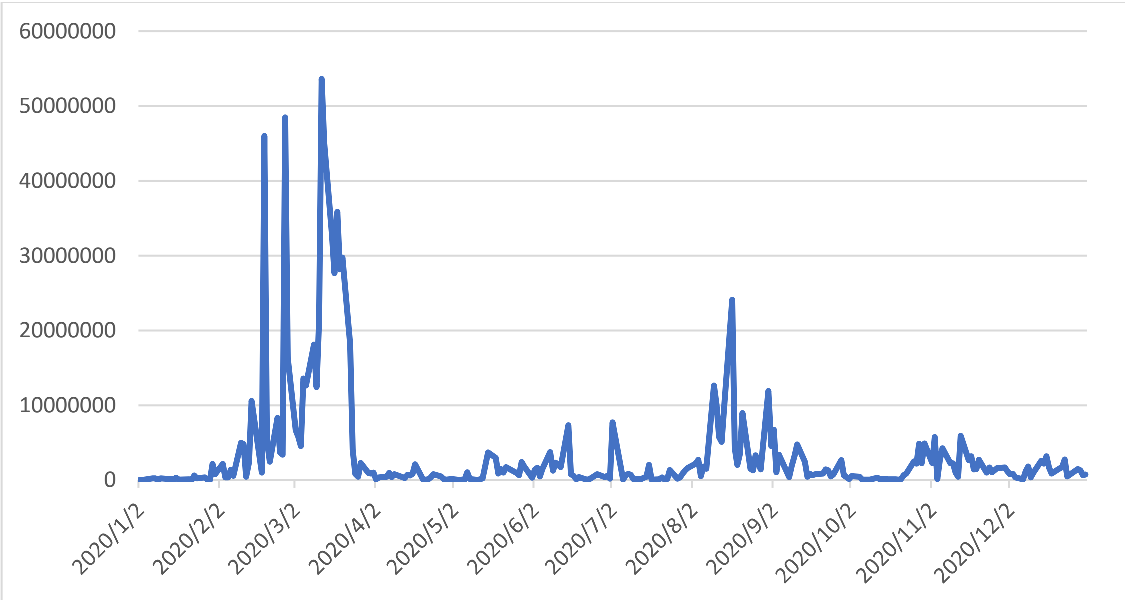
A. Insider Transactions and Market Performance

In this section, we examine the aggregate volume of insider trading during the COVID period. We also analyze the market performance and uncertainty to examine their potential correlations with insider trading activities, distinguishing between purchase and sell volumes. This analysis seeks to address our primary research question concerning the patterns and motivations of insider trading amidst the COVID crisis. We assess insider trading activities during the pandemic by evaluating three key variables: the dollar volume of insider transactions, the number of insider transactions, and the number of insiders involved in these transactions.

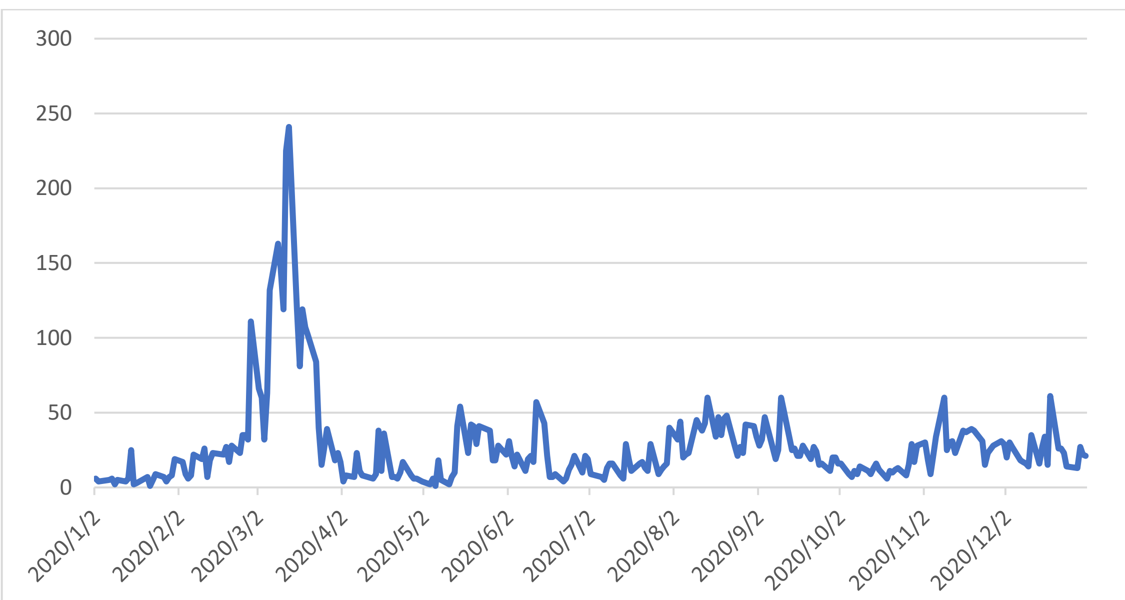
Figure 1: Insider Purchase Activities during Pandemic

We calculate the dollar volume of insider transactions by using the number of shares traded times the price of shares traded. After that, we aggregate the dollar volume of insider transactions for each trading day. Our primary variables also include the number of insider transactions and the number of insiders engaged in trading. The figure plots the variation of these variables on insider purchase activity throughout 2020. Panel A illustrates the results based on the dollar volume of insider purchase transactions. Panel B presents the outcomes related to the number of insider purchase transactions. Meanwhile, Panel C presents the data concerning the number of insiders involved in purchase transactions.

Panel A: Dollar Volume of Insider Purchase Transaction



Panel B: Number of Insider Purchase Transactions



Panel C: Number of Insiders Engaged in Purchase Transactions

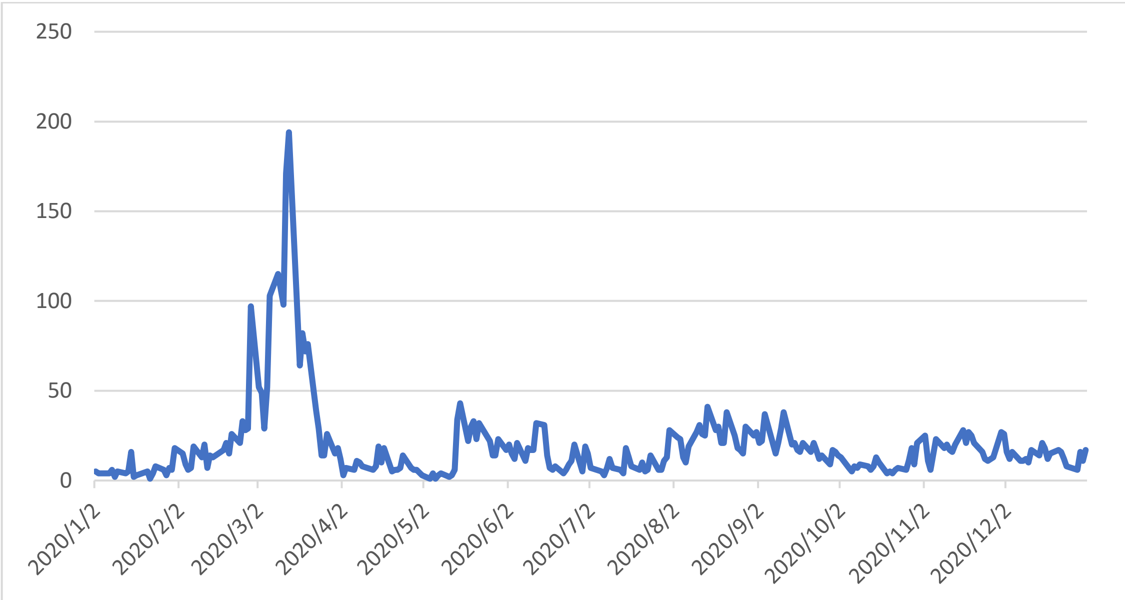
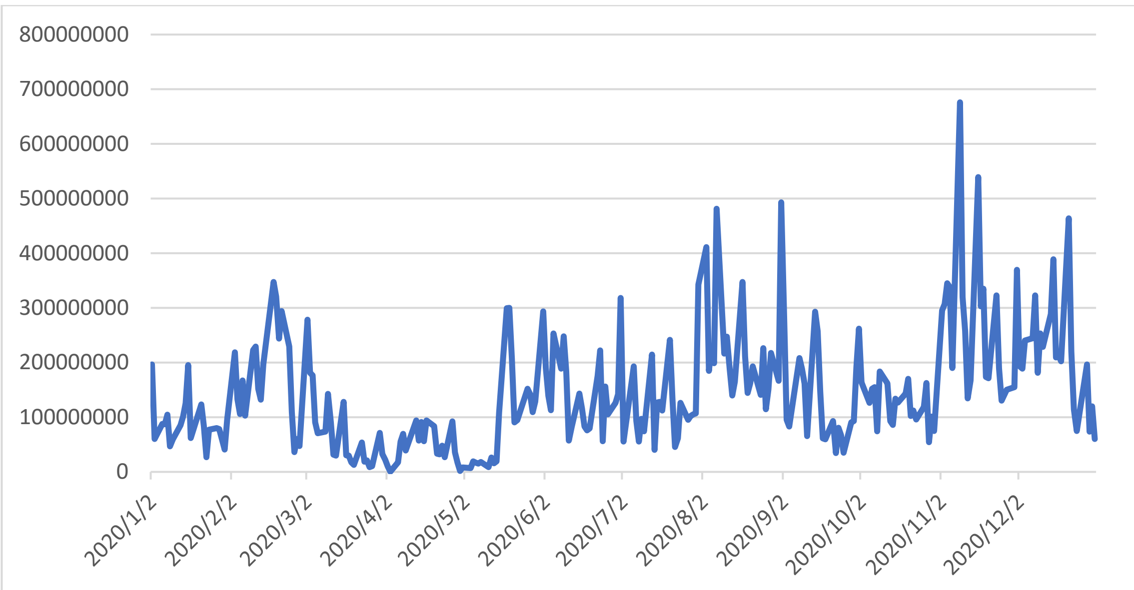


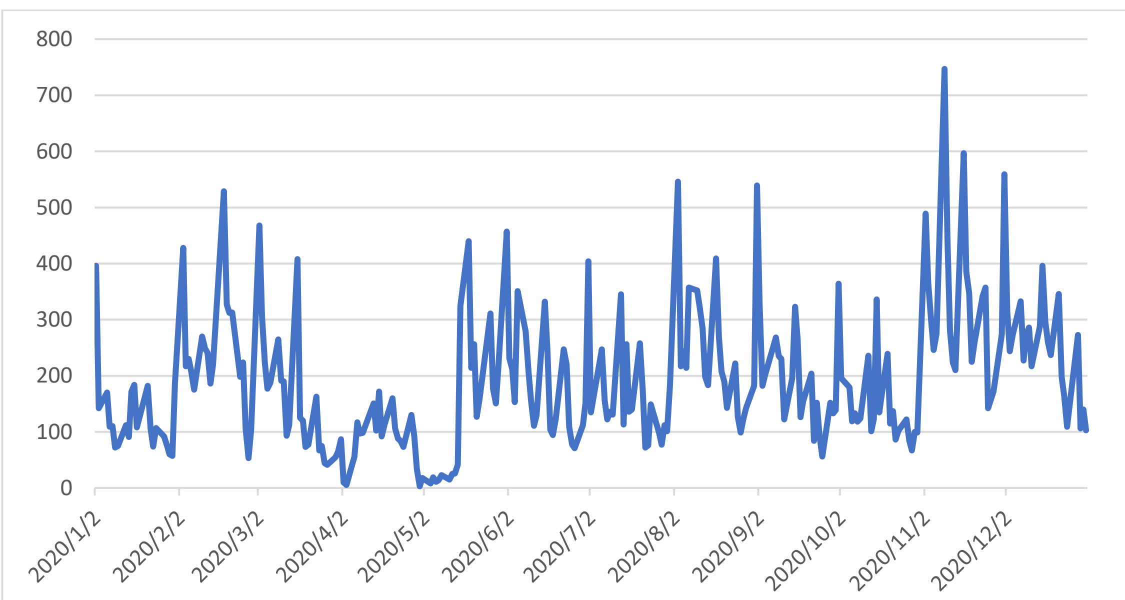
Figure 2: Insider Sell Activities during Pandemic

We calculate the dollar volume of insider transactions by using the number of shares traded times the price of shares traded. After that, we aggregate the dollar volume of insider transactions for each trading day. Our primary variables also include the number of insider transactions and the number of insiders engaged in trading. The figure plots the variation of these variables on insider sell activity throughout 2020. Panel A illustrates the results based on the dollar volume of insider sell transactions. Panel B presents the outcomes related to the number of insider sell transactions. Meanwhile, Panel C presents the data concerning the number of insiders involved in sell transactions.

Panel A: Dollar Volume of Insider Sell Transaction



Panel B: Number of Insider Sell Transactions



Panel C: Number of Insiders Engaged in Sell Transactions

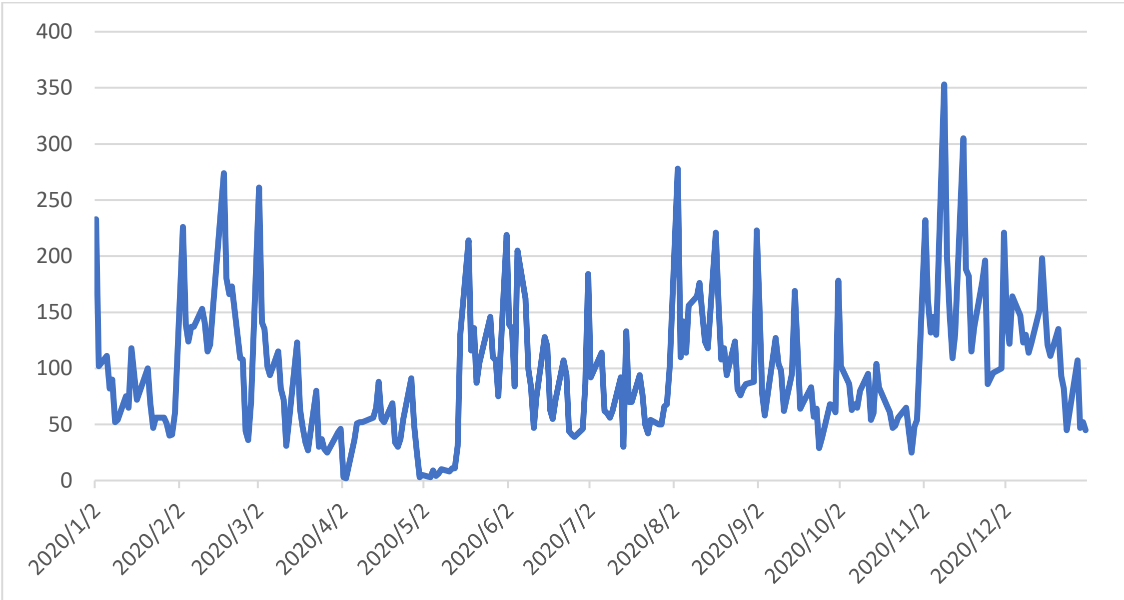


Figure 1 presents the variables associated with insider purchase transactions, while Figure 2 presents the variables related to insider sell transactions. We observe a significant increase in insider purchase transactions from late February to early April 2020. Insider purchase transactions peaked around March 13th, 2020. This trend is consistent across three distinct measures.

Conversely, our analysis reveals distinct patterns in sell transactions. Notably, there was a fourfold increase in both the frequency and magnitude of insider sell transactions throughout 2020. A closer examination of the data indicates heightened activity during specific intervals: from late January to mid-March, from mid-May to mid-June, from late July to mid-September, and from late October through the end of 2020. This trend remains consistent when evaluated using three distinct measures. Specifically, insider sell transactions hit their lowest point around April 2nd and peaked on November 19th, 2020.

Additionally, we divide a month into the beginning of the month, the middle of the month and the end of the month. Then, we find the average dollar volume of insider transactions, the average number of insider transactions and the average number of insiders engaged in transactions, over the past 5 years, January 1, 2015-December 31, 2019. We still categorize transactions into insider purchase transactions and insider sell transactions. Those plots exhibit a different pattern from 2020, which means that such activities were specific to 2020. Specifically, insider purchase transactions patterns in 2020 are significantly different from previous years. For sell transactions, although the patterns are relatively similar, the number of insiders and transactions involved in 2020 is much higher than the average of the previous five years. The past 5-year insider transaction data figures are presented in the Appendix Section.

To investigate the potential relationship between market performance and uncertainty, we sourced relevant data from Yahoo Finance. Specifically, to gauge market performance, we utilized the S&P 500 as our benchmark index. Meanwhile, to assess market uncertainty, we employed the Chicago Board Options Exchange's CBOE Volatility Index (VIX) as our metric.

Figure 3

This chart illustrates the performance of the S&P 500 index from January 2020 to December 2020. The S&P 500 serves as a prominent benchmark for gauging the U.S. stock market's health and, by extension, the broader economy's vitality.

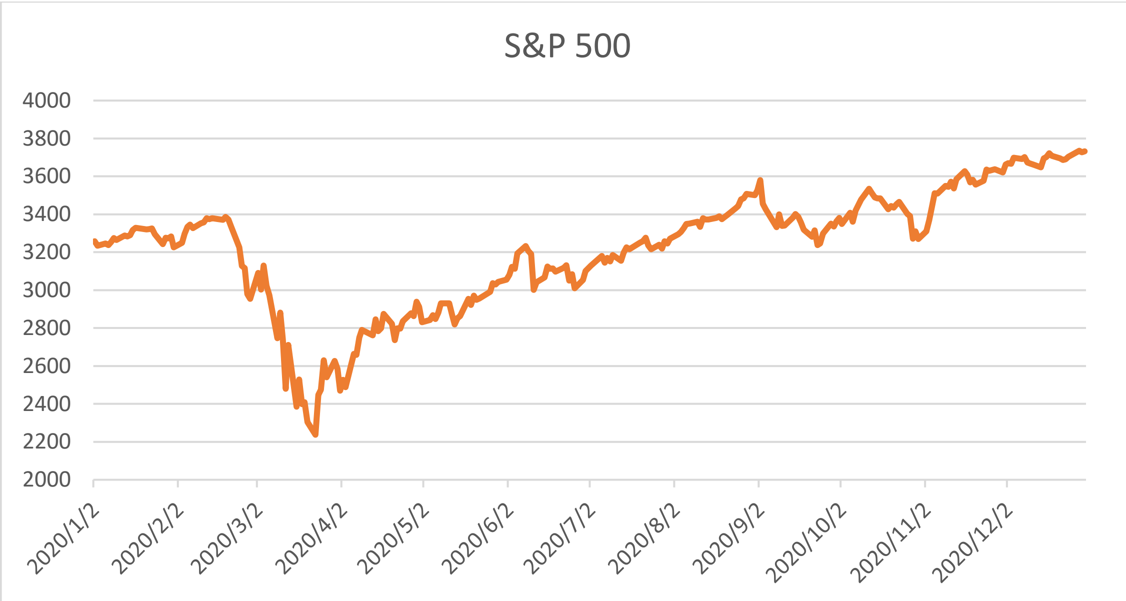


Figure 4

This chart depicts the VIX, also known as the CBOE Volatility Index, from January 2020 to December 2020. Often termed the "market fear" index, the VIX gauges the market's anticipated future volatility. Typically, a higher VIX indicates heightened economic volatility and increased investor anxiety.

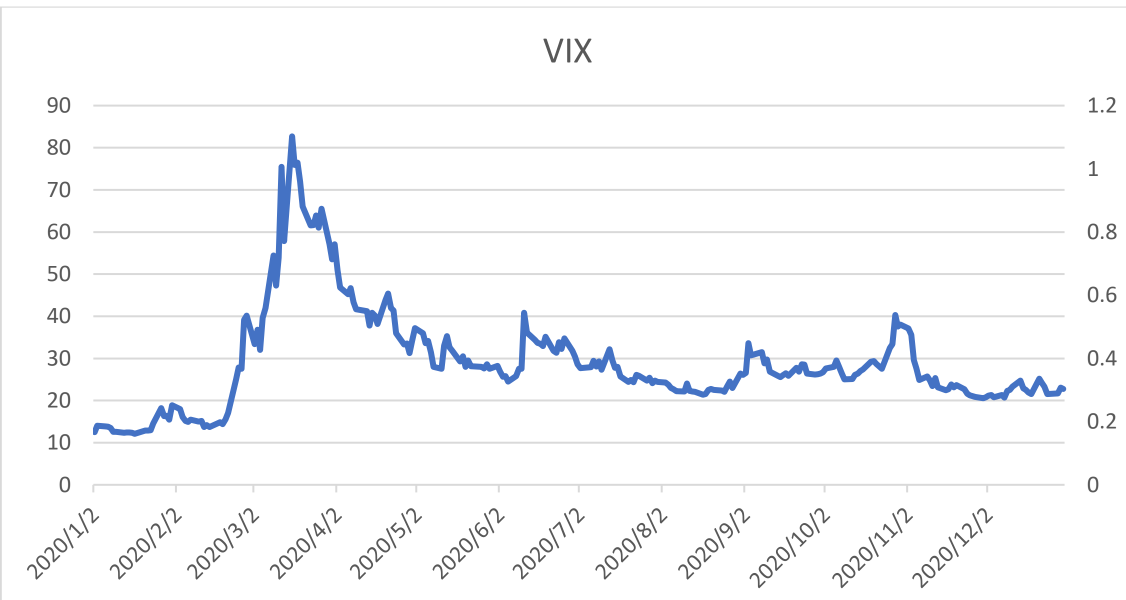


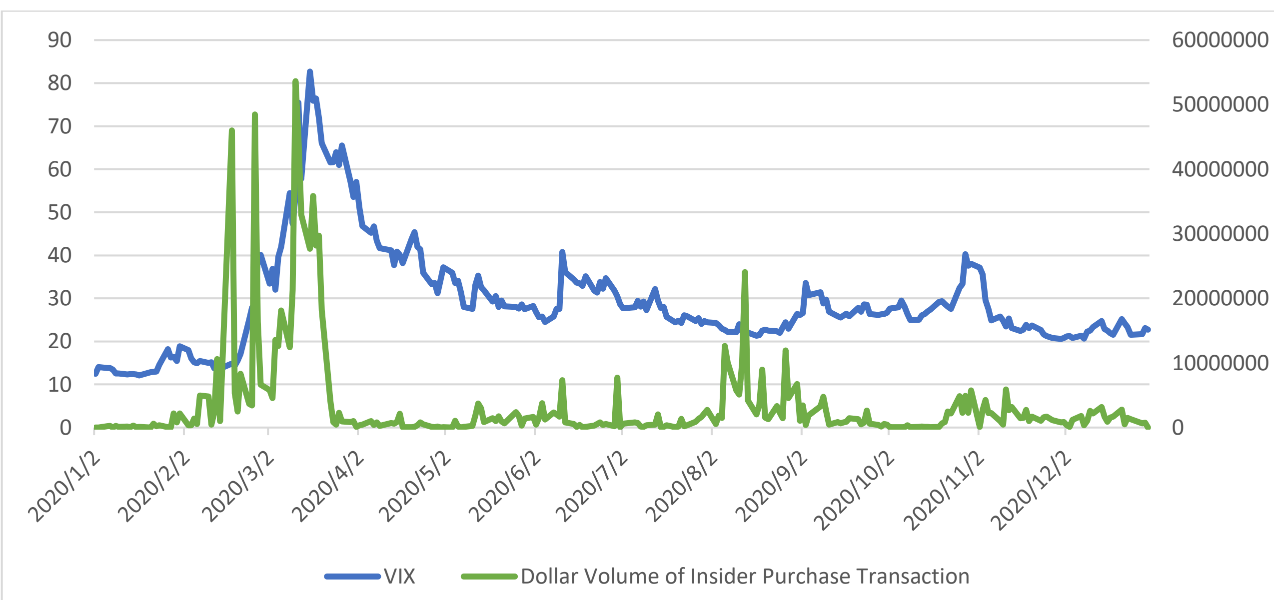
Figure 3 presents the market performance, and Figure 4 presents the market uncertainty. We note that the VIX experienced a substantial surge beginning in late February 2020, attributed to the widespread panic induced by COVID. Concurrently, the S&P 500 declined by more than 35% during this timeframe. The market began its recovery in early April; however, while the VIX decreased, it remained elevated compared to levels observed before March. The inverse trends of the VIX and the S&P 500 are evident: as market performance declines, the corresponding market uncertainty and volatility rise. The VIX attained its peak on March 16th, while the bottom for the S&P 500 occurred slightly later, on March 23rd.

To observe the relations between insider transactions and market performance and uncertainty, we combine the insider transactions and market measures in the same figures. In Figure 5, combined with the VIX, we find that insiders make insider purchase transactions before the VIX rises. The pattern is most pronounced between late February and late March 2020. During this period, the insider purchase transaction reached its highest value of dollar volume on March 11th, while the VIX reached its highest value on March 16th. This relationship also holds for the number of insider purchase transactions, and the number of insiders engaged in purchase transactions.

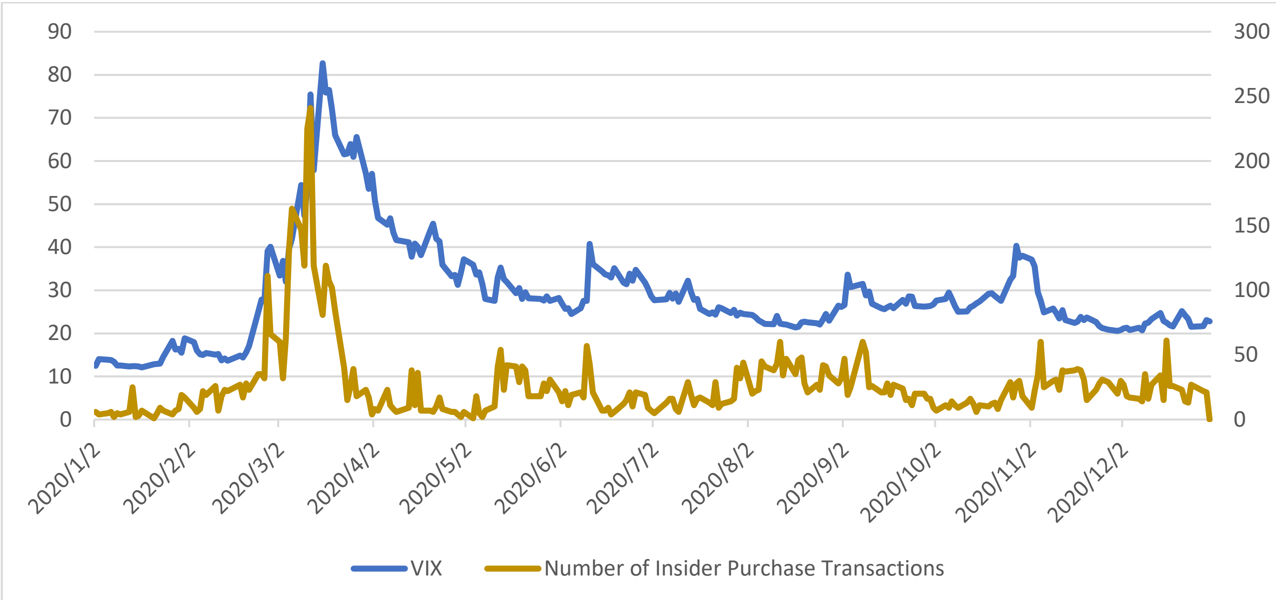
Figure 5: Market Performance and Insider Purchase Activity during Pandemic

We combine the VIX with the dollar volume of insider purchase transactions, number of insider purchase transactions, and number of insiders engaged in purchase transactions, shown in Panel A, Panel B, and Panel C. We combine the S&P 500with the dollar volume of insider purchase transactions, number of insider purchase transactions, and number of insiders engaged in purchase transactions, shown in Panel D, Panel E, and Panel F. By combining market performance and insider trading activities, we can visualize the connection between the two to explore the determinants behind insider trading. The time period is from January 2020 to December 2020.

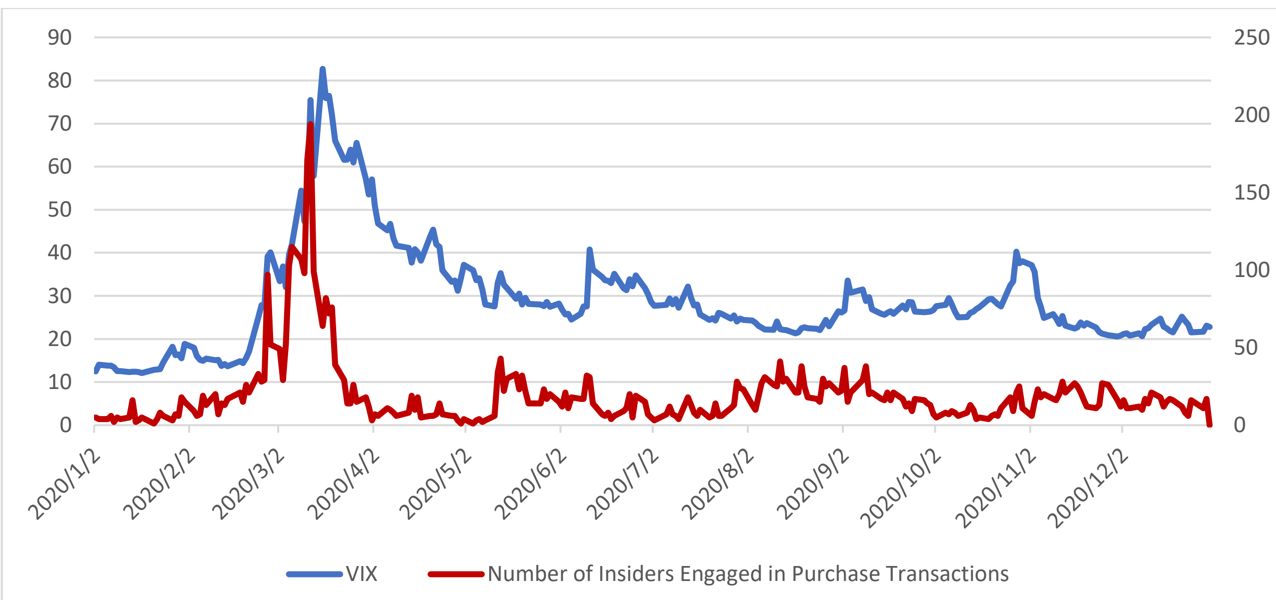
Panel A: VIX and Dollar Volume of Insider Purchase Transaction



Panel B: VIX and Number of Insider Purchase Transactions



Panel C: VIX and Number of Insiders Engaged in Purchase Transactions



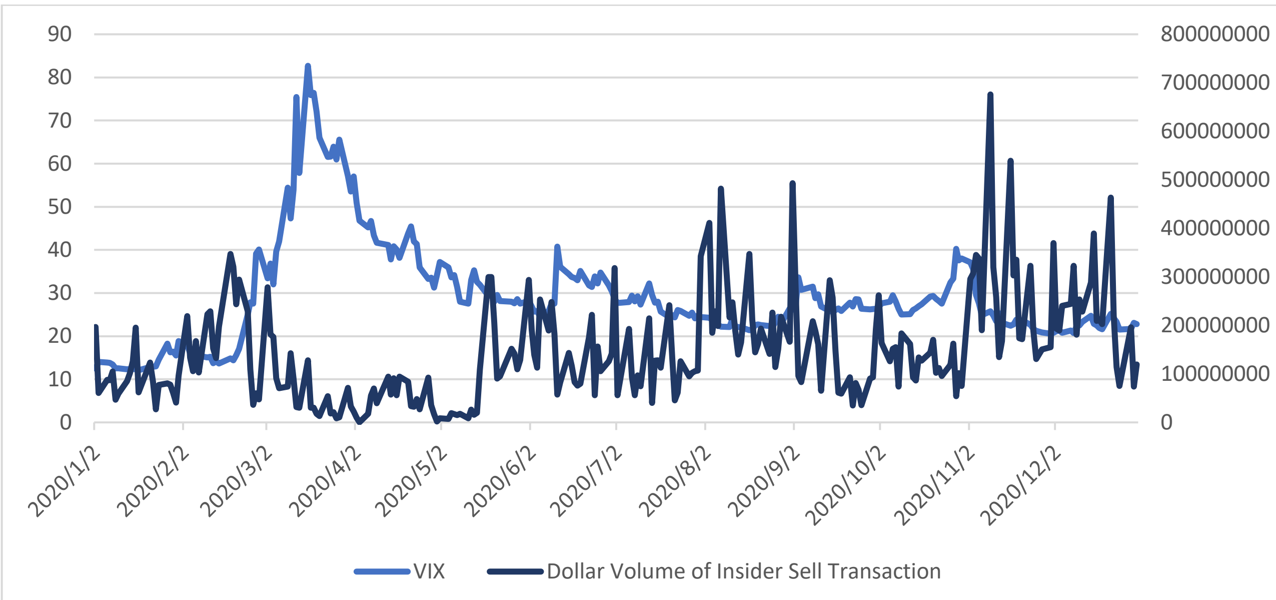
In Figure 6, combined with the VIX, we find that insiders make a large number of sell transactions before the VIX rises. Insider sell transactions decrease as the VIX rises and continue to decrease after the VIX begins to fall. After the VIX returns to its average level, sell transaction volume increases. This pattern is most significant between early February and mid-May 2020. During this period, Insider Sell Transaction reached its highest value of dollar volume on February 18th, its lowest value of dollar volume on April 3rd, and its second highest value of dollar volume on May 18th. VIX reached its highest value on March

16th. This relationship also holds for the number of insider sell transactions, and the number of insiders engaged in sell transactions.

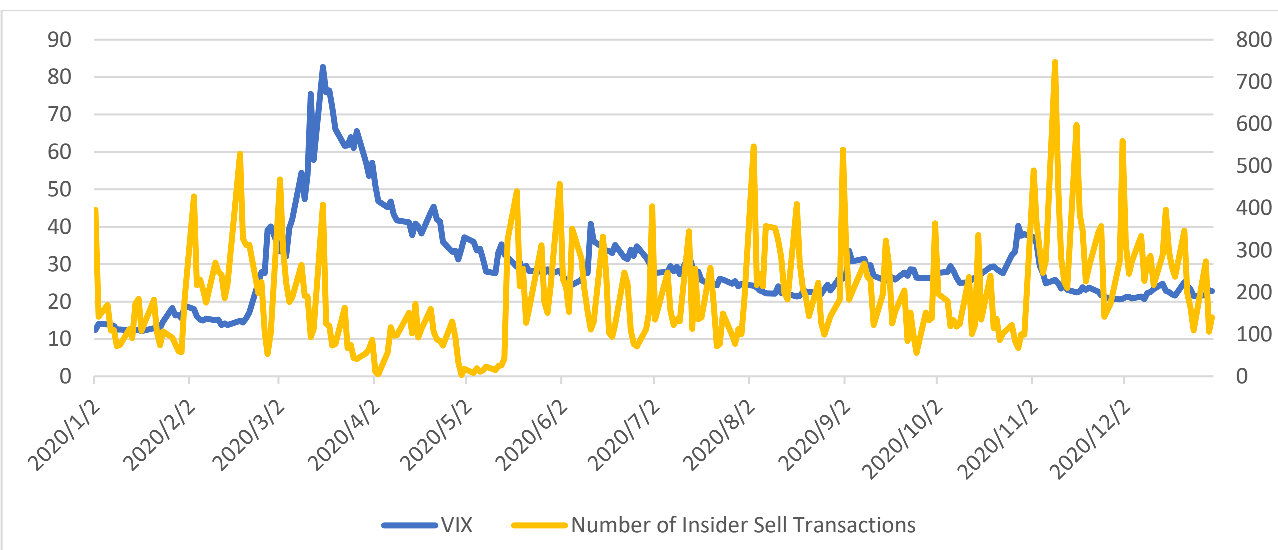
Figure 6: Market Performance and Insider Sell Activity during Pandemic

We combine the VIX with the dollar volume of insider sell transactions, number of insider sell transactions, and number of insiders engaged in sell transactions, shown in Panel A, Panel B, and Panel C. We combine the S&P 500with the dollar volume of insider sell transactions, number of insider sell transactions, and number of insiders engaged in sell transactions, shown in Panel D, Panel E, and Panel F. By combining market performance and insider trading activities, we can visualize the connection between the two to explore the determinants behind insider trading. The time period is from January 2020 to December 2020.

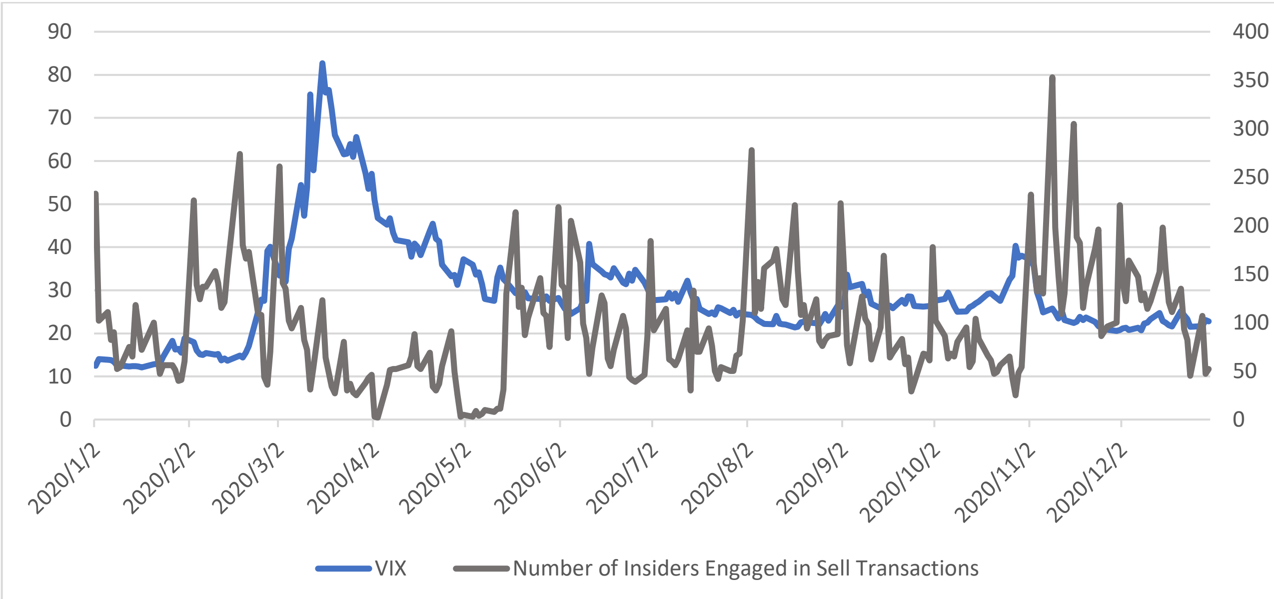
Panel A: VIX and Dollar Volume of Insider Sell Transaction



Panel B: VIX and Number of Insider Sell Transactions



Panel C: VIX and Number of Insiders Engaged in Sell Transactions



By combining market performance and insider trading activities, we can visualize the connection between the variables and find that insiders adopted a clear contrarian trading stance during the pandemic. To further explore the hidden determinants, we further categorize and perform regressions on insider trading activities.

B. Trends of Routine trades and Opportunistic trades

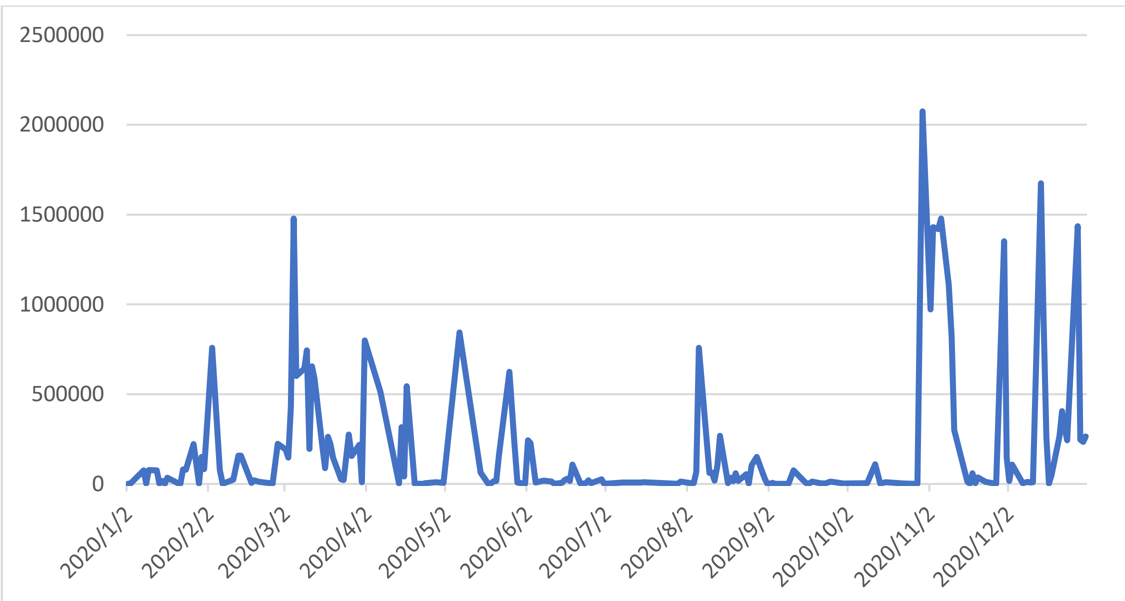
In this section, we aim to ascertain whether all insider transactions in 2020 were influenced by the year's unique circumstances and determine the extent to which transactions were driven by insiders possessing specific, non-public information during the 2020 epidemic. Adopting the trade-level measure from Cohen, Malloy, and Pomorski (2012), we differentiate between routine trades and opportunistic trades. This approach permits an individual trader to partake in both types of activities—routine and opportunistic. This categorization aids us in more effectively pinpointing the speculative behaviors of market insiders.

When an executive officer engages in trading activities during the same months for a minimum of three consecutive years, we categorize the subsequent transactions in these specific months, encompassing those in the first two years, as routine trades. Any transactions conducted in months other than these are classified as opportunistic trades. Based on the definition, we expect that transactions defined as "routine" cannot reflect the specific changes resulting from the COVID pandemic in 2020. Figure 7 plots the results for insider routine purchase transactions, and Figure 8 presents the results for insider routine sell transactions. We note significant discrepancies between the trends of both routine purchase and sell transactions when compared to the overall trend of insider transactions in 2020. Specifically, routine transactions demonstrate relative consistency and manifest a cyclical pattern. Routine insider transactions are primarily done for the liquidity or other ordinary reasons, making them less informative about insider transactions and less relevant to our research questions. Consequently, we posit that insider routine trades in 2020 were not influenced by prevailing market conditions and, as such, cannot be considered predictive of future market movements for that year.

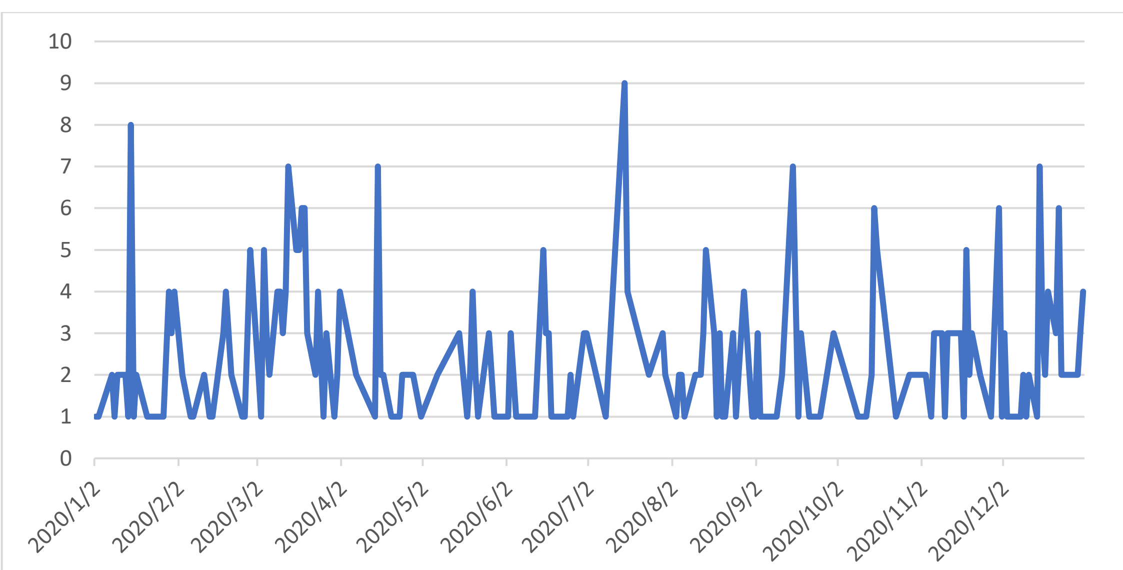
Figure 7

We categorize insider transactions into routine and opportunistic trades. For the routine transactions, this chart displays the dollar volume of insider purchase transactions, the count of insider purchase transactions, and the number of insiders participating in purchase transactions. Panel A illustrates the results based on the dollar volume of insider routine purchase transactions. Panel B presents the outcomes related to the number of insider routine purchase transactions. Meanwhile, Panel C presents the data concerning the number of insiders involved in routine purchase transactions.

Panel A: Dollar Volume of Insider Routine Purchase Transaction



Panel B: Number of Insider Routine Purchase Transactions



Panel C: Number of Insiders Engaged in Routine Purchase Transactions

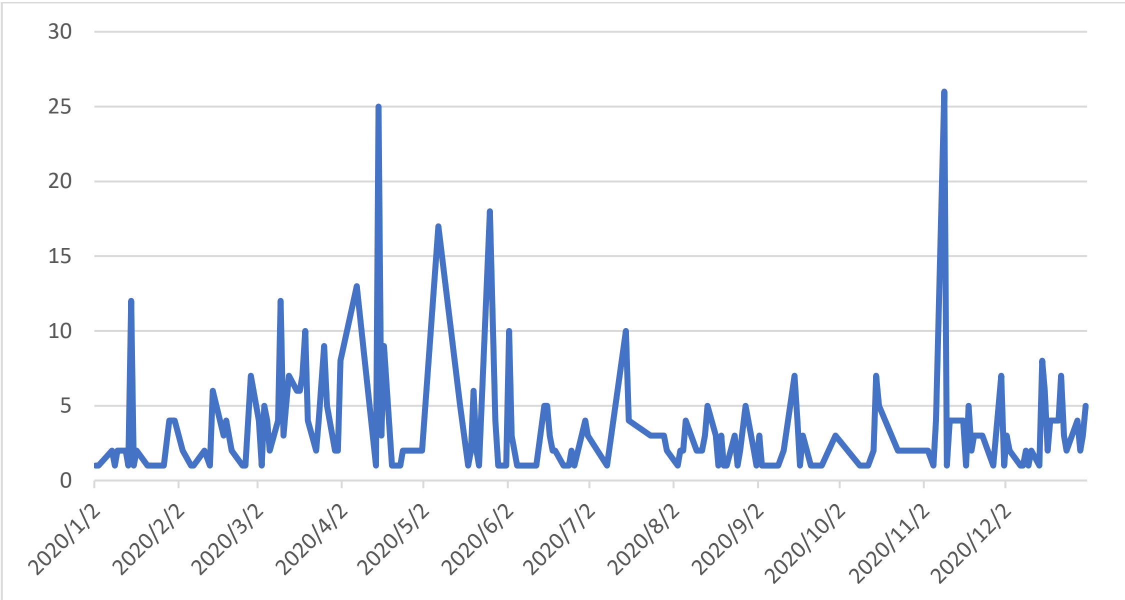
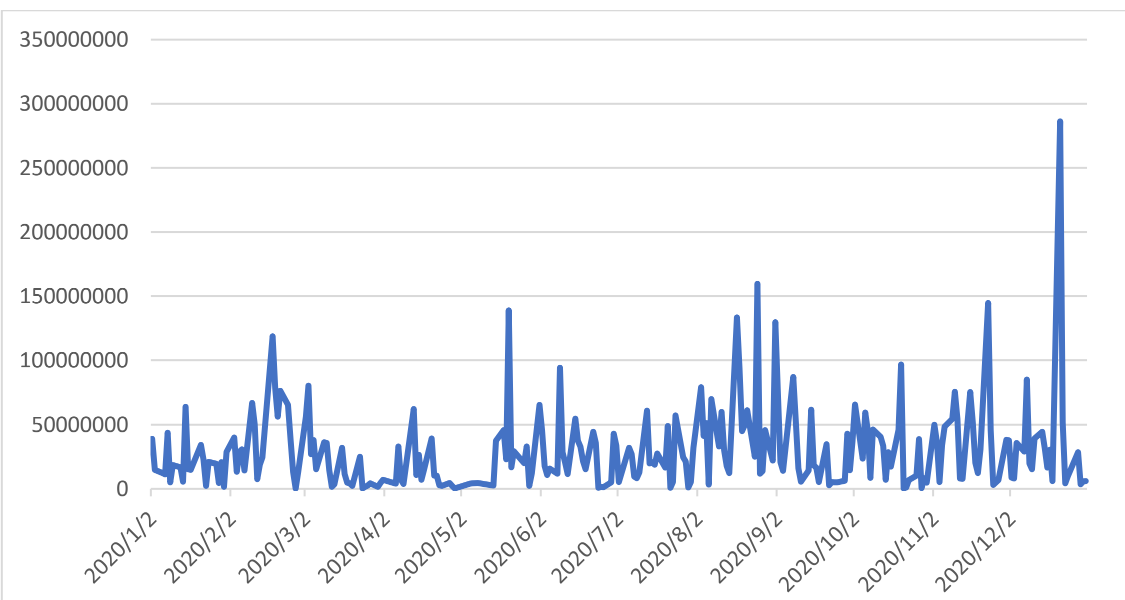


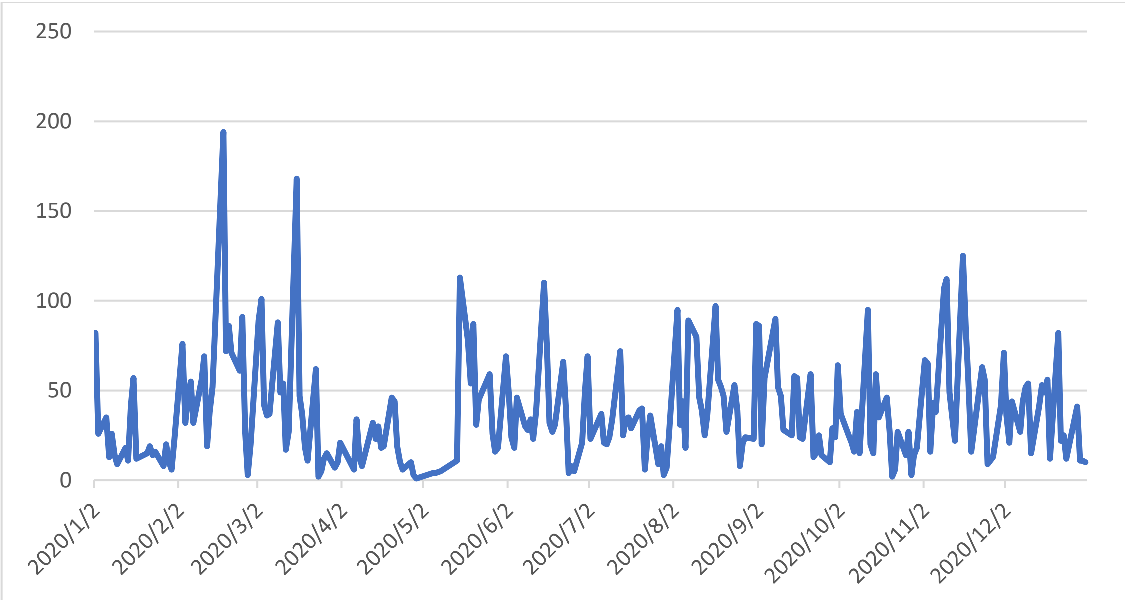
Figure 8

We categorize insider transactions into routine and opportunistic trades. For the routine transactions, this chart displays the dollar volume of insider sell transactions, the count of insider sell transactions, and the number of insiders participating in sell transactions. Panel A illustrates the results based on the dollar volume of insider routine sell transactions. Panel B presents the outcomes related to the number of insider routine sell transactions. Meanwhile, Panel C presents the data concerning the number of insiders involved in routine sell transactions.

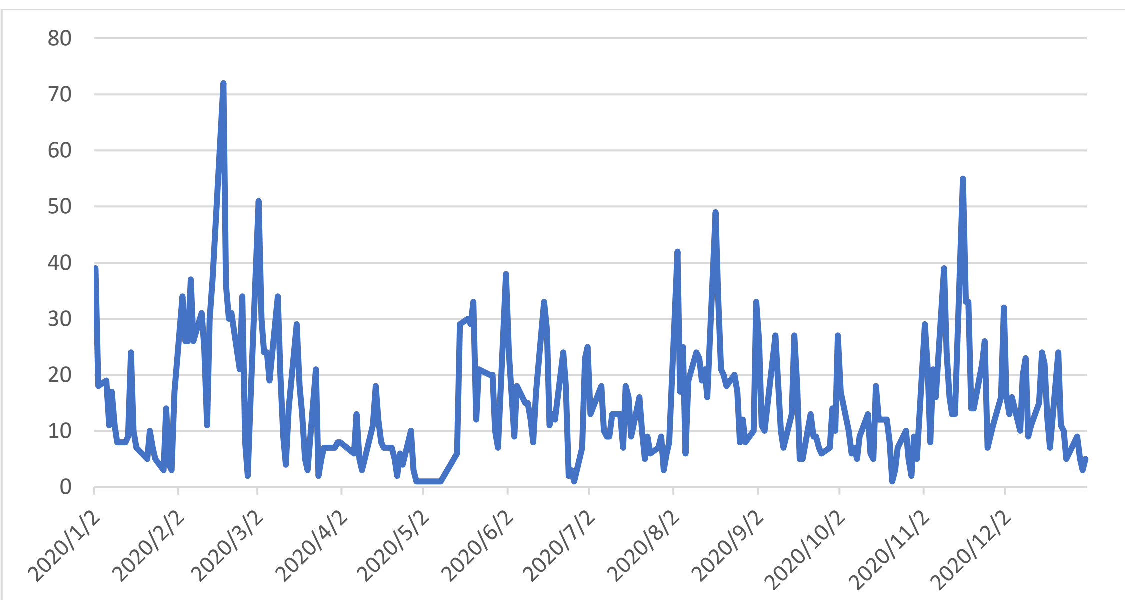
Panel A: Dollar Volume of Insider Routine Sell Transaction



Panel B: Number of Insider Routine Sell Transactions



Panel C: Number of Insiders Engaged in Routine Sell Transactions

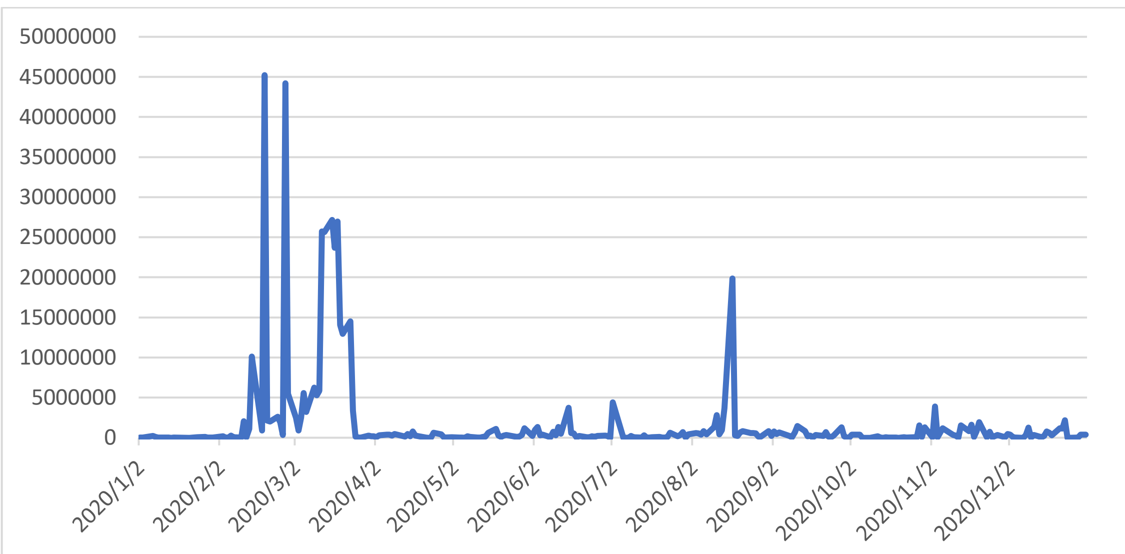


Based on the definition of opportunistic transactions, we anticipate that insiders traded differently during the pandemic compared to other periods. Furthermore, their opportunistic trades are likely to be significantly swayed by the prevailing market conditions and should possess the ability to predict subsequent firm returns. The COVID pandemic introduces a multitude of uncertainties and a substantial information asymmetry. Certain opportunities arise under specific circumstances, such as the implementation of government stay-at-home policies and the successful development of a COVID vaccine. In these instances, individuals with privileged information can take advantage of these insights to engage in preemptive trading before the news becomes public. For example, insiders predicted in advance that the market would be adversely affected by COVID in the future, and then they engaged in selling activities before the market. Alternatively, insiders, upon learning the news, invest in sectors related to healthcare and daily consumer goods.

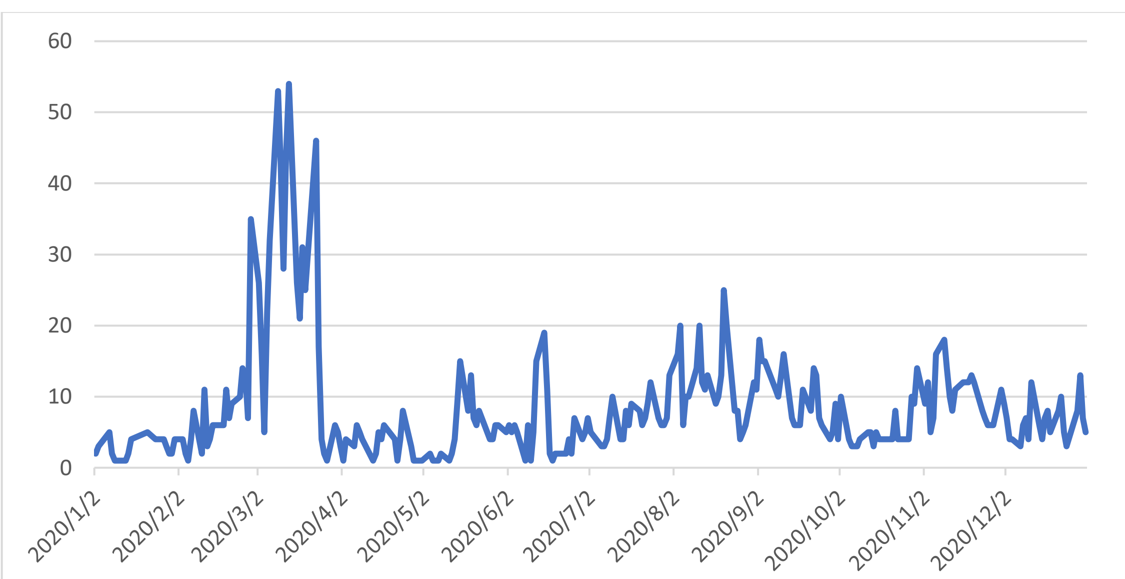
Figure 9

We categorize insider transactions into routine and opportunistic trades. For the opportunistic transactions, this chart displays the dollar volume of insider purchase transactions, the count of insider purchase transactions, and the number of insiders participating in purchase transactions. Panel A illustrates the results based on the dollar volume of insider opportunistic purchase transactions. Panel B presents the outcomes related to the number of insider opportunistic purchase transactions. Meanwhile, Panel C presents the data concerning the number of insiders involved in opportunistic purchase transactions.

Panel A: Dollar Volume of Insider Opportunistic Purchase Transaction



Panel B: Number of Insider Opportunistic Purchase Transactions



Panel C: Number of Insiders Engaged in Opportunistic Purchase Transactions

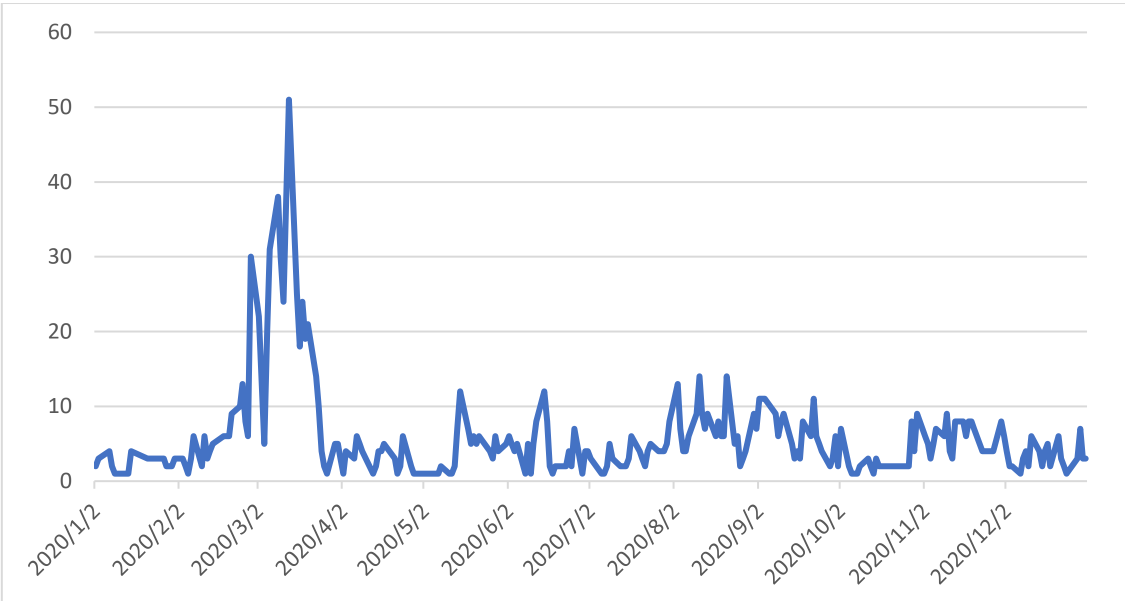
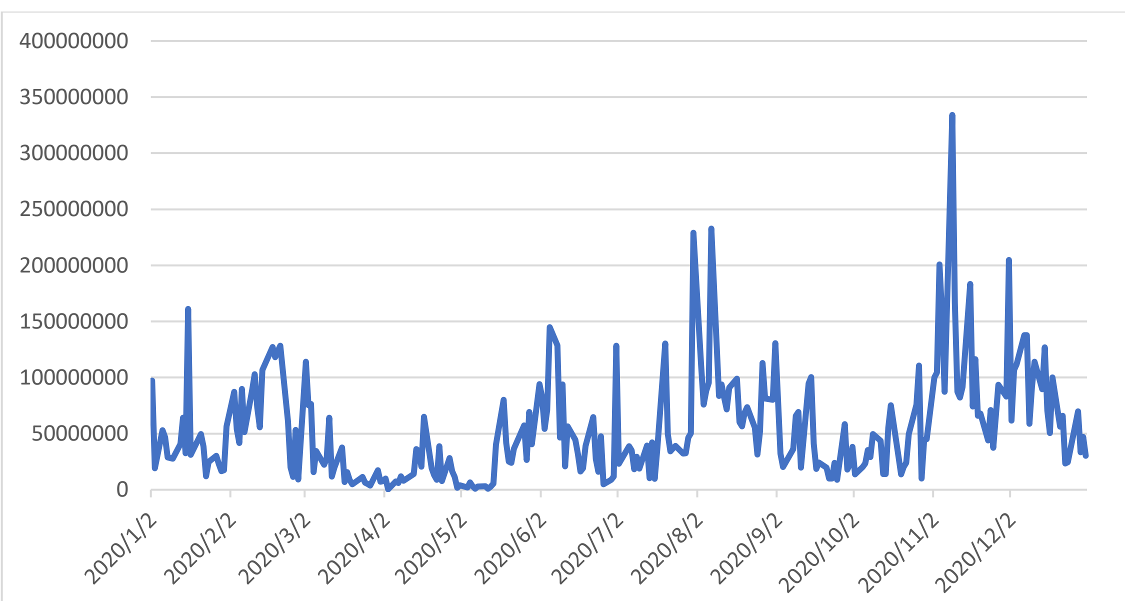


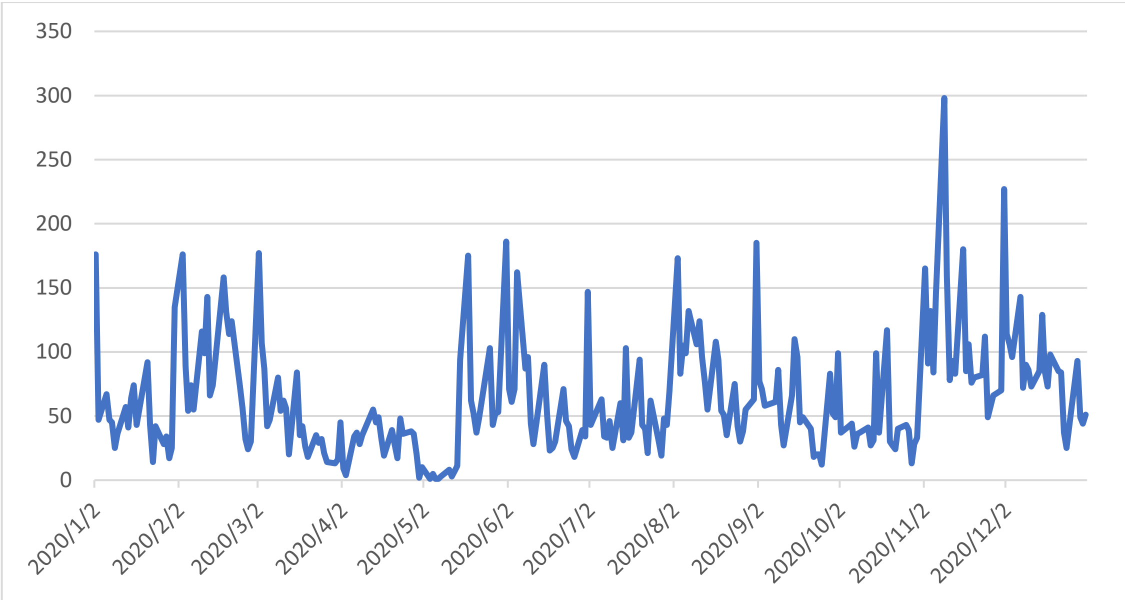
Figure 10

We categorize insider transactions into routine and opportunistic trades. For the opportunistic transactions, this chart displays the dollar volume of insider sell transactions, the count of insider sell transactions, and the number of insiders participating in sell transactions. Panel A illustrates the results based on the dollar volume of insider opportunistic sell transactions. Panel B presents the outcomes related to the number of insider opportunistic sell transactions. Meanwhile, Panel C presents the data concerning the number of insiders involved in opportunistic sell transactions.

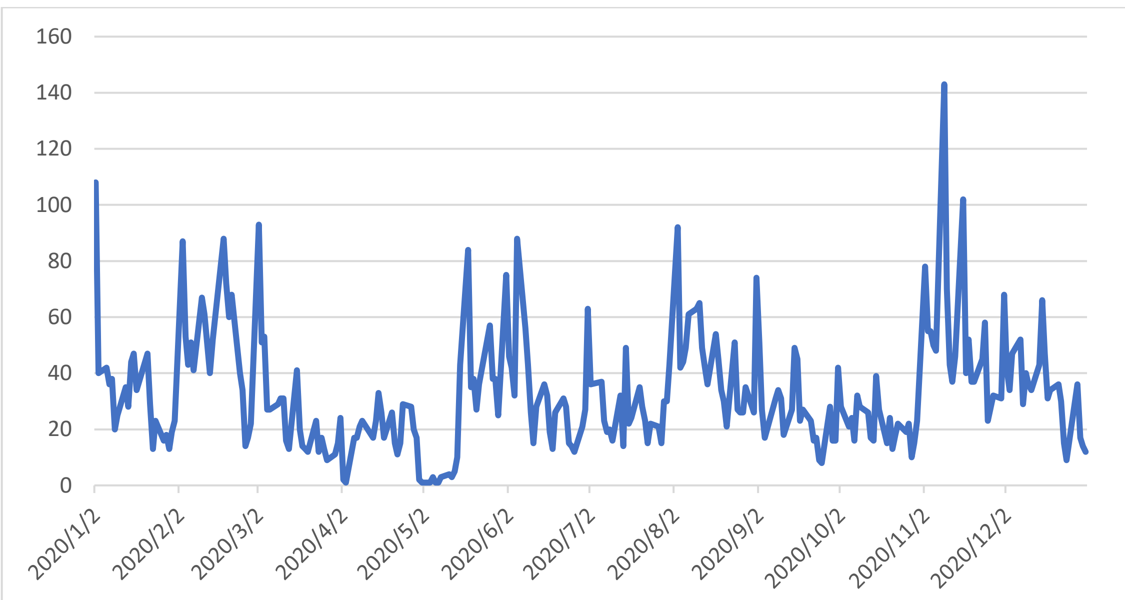
Panel A: Dollar Volume of Insider Opportunistic Sell Transaction



Panel B: Number of Insider Opportunistic Sell Transactions



Panel C: Number of Insiders Engaged in Opportunistic Sell Transactions



This trend is also clearly shown in Figure 9 and Figure 10. Figure 9 presents the variables associated with insider purchase transactions for opportunistic trades, while Figure 10 presents the variables related to insider sell transactions for opportunistic trades. Figure 9 shows that from the end of February to the middle of March, the dollar volume of insider purchase transactions, the number of purchase transactions, and the number of insiders engaged in purchase transactions increased substantially, and then fell back after the middle of March, but remained at a high level until the end of March. Figure 10 shows that from late January to mid-March, mid-May to mid-June, late July to mid-September, and late October to the end of 2020, the sell transaction experienced four times large increases. This trend remains consistent when evaluated using three distinct measures. It is evident that opportunistic trades are instrumental in influencing market fluctuations. The market's movements illustrated in Figure 1 and Figure 2 correspond closely with the patterns observed in opportunistic trades, encompassing both purchase and sell transactions.

C. Insider Transactions and Past Returns

In this section, we want to explore the determinants behind insider trading activities during the pandemic period. Firstly, we collect the daily return and monthly return separately from the CRSP database. After calculation, we obtain the previous day's return, the previous 7 days' cumulative return, the previous 30 days' cumulative return, the monthly return, the previous month's return, the previous three months' cumulative return, and the previous six months' cumulative return. The dependent variable is the net purchase ratio (NPR) calculated by dividing the total net share volume of insider transactions by the total aggregate share volume of insider transactions. Using both univariate and multivariate regressions of insider trading activities on past cumulative returns to test the determinants of insider trading. We used daily and monthly data for our analysis. The regression formulas are shown below:

$$NPR_{i,d} = a + b1RET_{i,d} + b2RET_{i,d-1} + b3RET_{i,[d-7,d]} + b4RET_{i,[d-30,d]} + \varepsilon_{i,d} \tag{1}$$

$$NPR_{i,d} = a + b1RET_{i,d} + b2RET_{i,d-1} + b3RET_{i,[d-7,d]} + b4RET_{i,[d-30,d]} + b5SIZE_{i,t} + b6BM_{i,t} + b7Illiqudity_{i,t} + b8Volatility_{i,t} + \varepsilon_{i,d} \tag{2}$$

$$NPR_{i,t} = a + b1RET_{i,t} + b2RET_{i,t-1} + b3RET_{i,[t-3,t]} + b4RET_{i,[t-6,t]} + \varepsilon_{i,t} \tag{3}$$

$$NPR_{i,t} = a + b1RET_{i,t} + b2RET_{i,t-1} + b3RET_{i,[t-3,t]} + b4RET_{i,[t-6,t]} + b5SIZE_{i,t} + b6BM_{i,t} + b7Illiqudity_{i,t} + b8Volatility_{i,t} + \varepsilon_{i,t} \tag{4}$$

Our primary dependent variable is the Net Purchase Ratio (NPR) – the measure of insider trading activities. $NPR_{i,d}$ denotes the company i's Net Purchase Ratio for day_i. $RET_{i,d-1}$ denotes the previous day's returns for $firm_i$. $RET_{i,[d-7,d]}$ denotes the previous 7 days' cumulative returns for $firm_i$. $RET_{i,[d-30,d]}$ denotes the previous 30 days' cumulative returns for $firm_i$. $NPR_{i,t}$ denotes the company i's Net Purchase Ratio for $month_i$. $RET_{i,t-1}$ denotes the previous month's returns for $firm_i$. $RET_{i,[t-3,t]}$ denotes the previous 3 months' cumulative returns for $firm_i$. $RET_{i,[t-6,t]}$ denotes the previous 6 months' cumulative returns for $firm_i$. In the formula (2) and (4), the control variables are included. The method of calculating the control variable is described in the summary statistic.

The results of the above regression for the daily data are shown in Table 2 and the results for the monthly data are shown in Table 3. There is a statistically significant negative relationship between NPR and firm past return, which holds for both univariate and multivariate regressions. This shows us that insiders adopted a clear contrarian trading strategy during the pandemic. To gain an advantage during this special period, the insider chooses to make purchase transactions when the return is low and sell transactions in large quantities when the return is high. Comparing the daily data results in Table 2 with the monthly data in Table 3, we see that both have significant negative effects. However, using the daily data, past returns have a stronger negative impact on NPR.

Table 2: Regressions of Insider Trading Activities on Returns with Daily Data

This table reports the results of regressing the insider trading activities measured by net purchase ratio (NPR) on the company returns. In this table, we use daily data for the regression. The dependent variable is NPR that calculated by dividing the total net share volume of insider transactions by the total aggregate share volume of insider transactions. We use the current day's return, the previous day's return, the previous 7 days' cumulative return, and the previous 30 days' cumulative return as independent variables. Control variables are included in the second regressions under each dependent variable. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1, 2020 to December 31, 2020.

	NPR	
	(1)	(2)
RET_d	-1.412***	-1.432***
	(-15.82)	(-17.42)
RET_{d-1}	-0.836***	-0.634***
	(-7.57)	(-6.24)
$RET_{d-7,d}$	-0.682***	-0.458***
	(-11.83)	(-8.64)
$RET_{d-30,d}$	-0.595***	-0.526***
	(-22.55)	(-20.89)
Size		-0.001***
		(-3.37)
BM		0.214***
		(51.70)
IVOL		6.663***
		(37.45)
Illiquidity		0.012***
		(11.81)
Adjusted R^2	0.093	0.2711
#of Observations	21,765	21,549

Table 3: Regressions of Insider Trading Activities on Returns with Monthly Data

This table reports the results of regressing the insider trading activities measured by net purchase ratio (NPR) on the company returns. In this table, we use monthly data for the regression. The dependent variable is NPR calculated by dividing the total net share volume of insider transactions by the total aggregate share volume of insider transactions. We use the current month's return, the previous month's return, the previous 3 months' cumulative return, and the previous 6 months' cumulative return as independent variables. Control variables are included in the second regressions under each dependent variable. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1, 2020 to December 31, 2020.

	NPR	
	(1)	(2)
RET_m	-0.568***	-0.531***
	(-15.80)	(-15.32)
RET_{m-1}	-0.219***	-0.251***
	(-4.77)	(-5.45)
$RET_{m-3,m}$	-0.158***	-0.085***
	(-5.47)	(-2.88)
$RET_{m-6,m}$	-0.099***	-0.119***
	(-6.39)	(-7.22)
Size		-0.001**
		(-1.87)
BM		0.204***
		(29.50)
IVOL		7.780***
		(26.58)
Illiquidity		0.013***
		(5.95)
Adjusted R^2	0.0626	0.2334
#of Observations	9,592	9,506

D. Informational Value and Predictive Capability

In this section, we examine whether insider trading transactions can help to forecast firm's future performance. Based on the insider trading literature, insider transactions carry significant information content about a firm's future performance. We would like to further discuss the informational value inherent in insider trading and assess its predictive capability for future firm returns during that specific period. We run both univariate and multivariate regressions of cumulative returns on insider trading activities to test the predictive power of insider transactions. The dependent variable is the firm's future return. We separately test firm performance over the next 1 month, the next 3 months, the next 6 months, and the next 12 months. We still use NPR to denote insider transaction activities. The regression formulas are shown below:

$$RET_{i,[t,t+\tau]} = a + b1NPR_{i,t} + b2RET_{i,[t-1,t]} + b3RET_{i,[t-3,t]} + b4RET_{i,[t-6,t]} + \varepsilon_{i,t} \quad (5)$$

$$RET_{[t,t+\tau]} = a + b1NPR_{i,t} + +b2RET_{i,[t-1,t]} + b3RET_{i,[t-3,t]} + b4RET_{i,[t-6,t]} + b5RET_{i,[t-12,t]} + b6SIZE_{i,t} + b7BM_{i,t} + b8Illiqudity_{i,t} + b9Volatility_{i,t} + \varepsilon_{i,t} \quad (6)$$

where $RETs_{i,[t,t+\tau]}$ denotes the cumulative returns for $firm_i$ during the time from t to t $+$ τ. $NPR_{i,t}$ denotes the company i's Net Purchase Ratio for $month_i$. $RET_{i,[t-1,t]}$ denotes the previous month's returns for $firm_i$. $RET_{i,[t-3,t]}$ denotes the previous 3 months' cumulative returns for $firm_i$. $RET_{i,[t-6,t]}$ denotes the previous 6 months' cumulative returns for $firm_i$. $RET_{i,[t-12,t]}$ denotes the previous 12 months' cumulative returns for $firm_i$. In the formula (6) the control variables are included. The method of calculating the control variable is described in the summary statistic section.

Table 4 shows the results of predictive capability. For the future return in the next 1 month, the next 3 months, the next 6 months, and the next 12 months, we consistently identify a statistically significant positive relationship between NPR (Net Purchase Ratio) and the forthcoming performance of the company. This observation remains robust and holds true across both univariate and multivariate regression models. Such consistent findings underscore the potency of the insider trading literature as a predictive tool, particularly in forecasting the future trajectory of a company's performance. Given the unique challenges and uncertainties presented by the COVID era, our results reaffirm the invaluable insights offered by insider trading patterns, reinforcing their predictability of firm future performance.

E. Distinguishing Analysis Between Routine and Opportunistic Insider Transactions

We then shift our emphasis towards opportunistic transactions. We believe that opportunistic transactions, as opposed to routine ones, provide a more genuine reflection of insiders' perspectives and predictions based on current and foreseeable market dynamics. Given their discretionary nature, opportunistic transactions offer deeper insights into insiders' assessments of firm value and future prospects, especially during turbulent times like the COVID period. Thus, it becomes crucial to delve deeper into these transactions to garner a comprehensive understanding of insider behaviors and the underlying motivations driving them. Using trade-level classification, we separate the insider transactions into routine transactions and opportunistic transactions. Table 5 shows the results of regressions of opportunistic insider trading activities on past returns with daily data. Table 6 shows the results of regressions of opportunistic insider trading activities on past returns with monthly data. There is a statistically significant negative relationship between NPR and firm past return, and the results hold for both univariate and multivariate regressions. This pattern, which is consistent in different types of analysis, suggests that insiders tend to purchase when the firm hasn't been doing well and sell when it's been doing better. What's more interesting is that this "buy low, sell high" behavior is especially noticeable in opportunistic trades or trades made based on unique insights or opportunities. During the COVID period, insiders seemed to act more on these opportunities, possibly because they had specific knowledge about their companies. Overall, our findings match what we expected based on earlier results. That is, during the pandemic, insiders, especially those making opportunistic trades, were acting as contrarian investors.

Table 4: Regressions of Future Returns on Insider Trading Activities

This table reports the results of regressing the future company returns on insider trading activities measured by net purchase ratio (NPR). In this table, we use monthly data for the regression. The dependent variable is the company's cumulative returns for one month, three months, six months, and twelve months. The NPR is calculated by dividing the total net share volume of insider transactions by the total aggregate share volume of insider transactions Control variables are included in the second regressions under each dependent variable. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1, 2020 to December 31, 2020.

	RET_{m+1}		$RET_{m,m+3}$		$RET_{m,m+6}$		$RET_{m,m+12}$	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
NPR	0.023^{***}	0.011^{***}	0.050^{***}	0.028^{***}	0.0789^{***}	0.046^{***}	0.240^{***}	0.156^{***}
	(8.25)	(3.54)	(10.12)	(5.09)	(10.28)	(5.28)	(18.33)	(10.41)
RET_{m-1}	0.018	0.037^{***}	-0.011	0.016	0.066^{*}	0.101^{***}	-0.202^{***}	-0.208^{***}
	(1.37)	(2.79)	(-0.49)	(0.68)	(1.9)	(2.68)	(-3.39)	(-3.22)
$RET_{m-3,m}$	-0.069^{***}	-0.068^{***}	-0.070^{***}	-0.077^{***}	0.066^{***}	0.073^{***}	0.016	0.024
	(-8.49)	(-8.1)	(-4.93)	(-5.03)	(3)	(3.02)	(0.41)	(0.59)
$RET_{m-6,m}$	0.068^{***}	0.064^{***}	0.090^{***}	0.093^{***}	0.012	0.003	-0.050^{**}	-0.077^{***}
	(12.62)	(11.36)	(9.49)	(9.14)	(0.84)	(0.21)	(-1.98)	(-2.78)
$RET_{m-12,m}$	-0.015^{***}	-0.016^{***}	-0.028^{***}	-0.034^{***}	-0.043^{***}	-0.051^{***}	-0.034^{***}	-0.050^{***}
	(-4.62)	(-4.8)	(-5.02)	(-5.72)	(-4.92)	(-5.44)	(-2.29)	(-3.11)
Size		0.001		-0.001		-0.001^{**}		-0.001
		(0.06)		(-1.24)		(-2.01)		(-0.34)
BM		-0.013^{***}		-0.016^{***}		-0.006		0.026^{***}
		(-6.13)		(-4.15)		(-0.94)		(2.52)
IVOL		1.756^{***}		2.800^{***}		3.298^{***}		8.176^{***}
		(20.31)		(17.8)		(13.33)		(19.26)
Illiquidity		-0.000		-0.002		-0.002		-0.002
		(-0.55)		(-1.5)		(-0.99)		(-0.51)
Adjusted R^2	0.0242	0.0729	0.0197	0.058	0.0152	0.0363	0.0463	0.0897
#of Observations	9,592	9,506	9,592	9,506	9,592	9,506	9,592	9,506

Table 5: Regressions of Opportunistic Insider Trading Activities on Returns with Daily Data

This table reports the results of regressing the opportunistic insider trading activities measured by net purchase ratio (NPR) on the company returns. In this table, we use daily data for the regression. The dependent variable is NPR calculated by dividing the total net share volume of insider transactions by the total aggregate share volume of insider transactions. We use the current day's return, the previous day's return, the previous 7 days' cumulative return, and the previous 30 days' cumulative return as independent variables. Control variables are included in the second regressions under each dependent variable. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1, 2020 to December 31, 2020.

	NPR	
	(1)	(2)
RET_d	-1.580***	-1.39***
	(-10.14)	(-10.39)
RET_{d-1}	-1.520***	-0.752***
	(-8.10)	(-4.65)
$RET_{d-7,d}$	-0.365***	-0.582***
	(-3.88)	(-7.22)
$RET_{d-30,d}$	-0.611***	-0.475***
	(-13.01)	(-11.85)
Size		-0.001*
		(-1.77)
BM		0.205***
		(32.18)
IVOL		6.855***
		(25.55)
Illiquidity		0.012***
		(5.90)
Adjusted R^2	0.0868	0.2947
#of Observations	7,779	7,779

Table 6: Regressions of Opportunistic Insider Trading Activities on Returns with Monthly Data

This table reports the results of regressing the opportunistic insider trading activities measured by net purchase ratio (NPR) on the company returns. In this table, we use monthly data for the regression. The dependent variable is NPR calculated by dividing the total net share volume of insider transactions by the total aggregate share volume of insider transactions. We use the current month's return, the previous month's return, the previous 3 months' cumulative return, and the previous 6 months' cumulative return as independent variables. Control variables are included in the second regressions under each dependent variable. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1, 2020 to December 31, 2020.

	NPR	
	(1)	(2)
RET_m	-0.673***	-0.571***
	(-12.03)	(-11.22)
RET_{m-1}	-0.126*	-0.139**
	(-1.88)	(-2.23)
$RET_{m-3,m}$	-0.180***	-0.078*
	(-4.04)	(-1.88)
$RET_{m-6,m}$	-0.057**	-0.088***
	(-2.50)	(-3.8)
Size		-0.000
		(-1.05)
BM		0.191***
		(19.41)
IVOL		7.096***
		(17.72)
Illiquidity		0.011***
		(4.65)
Adjusted R^2	0.0615	0.2323
#of Observations	4,042	4,042

We then regress the future returns on the NPR of opportunistic transactions to test the predictive power of opportunistic insider trading activities. Table 7 presents the results. Overall, we find consistent results with the previous analysis. There is a statistically significant positive relationship between the NPR of opportunistic transactions and future company performance, and the results hold for both univariate and multivariate regressions. This indicates that when insiders, who are usually top executives, engage in opportunistic transactions, it can be a clue about how the company will perform in the future. The positive relation between the NPR of these transactions and future company success suggests that these insiders might be acting based on specific insights they have about upcoming events or company conditions. Our findings in Table 7, being consistent with prior analysis, give added confidence in the informative value of such insider trades. When these insiders make certain moves, it's worth paying attention, as it has the predictive power of the firm future performance.

We conducted a parallel analysis on routine insider transactions. The results of the daily data regression on past returns are presented in Table 8, while the findings from the monthly data regression are displayed in Table 9. From these analyses, we do not observe consistent patterns with routine insider transactions.

In essence, these transactions did not seem to be motivated by past returns. Therefore, we infer that routine insider transactions do not follow the contrarian trading trend. Table 10 presents the results of regressing future returns on routine insider transactions. The results reveal a significant positive correlation between future returns and insider trading activities. In summary, our findings suggest that during the pandemic period, while routine insider transactions seem to possess predictive capabilities regarding a firm's future returns, they do not adhere to the conventional contrarian approach.

Table 7: Regressions of Future Returns on Opportunistic Insider Trading Activities

This table reports the results of regressing the future company returns on the opportunistic insider trading activities measured by net purchase ratio (NPR). In this table, we use monthly data for the regression. The dependent variable is the company's raw returns for one month, three months, six months, and twelve months. The NPR is calculated by dividing the total net share volume of insider transactions by the total aggregate share volume of insider transactions Control variables are included in the second regressions under each dependent variable. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1, 2020 to December 31, 2020.

	RET_{m+1}		$RET_{m,m+3}$		$RET_{m, m+6}$		$RET_{m,m+12}$	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
NPR	0.020***	0.013***	0.045***	0.031***	0.080***	0.050***	0.241***	0.167***
	(4.72)	(2.61)	(6.18)	(3.58)	(6.51)	(3.48)	(12.25)	(7.24)
RET_{m-1}	0.004	0.022	-0.019	0.007	0.029	0.057	-0.305***	-0.317***
	(0.24)	(1.16)	(-0.6)	(0.21)	(0.55)	(1.01)	(-3.56)	(-3.57)
$RET_{m-3,m}$	-0.065***	-0.063***	-0.076***	-0.067***	0.080**	0.103***	0.018	0.088
	(-5.32)	(-4.96)	(-3.57)	(-3.04)	(2.27)	(2.73)	(0.33)	(1.47)
$RET_{m-6,m}$	0.066***	0.054***	0.076***	0.069***	0.005	-0.012	-0.064*	-0.127***
	(8.31)	(6.56)	(5.56)	(4.82)	(0.21)	(-0.5)	(-1.74)	(-3.30)
$RET_{m-12,m}$	-0.024***	-0.025***	-0.029***	-0.050***	-0.032**	-0.070***	0.004	-0.040
	(-5.21)	(-4.39)	(-3.69)	(-4.95)	(-2.40)	(-4.09)	(0.18)	(-1.46)
Size		0.000		-0.000		-0.000		-0.000
		(0.01)		(-0.5)		(-0.82)		(-0.21)
BM		-0.020***		-0.025***		-0.012		0.013
		(-6.37)		(-4.44)		(-1.23)		(0.89)
IVOL		1.721***		2.542***		3.145***		7.746***
		(13.57)		(11.44)		(8.37)		(13)
Illiquidity		-0.000		-0.001		-0.002		-0.003
		(-0.61)		(-1.21)		(-0.85)		(-0.78)
Adjusted R^2	0.0229	0.0738	0.0181	0.0559	0.0123	0.0328	0.0477	0.094
#of Observations	4,042	4,042	4,042	4,042	4,042	4,042	4,042	4,042

Table 8: Regressions of Routine Insider Trading Activities on Returns with Daily Data

This table reports the results of regressing the routine insider trading activities measured by net purchase ratio (NPR) on the company returns. In this table, we use daily data for the regression. The dependent variable is NPR calculated by dividing the total net share volume of insider transactions by the total aggregate share volume of insider transactions. We use the current day's return, the previous day's return, the previous 7 days' cumulative return, and the previous 30 days' cumulative return as independent variables. Control variables are included in the second regressions under each dependent variable. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1, 2020 to December 31, 2020.

	NPR	
	(1)	(2)
RET_d	-1.490***	-1.282***
	(-5.97)	(-5.63)
RET_{d-1}	0.302	0.319
	(1.03)	(-1.18)
$RET_{d-7,d}$	-0.228	-0.090
	(-1.55)	(-0.68)
$RET_{d-30,d}$	0.009	-0.054
	(0.15)	(-1.00)
Size		0.000
		(-0.48)
BM		0.197***
		(20.61)
IVOL		8.896***
		(16.58)
Illiquidity		0.083***
		(6.41)
Adjusted R^2	0.0125	0.2383
#of Observations	2975	2975

Table 9: Regressions of Routine Insider Trading Activities on Returns with Monthly Data

This table reports the results of regressing the routine insider trading activities measured by net purchase ratio (NPR) on the company returns. In this table, we use monthly data for the regression. The dependent variable is NPR calculated by dividing the total net share volume of insider transactions by the total aggregate share volume of insider transactions. We use the current month's return, the previous month's return, the previous 3 months' cumulative return, and the previous 6 months' cumulative return as independent variables. Control variables are included in the second regressions under each dependent variable. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1, 2020 to December 31, 2020.

	NPR	
	(1)	(2)
RET_m	0.097	0.145
	(0.92)	(1.46)
RET_{m-1}	-0.190	-0.185
	(-1.58)	(-1.62)
$RET_{m-3,m}$	-0.036	-0.043
	(-0.52)	(-0.63)
$RET_{m-6,m}$	0.042	0.086^{**}
	(-0.96)	(1.97)
Size		0.000
		(-0.44)
BM		0.203^{***}
		(12.41)
IVOL		6.275^{***}
		(6.35)
Illiquidity		0.060^{***}
		(4.17)
Adjusted R^2	0.0011	0.1794
#of Observations	1155	1155

Table 10: Regressions of Future Returns on Routine Insider Trading Activities

This table reports the results of regressing the future company returns on the routine insider trading activities measured by net purchase ratio (NPR). In this table, we use monthly data for the regression. The dependent variable is the company's raw returns for one month, three months, six months, and twelve months. The NPR is calculated by dividing the total net share volume of insider transactions by the total aggregate share volume of insider transactions Control variables are included in the second regressions under each dependent variable. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is from January 1, 2020 to December 31, 2020.

	RET_{m+1}		$RET_{m,m+3}$		$RET_{m, m+6}$		$RET_{m,m+12}$	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
NPR	0.022***	0.015**	0.093***	0.092***	0.139***	0.142***	0.224***	0.183***
	(2.82)	(1.78)	(5.80)	(5.32)	(6.25)	(5.73)	(6.22)	(4.50)
RET_{m-1}	0.084***	0.063**	-0.078	-0.210***	0.050	-0.052	-0.062	-0.198
	(2.65)	(2.00)	(-1.20)	(-3.23)	(0.56)	(-0.56)	(-0.42)	(-1.30)
$RET_{m-3,m}$	-0.091***	-0.094***	-0.120***	-0.079**	-0.022	0.032	-0.014	0.055
	(-4.81)	(-4.87)	(-3.09)	(-1.99)	(-0.4)	(0.57)	(-0.15)	(0.59)
$RET_{m-6,m}$	0.068***	0.084***	0.101***	0.130***	0.033	0.052	-0.076	-0.064
	(4.46)	(5.22)	(3.27)	(3.95)	(0.77)	(1.09)	(-1.08)	(-0.82)
$RET_{m-12,m}$	-0.006	-0.022***	0.002	-0.036**	-0.005	-0.043**	0.020	-0.021
	(-0.73)	(-2.66)	(0.10)	(-2.08)	(-0.23)	(-1.77)	(0.53)	(-0.53)
Size		0.000		0.000		0.000		0.000
		(0.12)		(-0.07)		(-0.88)		(-0.28)
BM		-0.015***		-0.034***		-0.032**		0.000
		(-3.14)		(-3.45)		(-2.23)		(-0.02)
IVOL		3.089***		6.315***		6.467***		10.451***
		(11.16)		(11.08)		(7.91)		(7.80)
Illiquidity		0.006		0.001		0.000		0.003
		(1.47)		(0.14)		(-0.02)		(0.14)
Adjusted R^2	0.0323	0.1472	0.0465	0.1627	0.0298	0.0943	0.0324	0.0840
#of Observations	1155	1155	1155	1155	1155	1155	1155	1155

IV. CONCLUSION

Our analysis of insider trading activities, during the times of the COVID pandemic, has provided noteworthy insights into the dynamics of the financial market and the behavior of corporate insiders. In this particular economic environment with unprecedented market volatility and economic uncertainty, we use three metrics to investigate the patterns of insider trading activities: the dollar volume of insider transactions, the number of insider transactions, and the number of insiders engaged in insider transactions. We find that from the end of February to the beginning of April, insider purchases experienced significant changes. In addition, compared with the previous 5 years, there was a fourfold increase in both the frequency and magnitude of insider sell transactions during the COVID period. We then combine the VIX and S&P 500 to analyze the relationship between market performance and insider trading activities, and we find that insiders adopted a clear contrarian trading stance during the pandemic.

We then explore the determinants of insider trading activities during the pandemic period. Regressing the insider trading activities measured by net purchase ratio (NPR) on the company's past returns, we find that the firm’s past performance served as the primary driver for insider transactions throughout the pandemic period. The result holds for both univariate and multivariate regressions, and both daily data and monthly data.

In the next section, we examine whether insider trading transactions can help to forecast firm's future performance. We regress the future company returns on insider trading activities measured by net purchase ratio (NPR) with monthly data and find a strong predictive capability of the insider trading activities for the firm’s future performance.

To make further analysis on which category of insider transactions contains the information content, we separate the insider transactions into routine transactions and opportunistic transactions. Performing similar regressions, we find that opportunistic insider transactions not only maintain their contrarian patterns but also retain their potency in predicting future returns.

APPENDIX

Insider Transactions and Market Performance across Industries

In this section, we analyze market performance across various industries and evaluate insider transaction trends within these sectors. Our goal is to discern which industries were most impacted by COVID and understand their performance trends during this period. Utilizing the CRSP database, we selected daily data spanning February 20, 2020, to March 23, 2020. Post-February 20, the stock market experienced a persistent decline, punctuated by sharp daily downturns influenced by international oil prices and the repercussions of COVID, a period colloquially termed the "2020 stock crash."

Utilizing the 2-digit SIC code, we computed the cumulative daily returns of various industries between February 20, 2020, and March 23, 2020, subsequently ranking these industries based on their returns. We integrated this return dataset with the Thomson Financial Insider Trading database to assess insider trading patterns. From our analysis, the top five industries, performance-wise, were food stores, motion pictures, general merchandise stores, trucking and warehousing, and chemicals and allied products. Conversely, the industries that underperformed the most were general construction, water transportation, amusement & recreation services, oil and gas extraction, and petroleum and coal products.

Industries	Cumulative Return (%)
General Construction	-0.754
Water Transportation	-0.706
Amusement & Recreation Services	-0.697
Oil and Gas Extraction	-0.681
Petroleum and Coal Products	-0.679
…	…
Trucking and Warehousing	-0.190
Miscellaneous Repair Services	-0.167
General M Erchandise Stores	-0.073
Motion Pictures	-0.053
Food Stores	0.007

The COVID pandemic provides context to understand the contrasting performances across industries. The implementation of lockdowns and adherence to social distancing measures temporarily halted many construction projects. Challenges like the absence of onsite workers and disruptions in the supply chain further compounded the issues. The water transportation sector, particularly cruises, grappled with its reputation as a high-risk contagion environment. Declining passenger counts and suspended cargo shipping, due to cross-border permissions, strained the financial health of these companies. Entertainment and recreational venues, such as theme parks, cinemas, and stadiums, experienced shutdowns or operated under stringent limitations, culminating in substantial revenue deficits. The oil and gas extraction industry faced an external shock on March 8, 2020, when Saudi Arabia instigated a price war against Russia, causing a precipitous drop in oil prices. With U.S. oil prices diving by 34% and both crude oil and Brent oil falling by 26% and 24% respectively, this sector bore the brunt. Related industries, like petroleum and coal products, were indirectly affected. Their fortunes were tied to oil and gas extraction, and the reduced demand for petroleum derivatives like gasoline further exacerbated their challenges.

During the lockdown, grocery stores and supermarkets, deemed essential, experienced surges in sales due to panic buying and an increased inclination towards home-cooked meals. Similarly, general merchandise stores, which stocked essentials including cleaning and personal protective items, saw an uptick in sales, further amplified by robust e-commerce platforms that catered to the growing online shopping trend. This digital shift significantly boosted the trucking and warehousing sectors. Home confinement drove an uptick in digital media consumption. Additionally, the critical role of disinfectants and medications during the pandemic spurred demand in the pharmaceutical segment of the chemicals industry, which actively sought to develop COVID remedies, thereby increasing demand for specific chemical products.

To perform a comprehensive analysis of insider trading activities during the 2020 stock crash, we categorized the top five industries as the top-performing group and the bottom five industries as the bottom-performing group based on the cumulative daily returns. Using the dollar volume of insider transactions, the number of insiders, and the number of insider transactions, we analyze the difference of insider trading activities between top-performing and bottom-performing groups.

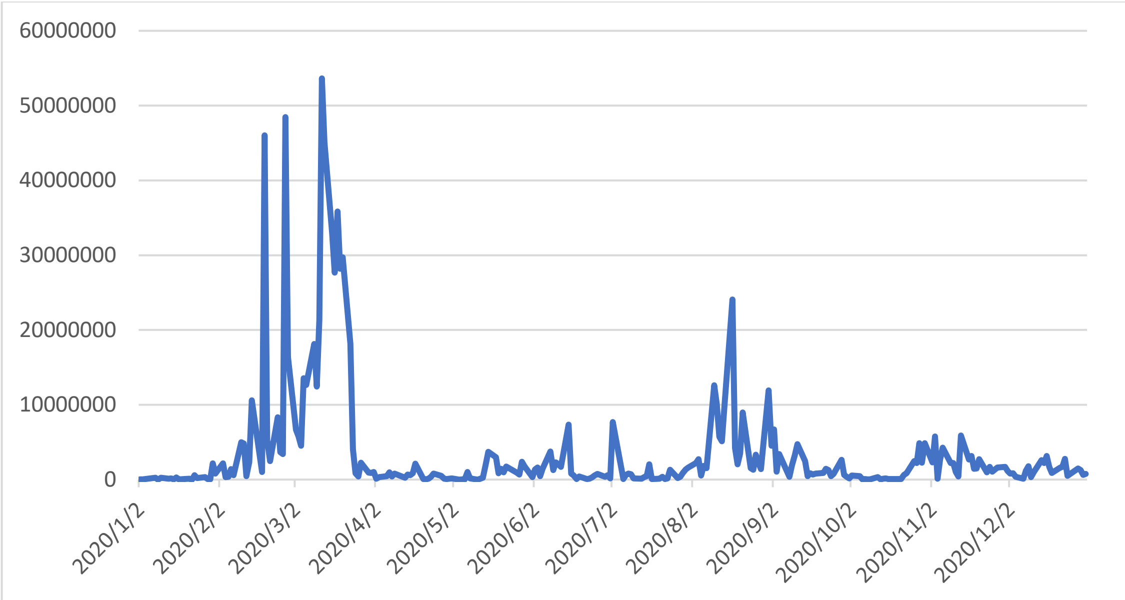
[Figure A5] [Figure A6]

Figure A5 illustrates the dollar volume and frequency of insider purchase transactions, while Figure A6 provides insights into the dollar volume and number of insider sell transactions. During the 2020 stock crash, as depicted in Figure A5, the bottom-performing industries exhibited more insider buying activities, both in terms of transaction volume and frequency, notably between March 4th and 10th. During the 2020 stock crash, as depicted in Figure A5, the bottom-performing industries exhibited more insider buying activities, both in terms of transaction volume and frequency, notably between March 4th and 10th. Figure A6 highlights that the top-performing industries dominated in insider selling, initiating elevated selling volumes from late February. Meanwhile, the bottom-performing group began ramping up their selling activities in early March-. Integrating the above observations, it is evident that insiders exhibit contrarian behavior. Leveraging their insider knowledge, they preemptively sell significant quantities of stocks from the top-performing group and purchase stocks from the bottom-performing group.

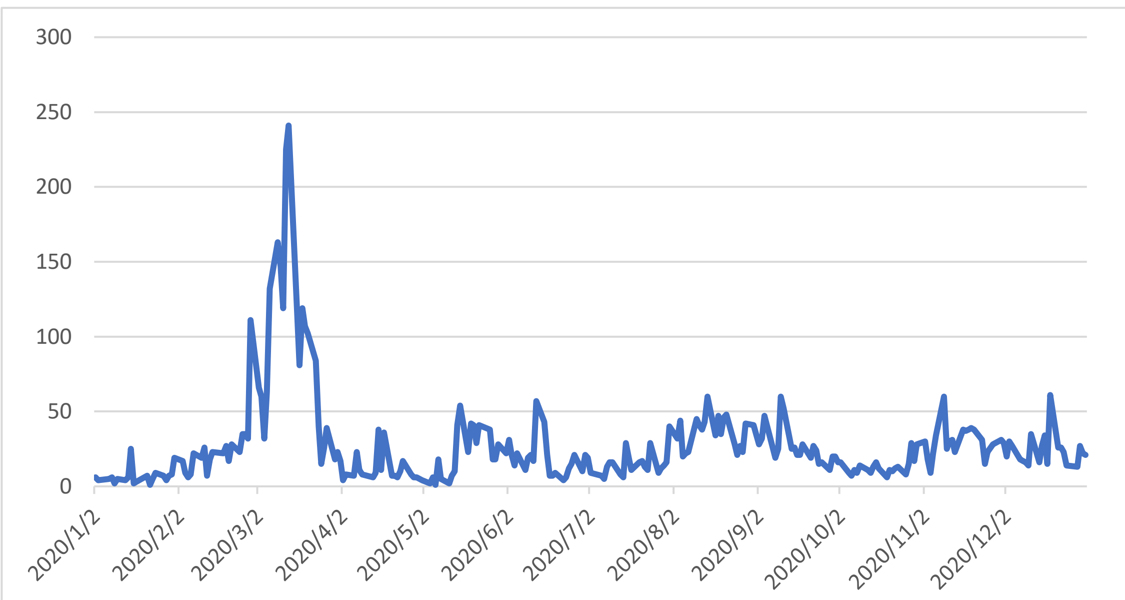
Figure A1

This chart shows the raw insider purchase transactions data. Our primary variables include dollar volume of insider purchase transaction, the number of insider purchase transactions and the number of insiders engaged in purchase transactions. The figure plots the variation of these variables on insider purchase activity throughout 2020.

Panel A: Dollar Volume of Insider Purchase Transaction for raw data



Panel B: Number of Insider Purchase Transactions for raw data



Panel C: Number of Insiders Engaged in Purchase Transactions for raw data

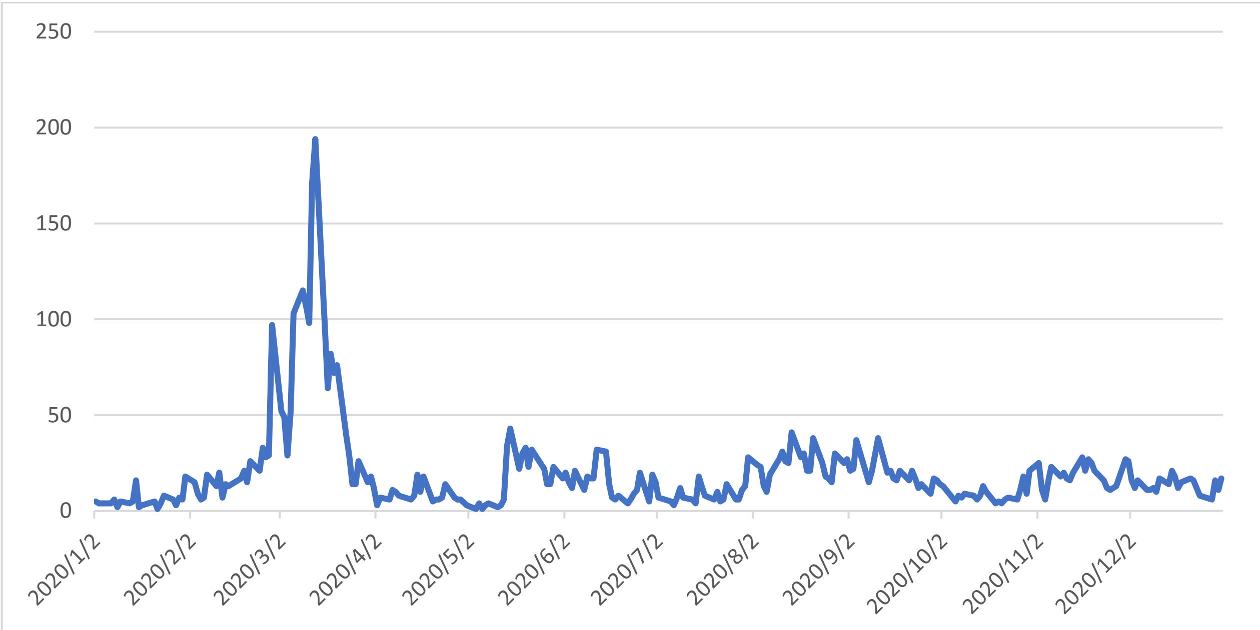
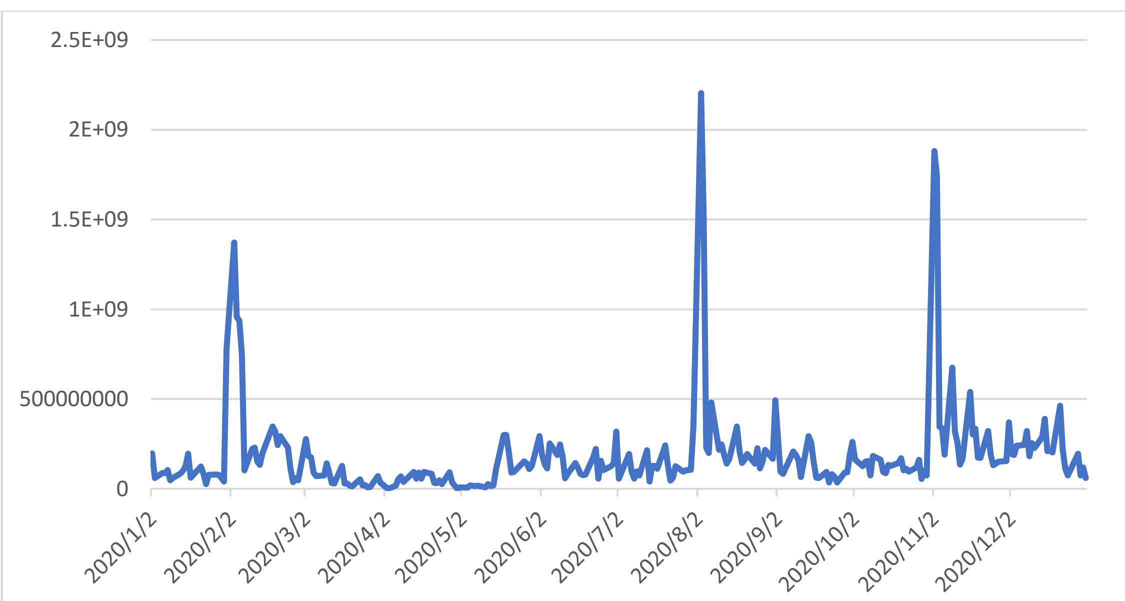


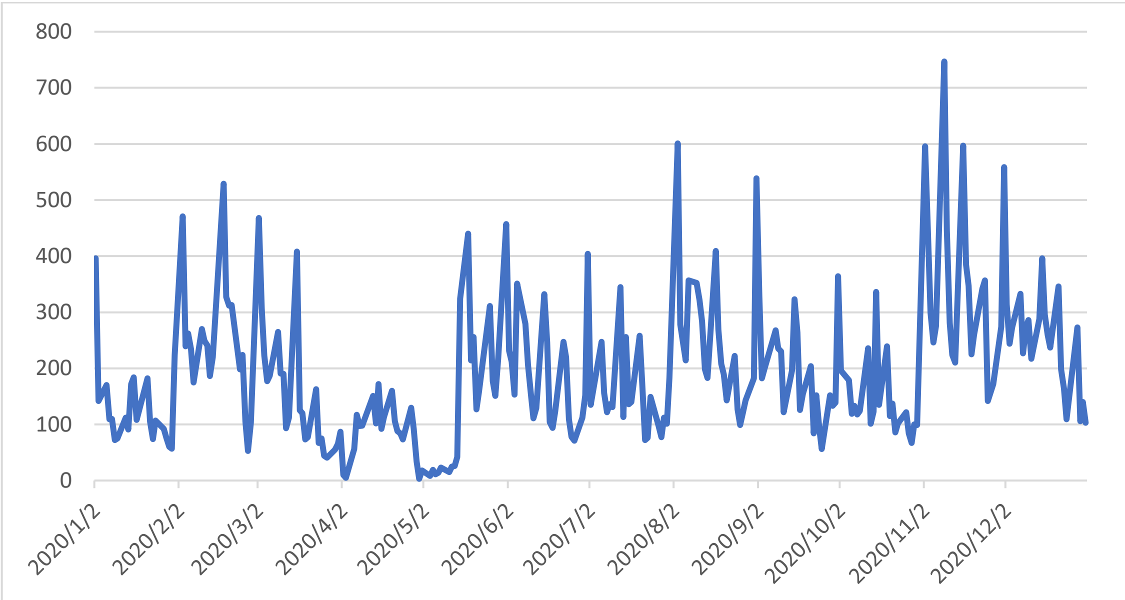
Figure A2

This chart shows the raw insider sell transaction data. Our primary variables include the dollar volume of insider sell transaction, the number of insider sell transactions and the number of insiders engaged in sell transactions. The figure plots the variation of these variables on insider sell activity throughout 2020.

Panel A: Dollar Volume of Insider Sell Transaction for raw data



Panel B: Number of Insider Sell Transactions



Panel C: Number of Insiders Engaged in Purchase Transactions

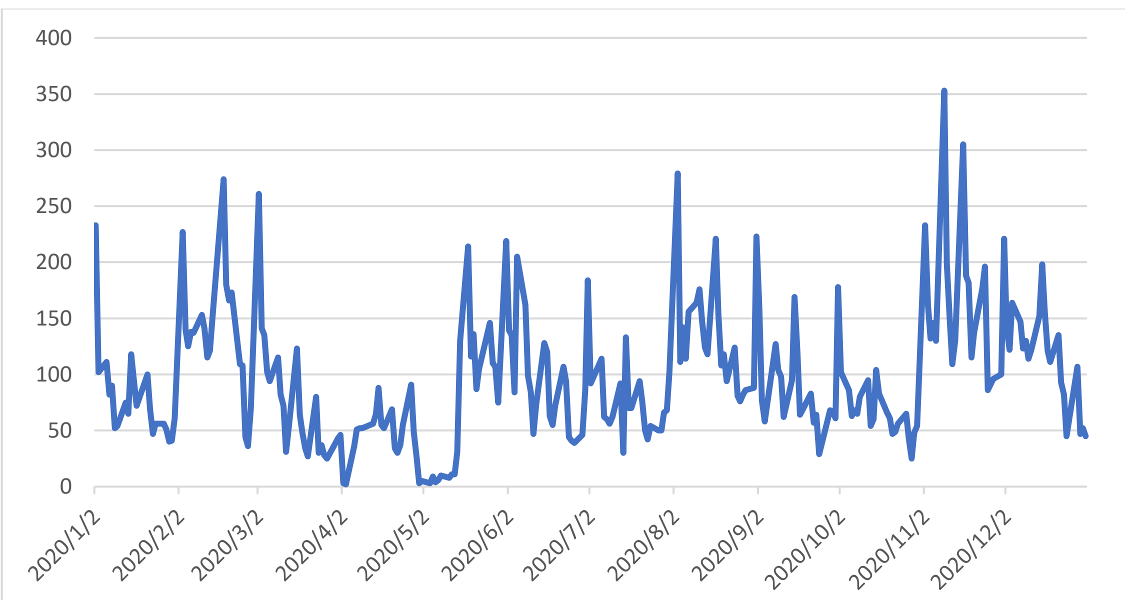
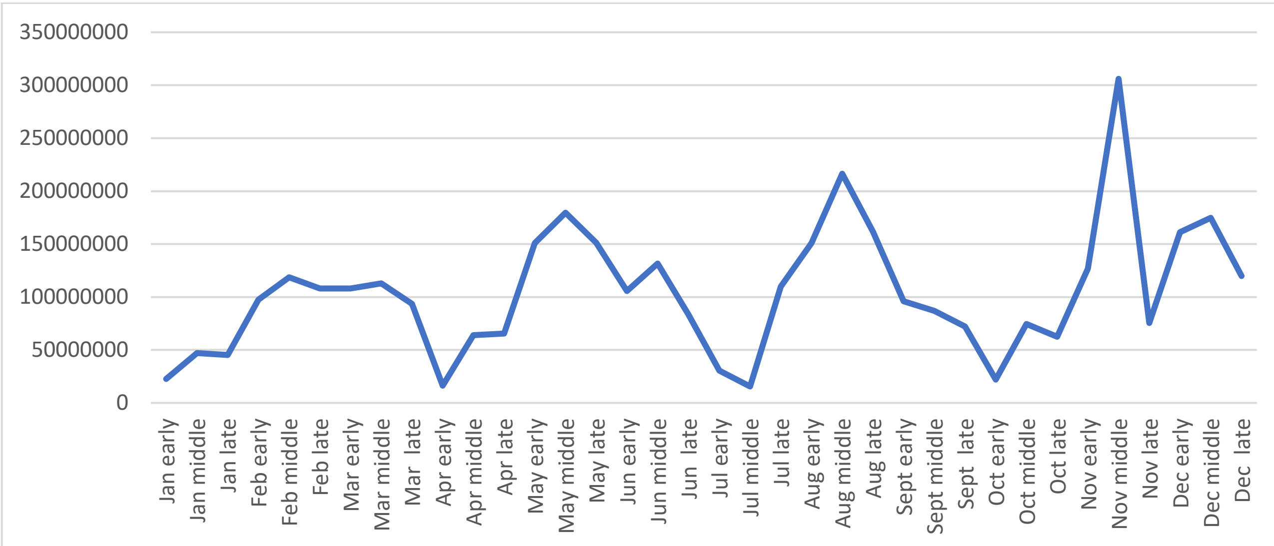


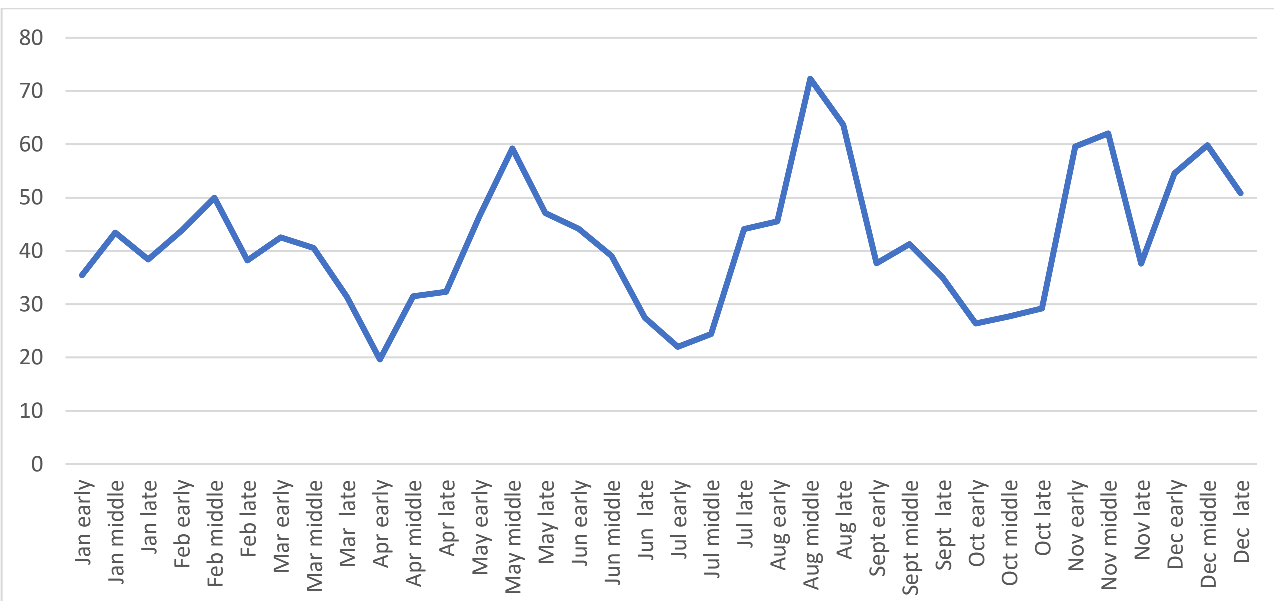
Figure A3

We divide a month into the beginning of the month, the middle of the month and the end of the month. This chart shows the average dollar volume of insider purchase transaction, the average number of insider purchase transactions and the average number of insiders engaged in purchase transactions, over the past 5 years, January 1, 2015-December 31, 2019. The figure plots the variation of these variables on insider purchase activity.

Panel A: Average Dollar Volume of Insider Purchase Transaction for past 5 years



Panel B: Average Number of Insider Purchase Transactions for past 5 years



Panel C: Average Number of Insiders Engaged in Purchase Transactions for past 5 years

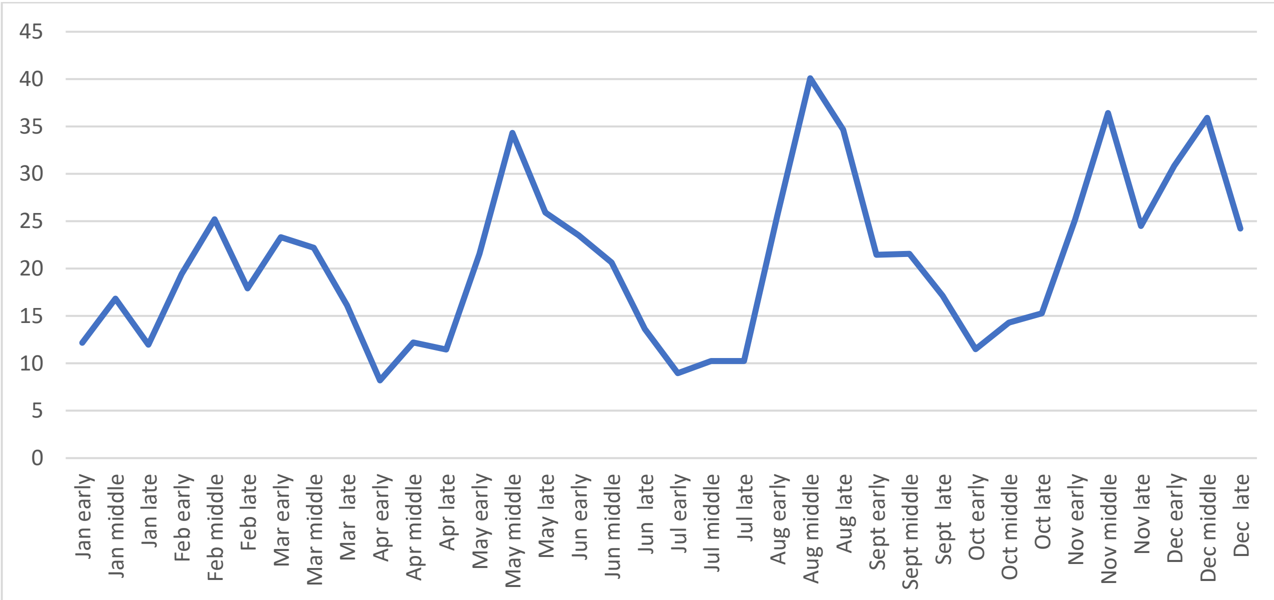
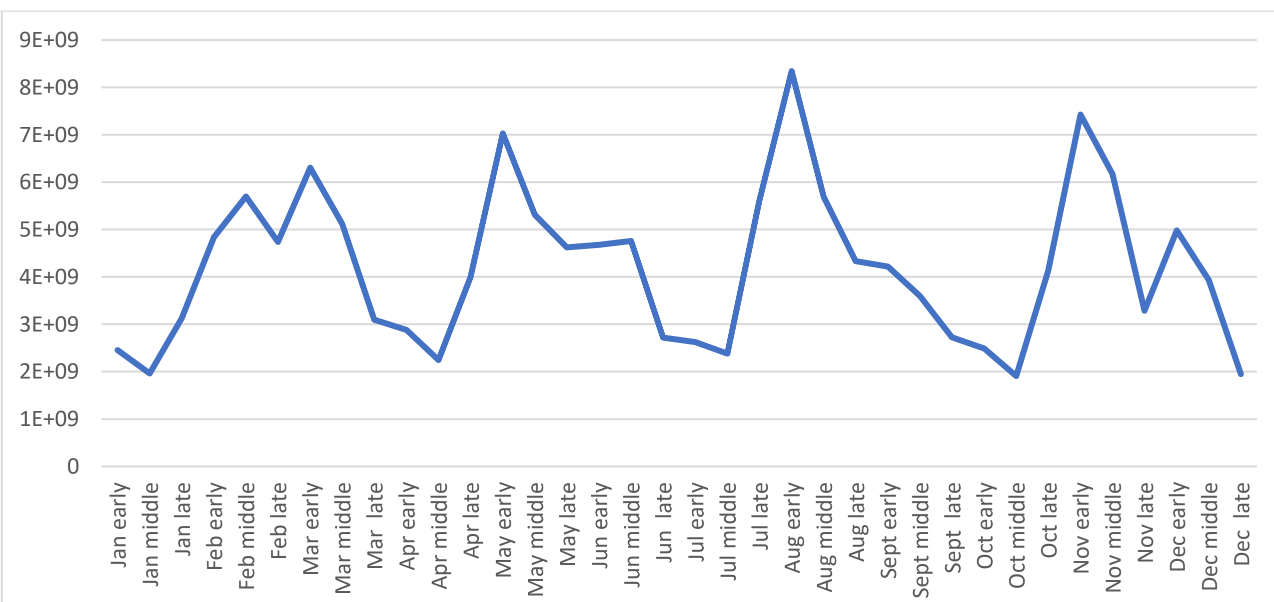


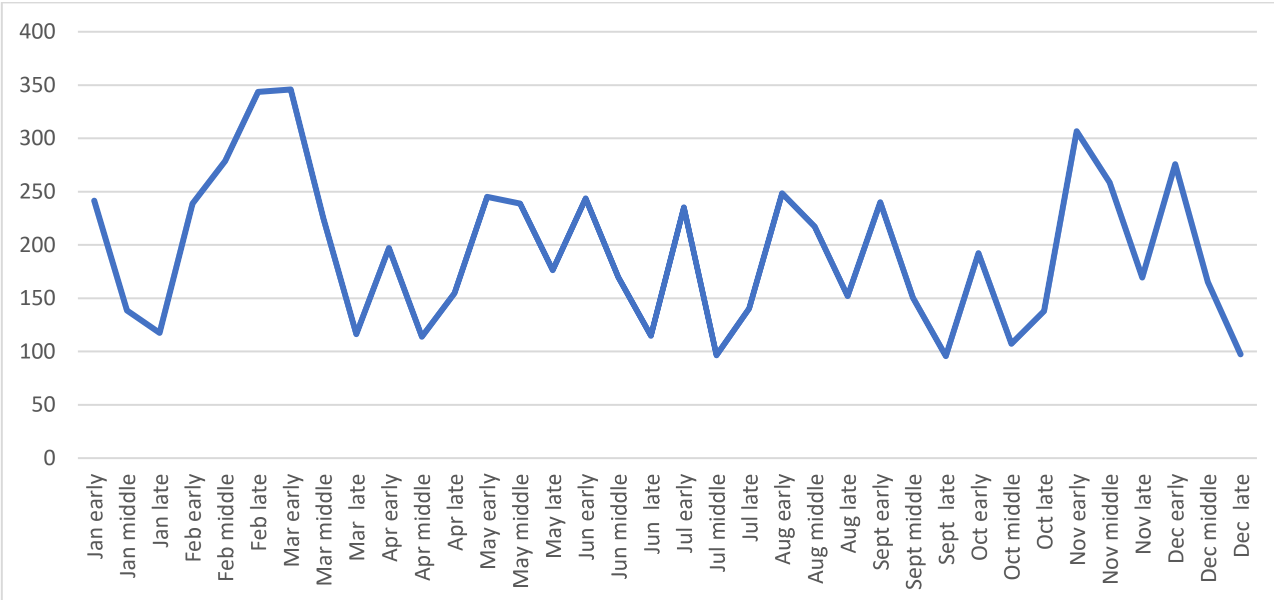
Figure A4

We divide a month into the beginning of the month, the middle of the month and the end of the month. This chart shows the average dollar volume of insider sell transaction, the average number of insider sell transactions and the average number of insiders engaged in sell transactions, over the past 5 years, January 1, 2015-December 31, 2019. The figure plots the variation of these variables on insider sell activity.

Panel A: Average Dollar Volume of Insider Sell Transaction for past 5 years



Panel B: Average Number of Insider Purchase Transactions for past 5 years



Panel C: Average Number of Insiders Engaged in Sell Transactions for past 5 years

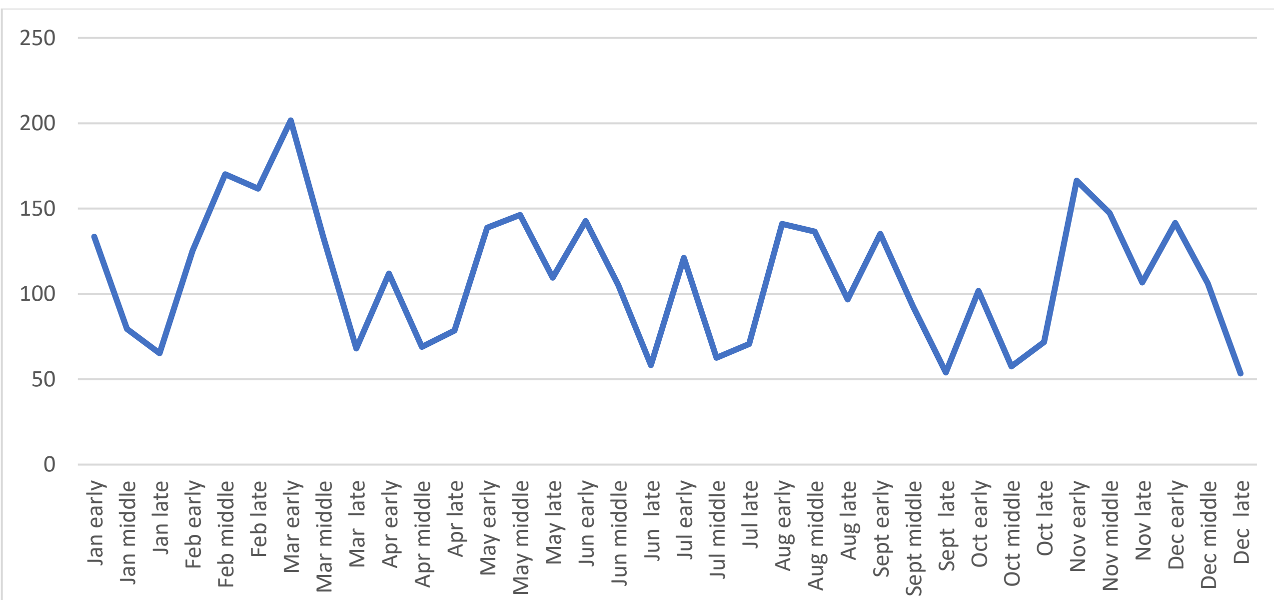
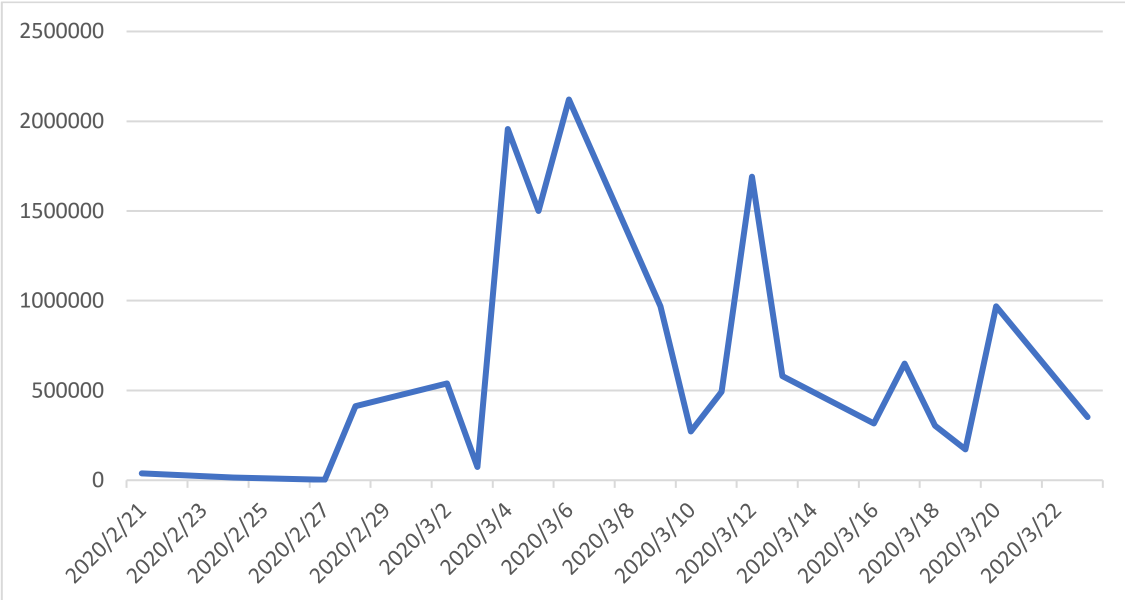


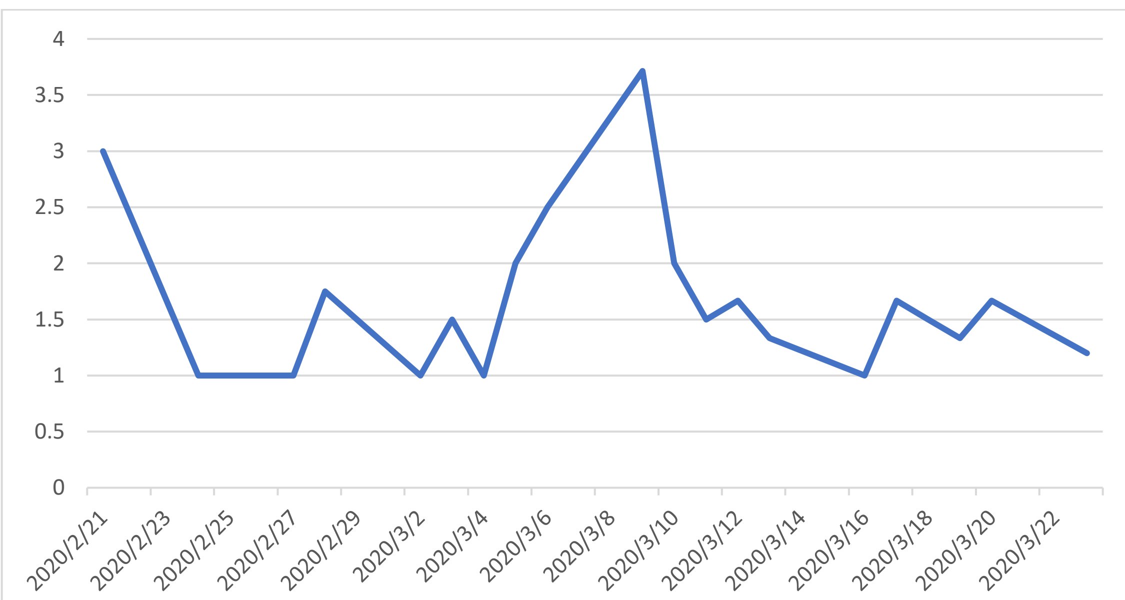
Figure A5: Insider Purchase Transactions across Industries

By combining the CRSP database and the Thomson Financial Insider Trading database, we find the top 5 industries and the bottom 5 industries that formed the top-performing group and the bottom-performing group, respectively, during the 2020 stock market crash. This chart shows the dollar volume of insider purchase transactions, the number of insiders purchase transactions scaled by the number of firms owed insiders, and the number of insiders engaged in purchase transactions scaled by the number of firms owed insiders for the top and bottom performing groups.

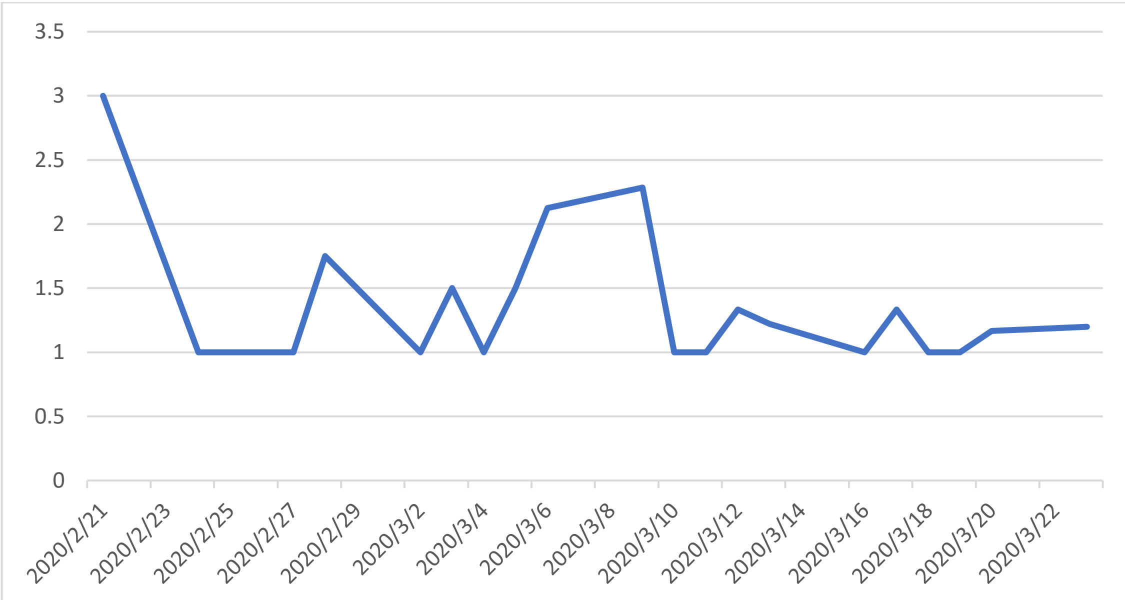
Panel A: Dollar Volume of Insider Purchase Transaction for the Bottom-performing Industry Group



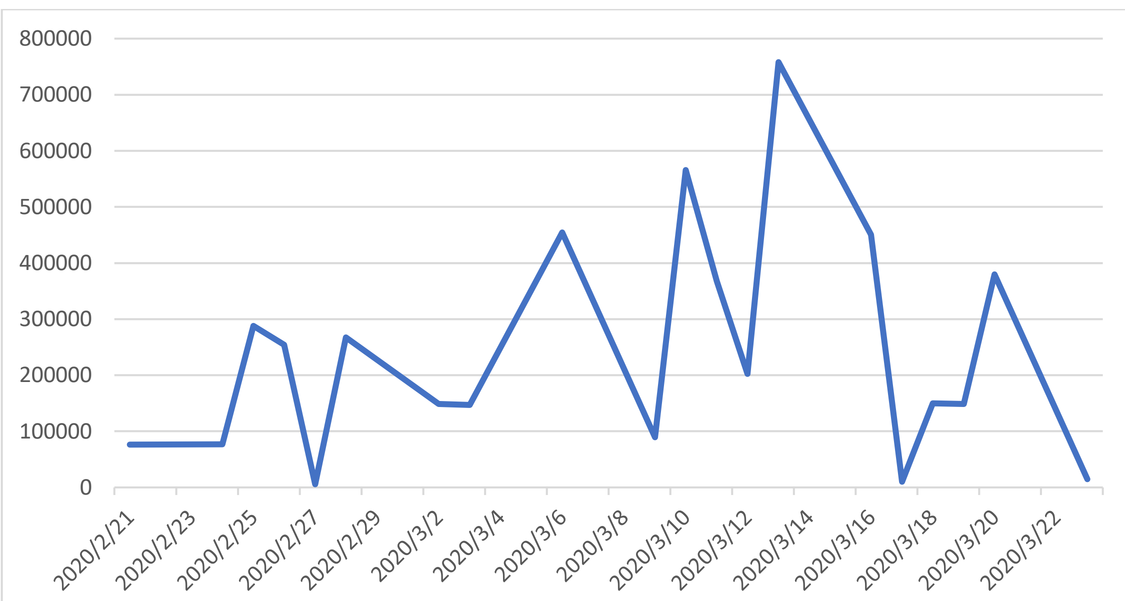
Panel B: Number of Insider Purchase Transactions, Normalized by the Number of Firms with Insider Ownership, for the Bottom -Performing Industry Group



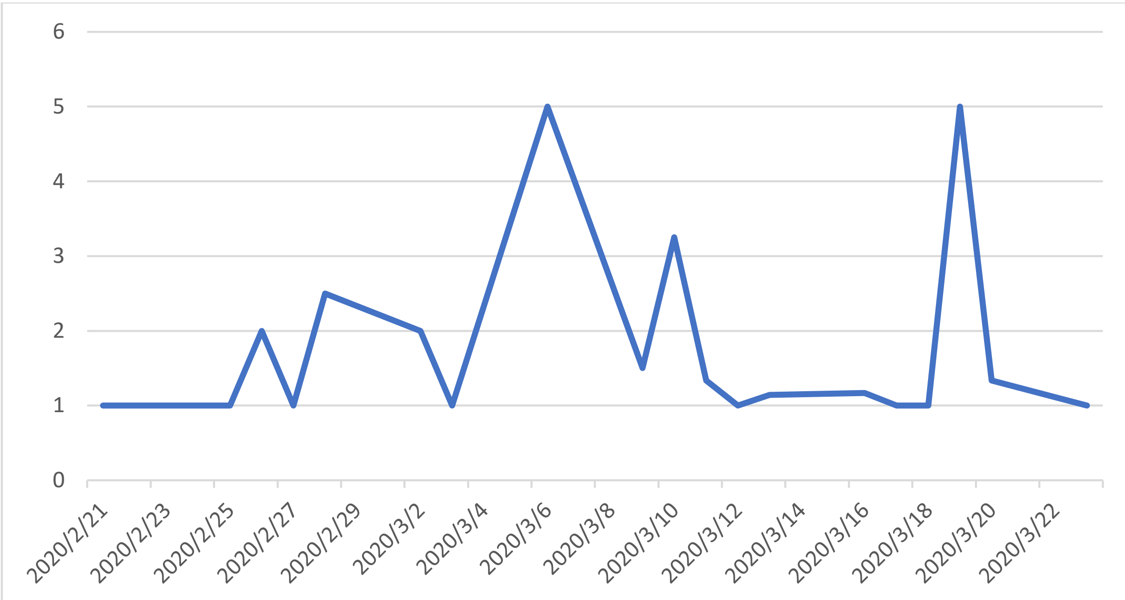
Panel C: Number of Insiders Engaged in Purchase Transactions, Normalized by the Number of Firms with Insider Ownership, for the Bottom -Performing Industry Group



Panel D: Dollar Volume of Insider Purchase Transaction for the Top-performing Industry Group



Panel E: Number of Insider Purchase Transactions, Normalized by the Number of Firms with Insider Ownership, for the Top-Performing Industry Group



Panel F: Number of Insiders Engaged in Purchase Transactions, Normalized by the Number of Firms with Insider Ownership, for the Top-Performing Industry Group

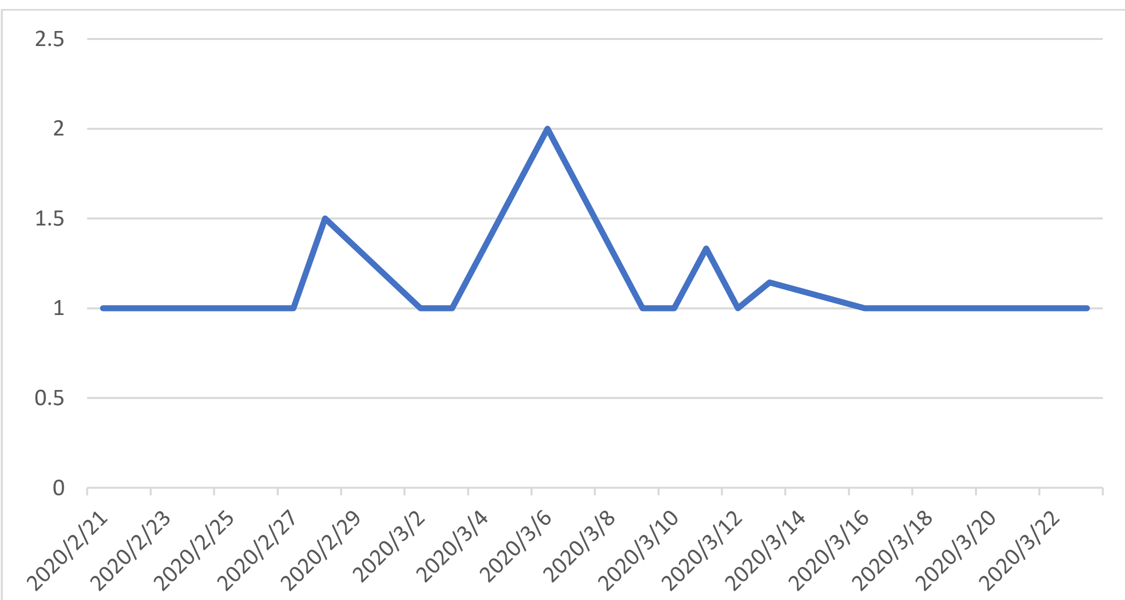
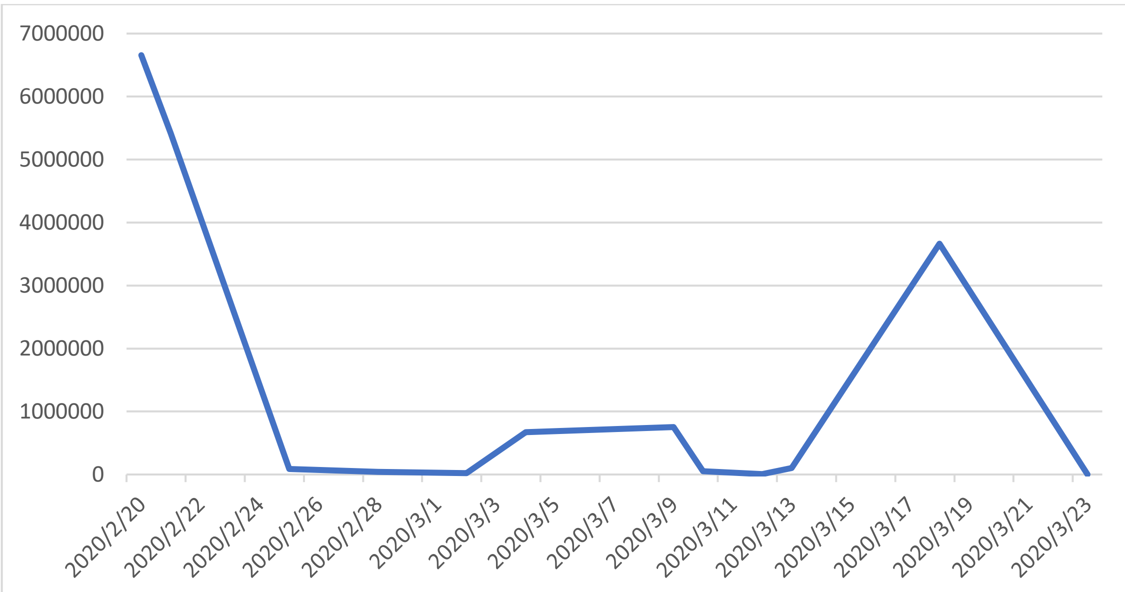


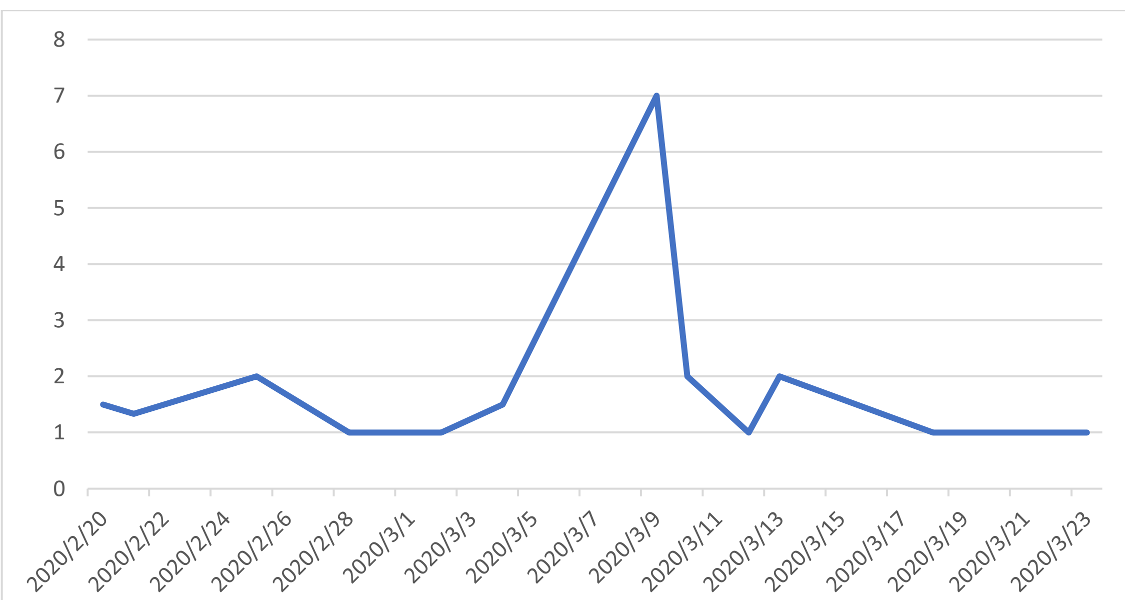
Figure A6: Insider Sell Transactions across Industries

By combining the CRSP database and the Thomson Financial Insider Trading database, we find the top 5 industries and the bottom 5 industries that formed the top-performing group and the bottom-performing group, respectively, during the 2020 stock market crash. This chart shows the dollar volume of insider sell transactions, the number of insider sell transactions, and the number of insiders engaged in sell transactions for the top and bottom performing groups.

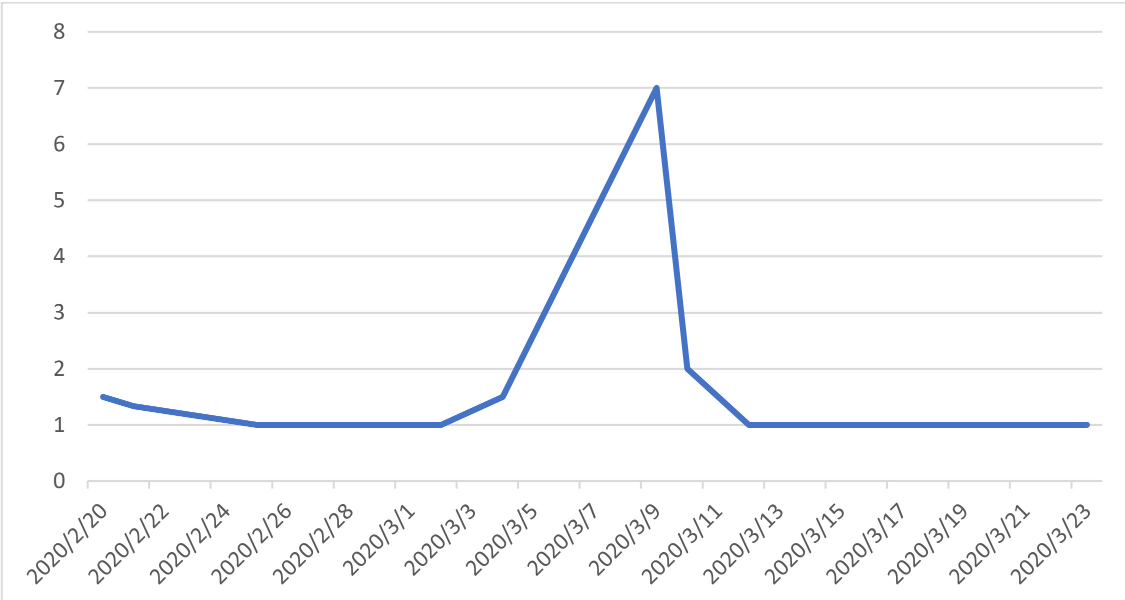
Panel A: Dollar Volume of Insider Sell Transaction for the Bottom-performing Industry Group



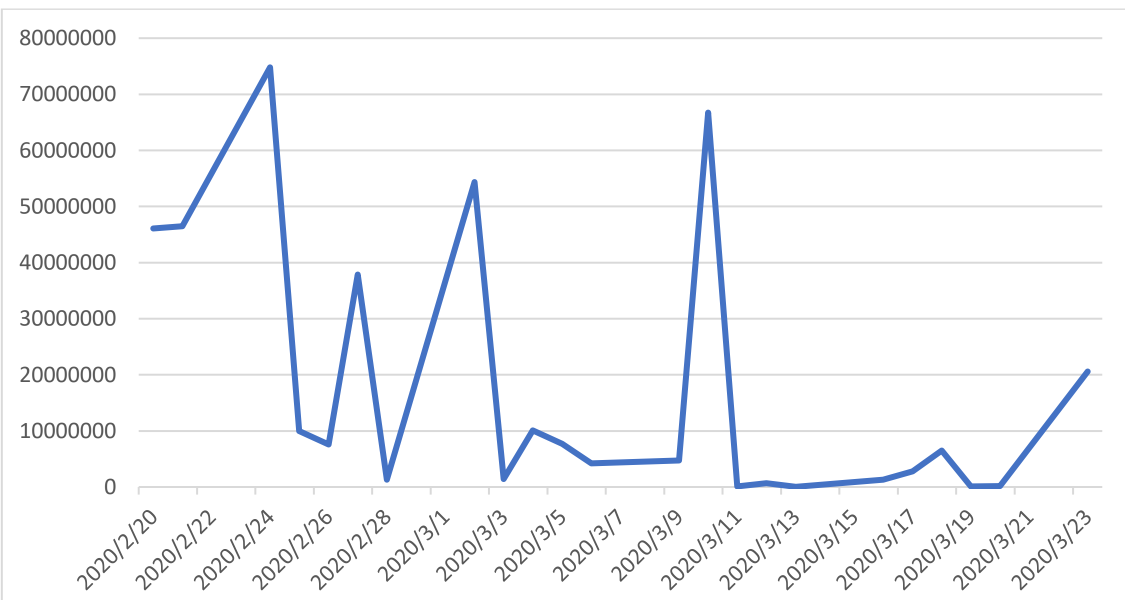
Panel B: Number of Insider Sell Transactions, Normalized by the Number of Firms with Insider Ownership, for the Bottom -Performing Industry Group



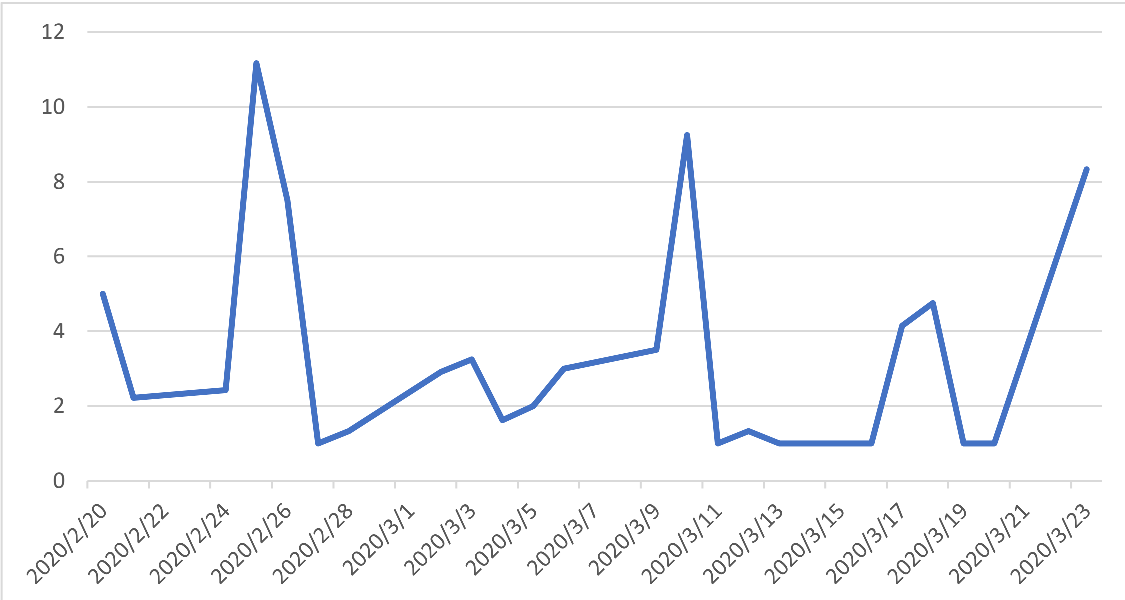
Panel C: Number of Insiders Engaged in Sell Transactions, Normalized by the Number of Firms with Insider Ownership, for the Bottom -Performing Industry Group



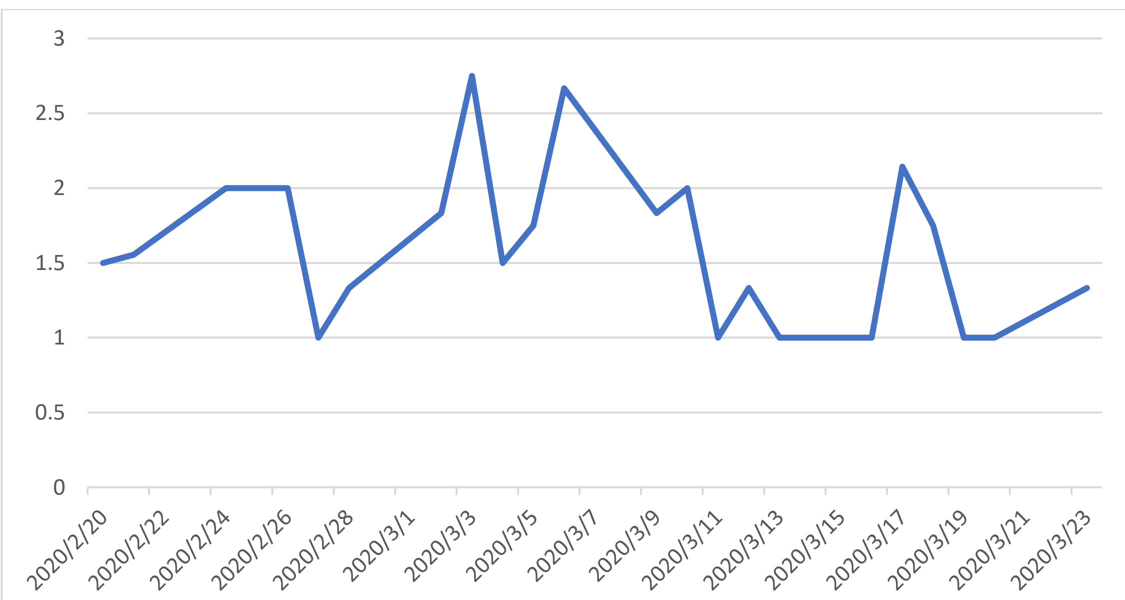
Panel D: Dollar Volume of Insider Sell Transaction for the Top-performing Industry Group



Panel E: Number of Insider Sell Transactions, Normalized by the Number of Firms with Insider Ownership, for the Top-Performing Industry Group



Panel F: Number of Insiders Engaged in Sell Transactions, Normalized by the Number of Firms with Insider Ownership, for the Top-Performing Industry Group



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