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Chapter 8

COVID-19 Effects on Intraday Stock Market Behavior

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Abstract

This chapter investigates the stock market implications of COVID-19 using high-frequency data. Our analysis covers three aspects. First, we compare intraday volatility patterns of the S&P 500 during COVID-19 with those before COVID-19. Second, we document changes to intraday return predictability of the S&P 500 before and during COVID-19. Third, we examine the Heston (1993) stochastic volatility model during COVID-19 and compare to previous market events. Our empirical findings suggest that, during COVID-19, there is more disagreement among market participants in processing new information, and market makers are more concerned about inventory risk.

8.1. Introduction

The COVID-19 pandemic has massively transformed our lives. Over 100 countries have implemented some form of lockdown in response to the pandemic, restricting the movement of a significant fraction of the world's population, which has greatly strained the global economy.

The rapid spread of COVID-19 also has had a major impact on financial markets, creating historically high levels of uncertainty.

Researchers have responded quickly to the onset of the COVID-19 pandemic. A novel literature centered around the financial market impact of COVID-19 has developed in a relatively short time frame. For example, Seven and Yilmaz (2020) examine the significant losses of equity markets worldwide in the first quarter of 2020 and find that fiscal support is positively associated with the subsequent recovery. Shehzad *et al.* (2020) apply the asymmetric power GARCH model to global equity markets and find that in some markets, COVID-19 resulted in higher volatility than the Global Financial Crisis (GFC), but in other markets, the GFC was associated with higher levels of volatility. These papers, and many others, have expanded our understanding of the financial market implications of COVID-19 in a timely manner, serving the important purpose of keeping policy-makers and investors informed.

While the literature around COVID-19 effects on financial markets has developed quickly, there has been limited insight into the intraday behavior of the stock market. We do not have a good grasp on the interaction among market participants throughout the trading day, or the resulting implications for market efficiency and risk management. We fill this gap by investigating the US stock market behavior before and during COVID-19 using high-frequency data, which allow us to compute more accurate volatility measures and provide a more granular view of stock market behavior.

Our investigation follows along three dimensions: the diurnal pattern of realized volatility, intraday return predictability, and the Heston (1993) model fit to intraday data. First, we construct realized volatility of the S&P 500, and we compare the intraday volatility pattern for trading days before and during COVID-19. Existing literature has document that intraday volatility tends to follow a "U" or a reverse "J" shape, with higher values near the open and the close (Andersen and Bollerslev, 1997; Harris, 1986). This observation can be attributed to clustered information incorporation into market prices at the open and market makers' inventory concerns at the market close. Consistent with the literature, we find that 30-minute realized volatilities follow a reverse "J" shape — highest at the open, lowest in the middle of the day, and high again in the final 30 minutes — for our full sample from 1998 to 2020. We divide the full sample into the COVID-19 period and the non-COVID period, and we find that intraday volatility is higher in every 30-minute interval during COVID-19 than the non-COVID sample: the percentage differences of 30-minute volatilities range between 68% and 149%. The annualized value of 30-minute volatilities averages 26% during COVID-19 versus 14% in the non-COVID sample. We also compare the intraday volatility pattern during COVID-19 to those in the 2001 recession and the Great Recession (2008). Volatilities during COVID-19 are 22–104% higher than the values in the 2001 recession, but do not appear to be significantly higher than those in the Great Recession.

The shape of diurnal volatility sheds light on potential changes in the behavior of market participants in different market events. We observe a "U" shape in the Great Recession and a reverse "J" shape during the 2001 recession. In contrast, there is a "J" shape during COVID-19: volatility is high at the open, low throughout the day, and highest in the final 30 minutes of trading. Furthermore, the opening and closing half-hours during COVID-19 have higher volatilities than the same half-hour periods in both the Great Recession and the 2001 recession. News about COVID-19 is often released in the evening after market close. Given our fear and lack of understanding of this novel disease, market participants can have a wide range of different interpretations of new information, which can contribute to elevated volatility at the market open. Concerns about uncertainty and market instability may motivate market makers to carry reduced overnight inventory during COVID-19 than usual, which may lead to higher volatility toward the end of the trading day as market makers trade more aggressively to reduce their inventory.

The second dimension we examine is intraday return predictability of the S&P 500 returns. We expand the analysis in Gao *et al.* (2018) to use non-overlapping, 30-minute returns to predict the returns in the final 30 minutes of the trading day. Using a different sample than Gao *et al.* (2018), we confirm there is strong predictive power for the final half-hour returns using the 1^{st} and 12^{th} half-hours. A 1% increase in the 1^{st} and 12^{th} half-hours is associated with a six- and ten-basis-point increase in the final half-hour, which is economically large considering that expected returns for the full trading day is about four basis points. Differing from Gao *et al.* (2018), we also uncover predictability for other half-hour periods, which can carry positive or negative coefficients depending on the time of day.

During COVID-19, the returns in the first half-hour continue to have strong positive predictive power for the returns in the final half-hour, but the general pattern for intraday predictability is different from the patterns for the full sample, the 2001 recession, or the Great Recession. In the COVID-19 sample, the most predictive periods for the final half-hour returns can be found in the middle of the trading day, rather than at the beginning or at the end. Furthermore, the economic magnitude of the predictive coefficients in the COVID-19 sample is several times larger compared to other samples.

Intraday return predictability is consistent with investors splitting up their orders into multiple trading sessions (Bogousslavsky, 2016), but this channel does not explain why the predictive coefficients are much larger during COVID-19. We conjecture that elevated inventory risk for market makers may be associated with the unique intraday return predictability pattern during COVID-19. Market makers who provide liquidity must trade in the same direction to unload their inventory. For example, if there is selling pressure during the trading day and market makers buy to meet this demand, they must sell before the market close to offset their long positions — downward price pressure during the trading day would lead to downward price pressure in the closing hours. If market makers are especially sensitive about inventory risk during COVID-19, the direction of order flow during the trading day may become more prominently related to the direction of flow in the closing hours. To the extent price pressure is reflected in returns, we would also observe stronger return predictability.

To complement our reduced-form analysis of volatility and predictability, we also take a structural approach to understand the behavior of volatility during COVID-19. We estimate the stochastic volatility model of Heston (1993) using intraday realized volatilities. The stochastic volatility process in the Heston (1993) model succinctly summarize the behavior of volatility using three parameters: speed of mean-reversion, long-run volatility, and volatility of volatility. We follow Ellickson *et al.* (2018) to estimate these parameters using the generalized method of moments (GMM; Hansen, 1982).

During COVID-19, mean-reversion of the volatility process was found to be lower compared to the recent past, indicating that volatility is behaving in less predictable ways and can deviate from its long-run average value for extended periods. The long-run volatility parameter in the Heston (1993) model is higher during COVID-19 than the preceding years, but not as high as the estimates during the Great Recession. Similarly, the volatility of volatility parameter is also high during COVID-19, but not as high as the values during the Great Recession. From the perspective of the Heston (1993) model, while COVID-19 is associated with increased volatility and the uncertainty around volatility, these increases are not unprecedented. The values are comparable to the period in 2008 around the Great Recession.

This chapter fits into the burgeoning literature on the COVID-19 implications for financial markets. Albulescu (2020) uses robust least squares to show increases in volatility associated with COVID-19. Zhang *et al.* (2020) demonstrate that global equity market volatilities and correlations have increased substantially in response to the pandemic. Just and Echaust (2020) use a Markov switching model to illustrate how the relationship between the S&P 500 returns and implied volatility changed during COVID-19. Compared to these papers, our focus on intraday returns and volatility patterns provides a new perspective and expands our understanding of the financial effects of COVID-19.

This chapter is also related to three additional strands of literature, tied together through the lens of COVID-19. The literature on intraday volatility patterns at least goes back to Wood *et al.* (1985) and Harris (1986). More recently, Andersen and Bollerslev (1997) illustrate how to incorporate seasonality into GARCH-family models for a better statistical fit of intraday volatility. The primary source we refer to for the intraday return predictability literature is Gao *et al.* (2018), who document significant predictive power in the 1^{st} and 12^{th} half-hours of the trading day for the final half-hour returns on the S&P 500. There is a large literature available on modeling and estimating stochastic volatility models. Ellickson *et al.* (2018) demonstrate that fitting Heston (1993) models to high-frequency data can capture the empirical behavior of intraday realized volatility. Compared to these papers, our contribution is to connect these seemingly disparate literatures through the lens of COVID-19. Through three complementary exercises studying intraday volatility and returns, we gain a better understanding of how COVID-19 has impacted the US stock market on an intraday level.

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The chapter is organized as follows. Section 8.2 studies the diurnal volatility patterns in COVID-19. Section 8.3 compares intraday return predictability before and during COVID-19. Section 8.4 explores the Heston (1993) model. Section 8.5 concludes.

8.2. Diurnal Volatility Pattern during COVID-19

8.2.1. *Data*

Intraday market data come from the New York Stock Exchange (NYSE) Euronext Trades and Quotes (TAQ) database. We obtain one-minute level data aggregated from the trade component of TAQ for the SPDR S&P 500 ETF, SPY. Data fields include the timestamp, open, high, low, close in each minute during NYSE trading hours. We use the closing price to calculate return bars, which are then used to compute volatility and longer-horizon return series. Our sample is from January 1998 to June 2020.

8.2.2. *Intraday volatility*

There is a well-documented diurnal pattern in volatility — squared price changes during the course of a trading day tend to form a "U" or a reverse "J" shape with larger fluctuations near the open and the close (Andersen and Bollerslev, 1997; Harris, 1986). This pattern can be attributed to clustered information dissemination at the market open and inventory concerns at the market close. We compare the pattern in intraday volatility before and during COVID-19 to assess whether information dissemination or inventory considerations are different between COVID and non-COVID periods.

We take the COVID-19 sample to be from February 1, 2020, to the end of our data set on June 8, 2020. The pandemic certainly did not end on June 8, and many countries continue to struggle with COVID-19 past this date. However, to facilitate research progress we had to fix our sample.

For each trading day, we construct realized volatilities in the following way. We compute one-minute log returns r_t of the S&P 500, and we define the cumulative sum of squared returns S_t as follows:

$$S_t = \sum_{t_i < t} r_{t_i}^2 \tag{8.1}$$

where r_{t_i} is the return from t_{i-1} to t_i. Realized variance is calculated in the same way as Corradi and Distaso (2006):

$$RV_{t,t+j} = S_{t+j} - S_t \tag{8.2}$$

We compute realized variances for each half-hour of the trading day. The realized half-hour variances are annualized through multiplying by 13×252, then we take the square root for annualized volatility figures.

The 13 half-hour volatilities have similar time series variation and are highly correlated with one another. Figure 8.1 plots the time series of realized volatilities from the 1st half-hour, from 9:30 am to 10 am Eastern Time, and the 13th (final) half-hour, from 3:30 pm to 4 pm Eastern Time. The two times series track each other closely; they have a correlation of 0.8. For the ease of exposition, other half-hour volatilities are not shown on the figure, but they are also highly correlated with the 1st and 13th half-hours. The half-hour volatilities

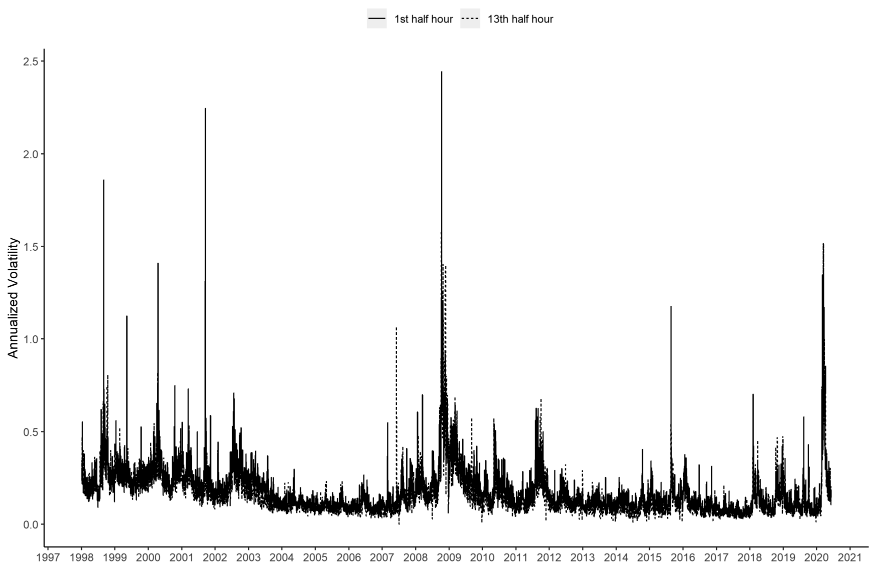

Figure 8.1. Time series variation of 1st and 13th half-hour volatilities.

Note: This figure plots the time series of realized volatilities from the 1st half-hour (9:30–10:00 am Eastern Time) and the 13th half-hour (3:30–4:00 pm Eastern time). Realized volatilities are annualized through multiplying by $\sqrt{13 \times 252}$.

also means move together closely with the daily realized volatility as well as the VIX index.

Although the 1st and 13th half-hour volatilities tend to co-move, they do not always behave in the same way. During 2001 and 2008, when macroeconomic conditions were poor, the 1st half-hour volatility was much higher than the 13th half-hour: in late 2001, the annualized volatility of the 1st half-hour jumped to over 200%, whereas the 13th half-hour volatility did not exceed 50%. In 2008, both volatilities rose sharply, with the 1st half-hour reaching almost 250% and the 13th half-hour passing 200%. There were also episodes, such as in 2007 and 2020, when the 13th half-hour volatility exceeded the 1st half-hour volatility. These differences illustrate that the diurnal pattern in volatility is time varying. Depending on the environment, we could see a "U," "J," or a reverse "J."

We calculate the time series averages of half-hour realized volatilities for the full sample, from January 1998 to June 2020. Figure 8.2 plots these intraday volatilities. The average volatility of the first

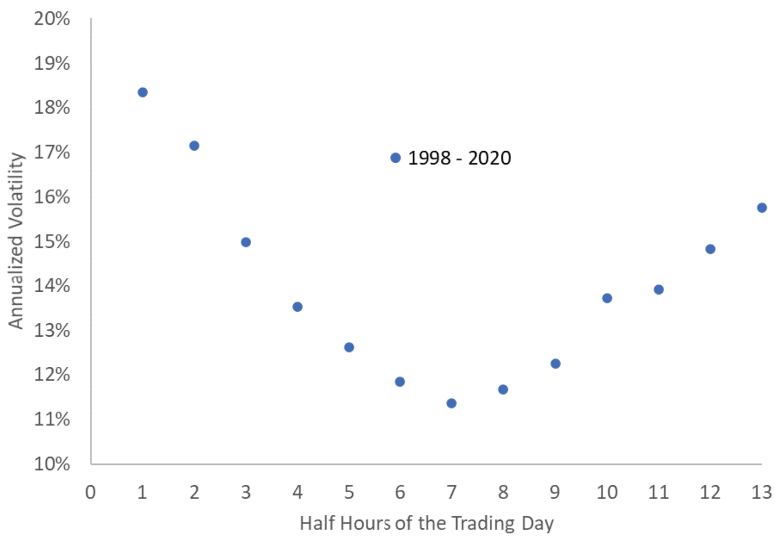

Figure 8.2. Unconditional diurnal volatility pattern.

Note: This figure plots the time series averages of realized volatilities by 30-minute intervals through the trading day. Half-hour volatilities are annualized through multiplying by $\sqrt{13 \times 252}$. The sample is from January 1998 to June 2020.

half-hour is the highest, the second half-hour is the second highest, and the final half-hour is the third highest. Trading hours in the middle of the day have markedly lower average volatilities than the values at market open or market close. This reverse "J" shape is consistent with the literature on intraday volatility, at least going back to Wood *et al.* (1985) and Harris (1986).

We turn our attention to comparing COVID-19 and non-COVID periods. Our COVID-19 sample starts on February 1, 2020. The first case of COVID-19 in the US was identified on January 20 (Holshue *et al.*, 2020). On January 30, the World Health Organization (WHO) declared a global health emergency, drawing the world's attention to the severity of COVID-19. January 31 marked the first major policy response to COVID-19: The Trump Administration restricted travel from China, further raising public awareness of the pandemic.

Our COVID-19 sample ends on June 8, 2020. The COVID-19 pandemic continues past this date, but we feel it is important to study existing data in a timely manner rather than to wait, much as the medical field has done. Insights from the medical research community have greatly improved our understanding of COVID-19 and influenced public policy responses, even though many results are based on limited data. Our understanding of COVID-19 will continue to evolve as additional data become available.

Figure 8.3 compares the diurnal volatility pattern during COVID-19 with the pattern in the non-COVID period. The non-COVID period includes all trading days prior to February 1, 2020. Volatility is significantly elevated during the COVID-19 sample than the non-COVID sample — each half-hour volatility is higher in the COVID-19 sample than the non-COVID sample, and the average of all 13 half-hour volatilities is 26% during COVID-19 versus 14% outside of COVID-19. The lowest half-hour volatility during COVID-19, which occurs in the sixth half-hour between 12 pm and 12:30 pm Eastern Time, is 21.5% — higher than the highest half-hour volatility in the non-COVID sample.

Volatility differences between the COVID and non-COVID periods are economically significant. During COVID-19, percentage differences in volatility to non-COVID days range from 68% (10^{th} half-hour) to 149% (13^{th} half-hour). COVID-19 presented the real economy with substantial challenges, which translated to higher uncertainty for investors in financial markets.

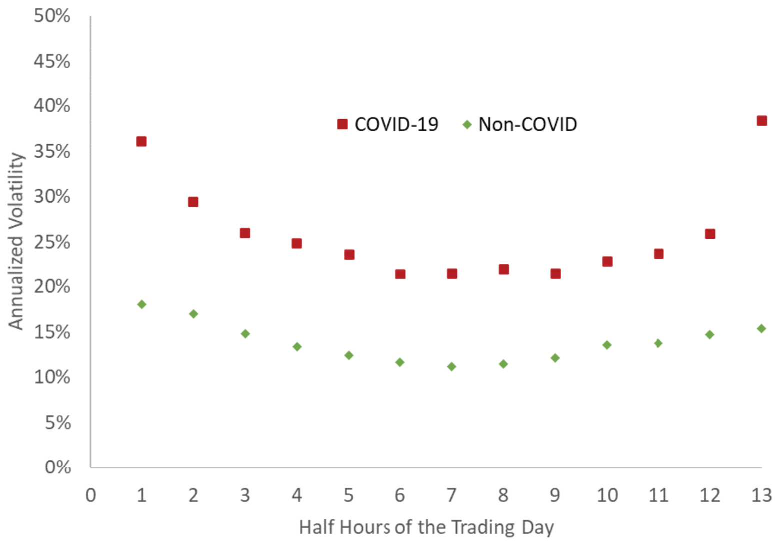

Figure 8.3. Diurnal volatility pattern in COVID-19.

Note: This figure plots the time series averages of realized volatilities by 30-minute intervals through the trading day. The COVID-19 period goes from February 1, 2020, to June 8, 2020 (the end of our sample), and the non-COVID period covers the remaining trading days from January 1998 to January 2020. Half-hour volatilities are annualized through multiplying by $\sqrt{13 \times 252}$.

The intraday volatility shape is also somewhat different between the COVID-19 and non-COVID periods. During COVID-19, we observe a "J" shape: at the beginning of the trading day, volatility is 36%, which gradually decreases throughout the trading day until around lunchtime (12 pm to 2 pm) before rising back up to end the trading day at 38%, slightly higher than the first half-hour. In the non-COVID sample, intraday volatility appears more like a reverse "J" shape. Volatility starts the day at 18% in the first half hour, which gradually decreases toward the middle of the day before rising back to 15% in the last half-hour.

The boom and bust of the technology sector in the late 1990s led to an economic recession in 2001, and the 2008 GFC was associated with the Great Recession. In these recessions, concerns about the real economy, rather than a pandemic, drove changes to the stock market. We compare the diurnal volatility pattern during COVID-19 to the recessions of 2001 and 2008. We refer to the National Bureau of

Economic Research (NBER) dating of US Business Cycle Expansions and Contractions for the recession dates. According to the NBER, the 2001 recession began in April 2001 and ended in November 2001. The Great Recession began in January 2008 and ended in June 2009.

Figure 8.4 compares the intraday volatility pattern during COVID-19 with those from the 2001 and 2008 recessions. Compared to the 2001 recession, intraday volatilities during COVID-19 are higher in every half-hour interval. The average across 13 half-hours for the 2001 recession is 18.5%, which is 40% lower than the 26% average during COVID-19. Looking at each half-hour separately, percentage differences in volatility are 22% (2^{nd} half-hour) to 104% (13^{th} half-hour) between COVID-19 and the 2001 recession.

Volatility levels during the Great Recession are clearly higher than those during the 2001 recession. Compared to volatilities in

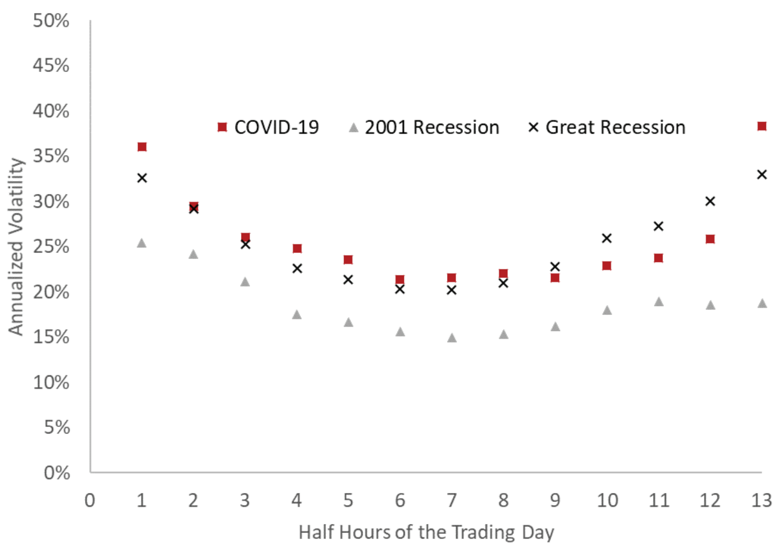

Figure 8.4. A comparison of diurnal volatility in COVID-19 and recessions.

Note: This figure plots the time series averages of realized volatilities by 30-minute intervals through the trading day. The COVID-19 period goes from February 1, 2020, to June 8, 2020 (the end of our sample). We use the NBER recession dates: the 2001 recession began on April 1, 2001, and ended November 30, 2001. The Great Recession began on January 1, 2008, and ended June 30, 2009. Half-hour volatilities are annualized through multiplying by $\sqrt{13 \times 252}$.

the Great Recession, COVID-19 volatility levels are not significantly higher. The 13 half-hour volatilities average to 25.5% during the Great Recession, almost as high as during COVID-19 (26%). COVID-19 volatilities tend to be higher in the first half of the trading day, but the volatilities during the Great Recession are higher in the afternoon from 1:30 pm to 3 pm Eastern time.

The shape of intraday volatility also differs across the stress events. Intraday volatility during COVID-19 makes a "J" shape — the final half-hour volatility is higher than the first half-hour, and the middle half-hours are the lowest. In comparison, the 2001 recession shows a reverse "J" shape, with the first half-hour volatility exceeding the final half-hour. Volatilities in the Great Recession show a symmetrical "U" shape: average volatility is 32.6% in the first half-hour, almost identical to 33% in the final half-hour.

What do the different intraday volatility patterns mean? Almost all earnings and major economic news are released before the market opens, so the market typically opens at such a level that reflects the new information (Gao *et al.*, 2018). Elevated volatility at the beginning of trading day reflects information processing by the market participants; disagreement among market participants leads to fluctuations in prices. Institutional investors tend to place strong emphasis on the closing stock prices (Cushing and Madhavan, 2000; Foucault *et al.*, 2005)). Market makers are also concerned with the closing minutes of the trading day, seeking to unload inventory to avoid overnight risk exposure. Volatility near the end of a trading day reflects inventory concerns as well as institutional investor's concerns about market stability.

During COVID-19, volatilities are higher than other samples for the opening and closing half-hours. News about COVID-19 is often released in the evening, after the end of the trading day. Given our limited understanding of COVID-19, investors may have drastically different assessments of new information, which can contribute to disagreement about new price levels, leading to elevated volatility at the beginning of the trading day. The same concern about uncertainty and market instability could lead to high volatility toward the end of the trading day. Market makers are especially motivated to not take on overnight risk during COVID-19, since inventory risk is magnified as the overall volatility in financial markets is substantially higher.

8.3. Intraday Return Predictability

Gao *et al.* (2018) document that the S&P 500 returns in the 1^{st} and 12^{th} half-hour of the trading day have significant predictive power for the returns in the final half-hour. Their findings are consistent with investors splitting up their order into multiple trading sessions (Bogousslavsky, 2016), or informed trading in the last half-hour in the same direction as the first half-hour. We expand this analysis to document the predictive power of each half-hour, thereby constructing an intraday pattern of the predictive coefficients for the S&P 500. We compare the predictability pattern before and during COVID-19 to see whether the pandemic has caused any changes to this intraday market dynamic.

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We follow Gao *et al.* (2018) to divide the trading day into 13 half-hour intervals. We run predictive regressions forecasting the final half-hour (3:30 pm to 4 pm Eastern Time) of S&P 500 returns:

$$r_{t,13} = \alpha + \beta r_{t,j} + \epsilon_t \tag{8.3}$$

where $r_{t,13}$ is the return on the S&P 500 index in the 13^{th} half-hour on day t; $r_{t,j}$ is the return in the j^{th} half-hour; and β is the predictive coefficient. We are interested in the sign and magnitude of β.

Table 8.1 presents the predictive regression results. Consistent with the findings in Gao *et al.* (2018), our full-sample results from 1998 to 2020 shows strong predictive power for the 1^{st} and 12^{th} half-hours.[1] A 1% increase in the returns in the first 30 minutes of the trading day is associated with a six-basis-point increase in the final half-hour, and a 1% increase in the 12^{th} half-hour returns is associated with a ten-basis-point increase in the final half-hour. Considering that the expected returns for the S&P 500 is about three or four basis points for the entire day, these predictive coefficients are economically large. Both coefficients are statistically significant at the 1% level, consistent with the statistical significance shown in Gao *et al.* (2018).

Aside from the 1^{st} and 12^{th} half-hours, Gao *et al.* (2018) do not emphasize the forecasting power of other periods. We find that the 2^{nd}, 4^{th}, 5^{th}, and 11^{th} half-hours all exhibit some predictability for

[1]The sample in Gao *et al.* (2018) is from 1993 to 2013.

Table 8.1. Intraday return predictability of half-hour returns.

Half-Hour Time (Eastern US)	**1** **9:30 am–10 am**	**2** **10 am–10:30 am**	**3** **10:30 am–11 am**	**4** **11 am–11:30 am**	**5** **11:30 am–12 pm**	**6** **12 pm–12:30 pm**
1998–2020	0.06^{***}	0.06^{***}	0.03	0.03^{*}	0.11^{***}	0.00
	(9.1)	(4.0)	(1.6)	(1.7)	(5.2)	(0.1)
COVID-19	0.08^{*}	0.25	-0.67^{***}	−0.10	0.61^{**}	−0.11
	(1.8)	(1.4)	(−3.7)	(−0.7)	(2.3)	(−0.4)
Great recession	0.17^{***}	0.02	0.03	−0.03	-0.50^{***}	0.12
	(3.9)	(0.2)	(0.2)	(−0.3)	(−3.6)	(0.9)
2001 recession	0.01	−0.03	−0.01	−0.12	−0.04	−0.13
	(0.4)	(−0.5)	(−0.1)	(−1.3)	(−0.4)	(−1.2)
Half-Hour Time (Eastern US)	**7** **12:30 pm–1 pm**	**8** **1 pm–1:30 pm**	**9** **1:30 pm–2 pm**	**10** **2 pm–2:30 pm**	**11** **2:30 pm–3 pm**	**12** **3 pm–3:30 pm**
1998–2020	-0.05^{**}	−0.01	-0.07^{***}	0.03	0.05^{***}	0.10^{***}
	(−2.1)	(−0.4)	(−3.1)	(1.6)	(2.7)	(6.5)
COVID-19	−0.07	−0.16	−0.19	0.03	0.40^{**}	−0.03
	(−0.4)	(−0.7)	(−0.8)	(0.1)	(2.2)	(−0.1)
Great Recession	0.04	0.03	0.16	-0.18^{*}	0.00	0.14
	(0.3)	(0.2)	(1.1)	(−1.7)	(0.0)	(1.4)
2001 recession	0.06	−0.07	-0.23^{**}	0.02	-0.20^{**}	0.21^{***}
	(0.6)	(−0.6)	(−2.3)	(0.3)	(−2.3)	(2.5)

Note: This table presents the forecasting coefficients in the following predictive regressions:

$$r_{t,13} = \alpha + \beta r_{t,j} + \epsilon_t$$

where $r_{t,13}$ is the return of the S&P 500 index in the 13^{th} half-hour of the trading day (3:30 pm to 4 pm Eastern Time) on day t, and $r_{t,j}$ is the return in the j^{th} half-hour. T-statistics are shown in parentheses. Statistical significance at the 10%, 5%, and 1% levels are shown with *, **, ***, respectively.

the 13th half-hour with positive coefficients of varying magnitudes, whereas the 7th and 9th half-hours have significantly negative coefficients. In particular, the 2nd, 5th, and 11th half-hours have positive coefficients that are significant at the 1% level. These predictive coefficients are on the same magnitude as those for the 1st and 12th half hours. The 4th half-hour shows a smaller coefficient of 0.03, significant at the 10% level. The 7th and 9th half-hours show predictive coefficients of –0.05 and –0.07, significant at the 5% and 1% levels, which are about the same size as the 1st half-hour but with the opposite sign. Predictability for the final half-hour of S&P 500 returns does not appear to be limited to the 1st and 12th half-hours; other half-hour intervals also exhibit significant predictability.

Intraday return predictability during COVID-19 shows a different pattern compared to the full sample. Since our COVID-19 sample only spans four months, we must be aware of sampling variation when interpreting the results. In a small sample, the point estimates are consistent, but the sizable standard errors make statistical inference more difficult. With this caveat in mind, let us compare the predictive coefficients during COVID-19 with those from the full sample.

In the COVID-19 sample, we continue to observe significant predictability in the 1st half-hour, and the predictive coefficient of 0.08 is close to the full-sample estimate of 0.06. Given the much shorter sample of COVID-19 compared to the full sample, the statistical significance on this coefficient is lower — it is significant at the 10% level, rather than the 1% level for the full sample. We also find significant predictive power for the 5th and 11th half-hours, consistent with the full-sample results. However, we no longer observe predictability for the 12th half-hour. In fact, its predictive coefficient during COVID-19 has a negative point estimate of –0.03, which stands in contrast to the full-sample estimate of 0.10. The 3rd half-hour, which does not predict the final half-hour in the full sample, shows a negative and large coefficient during COVID-19. Evidently, serial correlation of intraday returns shows substantial differences during COVID-19 compared to the full sample.

The economic magnitude of return predictability during COVID-19 also appears to be different compared to the full sample. The size of predictive coefficients is up to six times larger compared to the coefficients in the full sample. Even time periods that do not show statistically significant predictability may contain economically large coefficients, such as 0.25 for the 2nd half-hour, which is two to four times larger compared to the full sample predictive coefficients.

The Great Recession and the 2001 recession are associated with substantial negative shocks to the financial markets, although for different reasons than the COVID-19 pandemic. During the Great Recession, the first half-hour is the only period that contains a significant and positive predictive coefficient for the final half-hour of S&P 500 returns. The 5th and 10th half-hours have economically large negative coefficients: a 1% increase in the S&P 500 returns between 11:30 am and 12 pm is associated with a 50-basis point decrease of the S&P 500 returns between 3:30 pm and 4 pm, and a 1% increase in returns between 2 pm and 2:30 pm is associated with an 18-basis-point decrease. While the predictive coefficients are economically large for the 6th and 12th half-hours, they are not statistically significant at conventional levels.

In the 2001 recession, the morning trading hours do not exhibit predictive power for the final 30 minutes of S&P 500 returns. The 9th and 11th half-hours have rather large negative coefficients, –0.23 and –0.20. These values imply that a 1% increase in the 9th or 11th half-hour returns is associated with a 23- or 20-basis-point decline in the final half-hour of the S&P 500. The 12th half-hour has an economically and statistically large positive predictive coefficient for the 13th half-hour.

The Great Recession and the 2001 recession exhibit different patterns for intraday return predictability. For the Great Recession, the morning trading hours have stronger predictability, whereas the afternoon hours have stronger predictability during the 2001 recession. Return predictability during COVID-19 also appears to follow a distinct pattern, not resembling either recession. The most predictive periods are during the middle of the trading day, rather than at the beginning or toward the end, and the economic magnitude of return predictability is greater than any other period. Indeed, COVID-19 appears to have disrupted the normal stock market dynamics over the course of the trading day. While the channel proposed by Bogousslavsky (2016) still may be consistent with return predictability in the COVID-19 sample, predictive coefficients much larger than other samples suggest there may be additional drivers.

The diurnal volatility pattern during COVID-19 suggests more trading toward the end of the day, perhaps due to market makers concerned about increased inventory risk during a highly uncertain period. To the extent intraday returns reflect the demand of market participants, market makers who take the offsetting side of these transactions must trade in the same direction to unload their inventory. For example, if there is selling pressure during the trading day and market makers buy to meet this demand, they must sell before the market closes to offset their long positions. Selling pressure during the trading day translates to selling pressure of market makers at the end of the trading day, and any downward price pressure in these time periods would lead to a positive relationship between the returns. If market makers are especially sensitive about inventory risk during COVID-19, the direction of order flow during the trading day may become more prominently related to the direction of order flow in the closing hours. To the extent returns reflect demand, we would observe stronger return predictability.

8.4. Intraday Stochastic Volatility

Ellickson *et al.* (2018) show that the instantaneous volatility process can be described by the Heston (1993) model of stochastic volatility. We estimate Heston models using intraday data before and during COVID-19 to compare model parameters such as the volatility of volatility and the mean-reversion speed of the stochastic volatility component. This structural approach complements our reduced-form volatility analysis to uncover differences in volatility dynamics before and during COVID-19.

The stochastic volatility model of Heston (1993) assumes that price $X(t)$ follows a stochastic differential equation:

$$dX_t = \mu X_t dt + \sqrt{V}_t dW_t \tag{8.4}$$

where W_t is a Brownian motion, μ is the instantaneous mean, and $\sqrt{V}_t$ is the conditional volatility. The variance process V_t follows its own stochastic process:

$$dV_t = \kappa(\underline{c} - V_t)dt + \gamma\sqrt{V}_t dB_t \tag{8.5}$$

where B_t is a second Brownian motion, possibly correlated with W_t; $\underline{c}$ is the asymptotic mean of the variance process, also known as the long-term equilibrium level of variance since V_t mean-reverts towards $\underline{c}$; and κ is the rate of mean-reversion for the variance process V_t. A larger κ means faster reversion to the long-run variance level $\underline{c}$, whereas a smaller value for κ indicates slower mean-reversion. γ is the "volatility of volatility" that determines the variance of V_t.

A typical calibration of the Heston (1993) model uses Equations (8.4) and (8.5) to calculate parameter values from prices and returns. Ellickson *et al.* (2018) advocate estimating Equation (8.5) using intraday realized volatility, because realized volatility can provide a more precise measurement of the latent volatility process (Andersen and Bollerslev, 1997). We follow the estimation strategy laid out in Ellickson *et al.* (2018), which uses the generalized method of moments (Hansen, 1982) to estimate the model parameters. Because we do not use Equation (8.4) in our estimation strategy, the drift parameter μ and the correlation between the two Brownian motions are not parameters of interest. We focus on the three parameters in Equation (8.5): mean-reversion speed κ, the long-run variance $\underline{c}$, and the volatility of volatility γ.

We estimate the Heston (1993) model using 30-minute realized volatilities. At the end of each month, we use the preceding two months (44 trading days, $13 \times 44 = 572$ observations) to estimate the Heston model. We obtain three series that allow us to investigate the time variation in the stochastic volatility process.

Figure 8.5 plots the mean-reversion parameter over time. For the ease of exposition, we present the three-month moving average. A larger value indicates a stronger tendency to revert to the long-run average volatility level, whereas a smaller value indicates weaker mean-reversion and a greater likelihood that the volatility deviates from the long-run average for an extended period.

From 1998 to 2020, the average mean-reversion parameter value is 0.28. There is substantial variation around this average value, especially before 2005. During times of economic stress, such as the recession in 2001 and the Great Recession of 2008, the mean-reversion parameter tends to decrease to around 0.1. In the COVID-19 sample, we observe a similar decrease in this mean-reversion parameter to a level below the unconditional average. It appears the uncertainty created by COVID-19 is associated with volatility behaving in less predictable ways, deviating from its average value for longer periods.

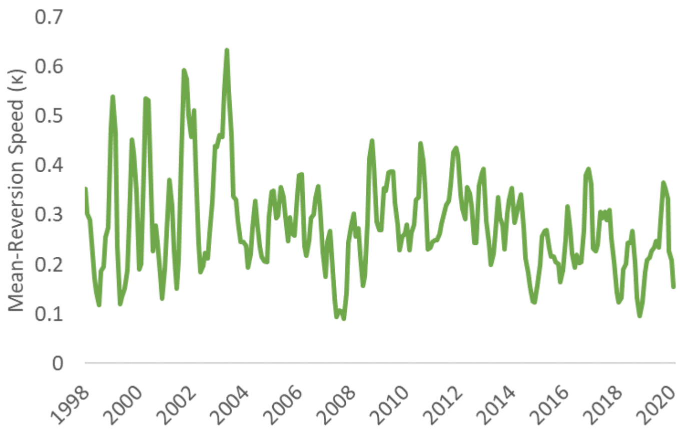

Figure 8.5. Mean-reversion speed of stochastic volatility in the Heston (1993) model.

Note: This figure shows the mean-reversion parameter in the Heston (1993) model, as a three-month moving average. Each month, the Heston (1993) model is estimated using two months (44 trading days) of 30-minute realized volatilities. The sample is from January 1998 to May 2020.

Figure 8.6 presents the long-run volatility in the Heston model from 1998 to 2020. This parameter was subdued in the mid-2000s and in the 2010s, consistent with the low VIX index during those periods. We observe a large positive move during the Great Recession and a similar sharp rise during COVID-19. However, the level of long-run volatility during the Great Recession is higher than the level during COVID-19. While the long-run volatility during COVID-19 appears quite high locally, especially compared to the single-digit VIX environment just prior to the pandemic, the long-run volatility parameter during the Great Recession is twice as high as the value during COVID-19. This finding is consistent with Figure 8.1, which shows that intraday realized volatility during COVID-19 is high relative to recent years, but not as high as the most volatile months during the Great Recession.

Figure 8.7 presents the volatility of volatility parameter in the Heston (1993) model. The prominent peak of the volatility of volatility parameter during the Great Recession resembles the long-run volatility pattern in Figure 8.6. During crisis periods, not only is market volatility higher than usual but also it is more difficult to precisely measure volatility. The volatility of volatility parameter dropped to

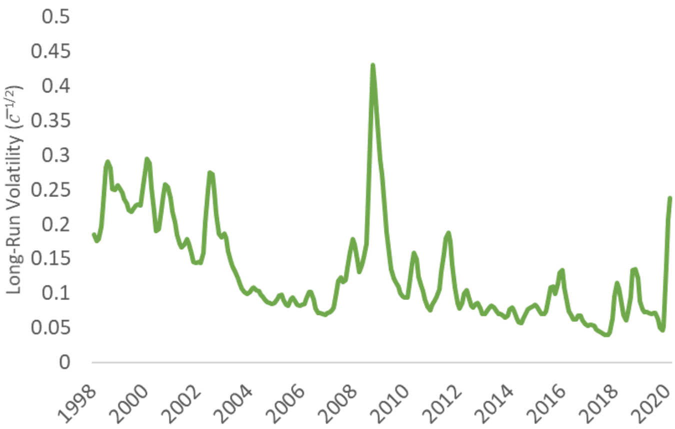

Figure 8.6. Long-run volatility in the Heston (1993) model.

Note: This figure shows the long-run volatility parameter in the Heston (1993) model, as a three-month moving average. We take the square root of the long-run variance, $\underline{c}$ to be the long-run volatility. Each month, the Heston (1993) model is estimated using two months (44 trading days) of 30-minute realized volatilities. The sample is from January 1998 to May 2020.

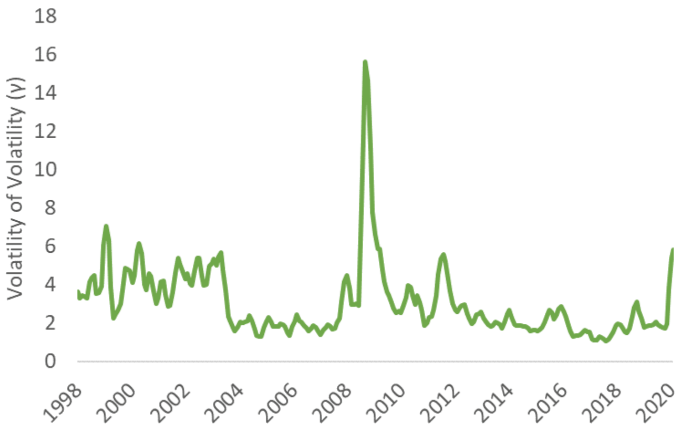

Figure 8.7. Volatility of volatility in the Heston (1993) model.

Note: This figure shows the volatility of volatility parameter in the Heston (1993) model, as a three-month moving average. Each month, the Heston (1993) model is estimated using two months (44 trading days) of 30-minute realized volatilities. The sample is from January 1998 to May 2020.

very low values in the decade following the Great Recession, and only rose again in the COVID-19 sample. Although the volatility of volatility parameter during COVID-19 appears large compared to the preceding years, it is not as high as during the Great Recession. Indeed, there were numerous disruptions to the financial sector as well as the real economy during the Great Recession.

Prior to 2005, intraday trading was not as developed as the succeeding years. During this period, trading volumes were relatively low, as there were often large time gaps between valid trades. As such, intraday data prior to 2005 reflect poorer data quality in a less mature and less liquid market. In the preceding figures, the apparent noise in the Heston (1993) model parameters prior to 2005 is reflective of this underlying shift in market maturity and microstructure.

The Heston (1993) model gives us a structural way of looking at the behavior of volatility during COVID-19. The three parameters governing the stochastic volatility process shed light on the behavior of intraday volatility. First, the mean-reversion parameter is lower during COVID-19 than earlier years, because volatility behaves in less predictable ways during COVID-19 and can deviate from its long-term average for extended periods. This behavior is similar to that observed in the Great Recession, and the mean-reversion parameter estimate during COVID-19 resembles the value in the Great Recession.

Second, the long-run volatility parameter in the Heston (1993) model is higher during COVID-19 than recent years prior to COVID, but not as high as the long-run volatility estimate in the Great Recession. COVID-19 certainly marks significant disruptions and uncertainty in the financial markets, but apparently to a lesser extent than the most volatile times during the Great Recession. Third, volatility of volatility tells us about the uncertainty around volatility and how precisely we can estimate it. The uncertainty associated with COVID-19 has translated into higher volatility of volatility compared to recent years, but not as high as the values during the Great Recession.

8.5. Conclusion

In this chapter, we provide a unique perspective of the financial market implications of COVID-19 using intraday data. Consistent with existing studies, we find higher intraday volatility during COVID-19 compared to non-COVID periods. Volatilities in COVID-19 are also higher than those in the 2001 recession, but not significantly higher than the volatilities in the Great Recession. In fact, the most volatile months during the Great Recession are more volatile than the COVID-19 sample.

Stock return predictability during COVID-19 shows strong predictive power for the trading hours in the middle of the day, rather than at the beginning or at the end as Gao *et al.* (2018) documented. Our intraday volatility and return predictability results suggest that during COVID-19, there is more investor disagreement about new information and market makers are more concerned about inventory risk. GMM estimation of the Heston (1993) stochastic volatility model reveals that while COVID-19 is associated with increased volatility and uncertainty, this uncertainty is comparable to the Great Recession.

While the stock market has become more volatile as a response to COVID-19, some market participants may be well-positioned to benefit from such volatility. The economically large intraday return predictability is not only important in characterizing the behavior of stock market returns but also economically significant for investors who have the resources to implement trading strategies that capture this empirical observation. In a similar vein, with higher inventory risk, market makers who are able to appropriately manage their inventory risk during COVID-19 may be rewarded with a stronger competitive position. With fewer market makers willing to take inventory risk, the economic profit of market-making activities also likely goes up. On the flip side, investors who are not positioned to benefit from the elevated volatility levels would be better served by taking a long-term view rather than focus on the elevated day-to-day stock market fluctuations.

The far-reaching effects of COVID-19 will take time to be fully understood. In order to formulate appropriate policy responses as well as prepare for the next pandemic, we need to better understand not only the medical and social effects surrounding COVID-19 but also its implications for financial markets. While we take a step toward improving our understanding of the financial market impact of COVID-19, much more remains to be done. It would be interesting to study market reactions to particular events, such as the first confirmed infection in the US or the unscheduled Federal Open Market

Committee meetings of the Federal Reserve. Establishing a connection between intraday volatility patterns and investor behavior could be another fruitful direction.

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