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## Article

# Does an overconfidence bias affect stock return, trading volume, and liquidity? Fresh insights from the G7 nations

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# Does an overconfidence bias affect stock return, trading volume, and liquidity? Fresh insights from the G7 nations

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## ABSTRACT

The article extends the empirical literature on overconfidence bias in G7 stock markets during pre- and post-COVID-19 and provides additional evidence. Using vector autoregression and impulse response functions (IRFs), we analyze the overconfidence bias for the daily data from January 2015 to December 2021. Because the pertinent coefficients are positive and highly significant for only a few lags, there is a strong contemporaneity between market volume and market return in the pre-COVID-19 period of the Canadian and Italian stock markets. The study shows compelling evidence of overconfident behavior in the Italian market during the COVID-19 crisis. Along with trading volume, market liquidity influences overconfidence bias, which tracks market return but not vice versa. For investors, decision-makers, and market regulators, the study has significant ramifications in the current market turbulence caused by the COVID-19 pandemic. Furthermore, overconfidence contributes to the reported extra unpredictability due to the high level of sensitive data.

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## 1. Introduction

Global epidemics such as SARS, the H7N9 virus, the Ebola virus, and the COVID-19 pandemic have all occurred in the current century. Most studies that examined how these outbreaks affected the performance of the international stock markets found that they had a negative impact (Ali et al., 2020). Goodell (2020) asserts that the current COVID-19 pandemic has a detrimental effect on the global economy. The stock market's performance has suffered the most harm due to the epidemic (Hassan et al., 2020; Rabbani et al., 2022; Shaik et al., 2023; Sharif et al., 2020). In the financial markets, the COVID-19 crisis significantly increased unpredictability and instability (Hassan et al., 2021, 2022). Investors in the financial market consistently make mistakes and display a variety of behavioral biases that affect their judgment (Boussaidi, 2022). "Overconfidence Bias" is one of these biases. This bias is pronounced during times of crisis when investors engage in excessive trading and the market is very volatile (Gupta et al., 2018). Heimer et al. (2020) provide evidence that people expect to be exposed to COVID-19 on a much smaller personal scale than the general population, leading to the phenomenon known as overconfidence, which is defined as the difference between the expected public and private dangers. In a different study, Apergis (2022) found that households with younger people and higher incomes tend to have higher

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rates of overconfidence. In other words, respondents from higher-income groups view their risk as higher than those from lower-income groups because they think they will be less exposed to COVID-19 than the general population. Their research indicates that behavioral biases contribute to the spread of COVID-19.

Numerous behavioral and empirical studies have found that individuals frequently demonstrate overconfidence in various circumstances. These studies' results identify three major overconfidence elements: individual miscalibration, the better-than-average effect, and self-attribution. Miscalibration happens when individuals overstate the accuracy of their information (Glaser et al., 2013; Kumar & Prince, 2022; Nair & Shiva, 2023; Soll, 1996). The better-than-average effect suggests that individuals exaggerate their talents in contrast to others and consider themselves beyond what is considered normal (Larrick et al., 2007). The bias toward self-attribution relates to individuals' misperception of controlling unexpected outcomes, assigning success to their talent and failure to external circumstances or poor fortune (Harper et al., 2023).

Inspired by the body of studies, boopen-accessth theoretical and empirical investigations in the field of behavioral finance have represented how investors act as an exaggeration of the reliability of their confidential data sources (Mahjoubi & Henchiri, 2024; Phan et al., 2020; Shrotryia & Kalra, 2023). They demonstrate that overconfidence impacts investors' behavior in securities markets and leads to inappropriate responses to sensitive data, a rise in trading quantity, as well as exorbitant stock price volatility (Abbes, 2013; Abbes Boujelbene et al., 2009; Azam & Baig, 2023; Boussaidi, 2022; Fayyaz Sheikh & Riaz, 2012; Kuranchie-Pong & Forson, 2022; Siwar, 2011; Zia et al., 2017).

Overconfidence bias overestimates one's intuitive thinking, judgments, and cognitive ability (Pompian, 2006). As a result, investors trade more frequently than ordinary investors, resulting in lower returns (Nofsinger, 2001). Also, during the COVID-19 pandemic scenario, a plethora of studies have been done (Azam et al., 2022; Kumar & Prince, 2022; Kuranchie-Pong & Forson, 2022; Mahjoubi & Henchiri, 2024; Shrotryia & Kalra, 2023). Still, it is the first paper that added liquidity as one of the endogenous variables other than market volume and returns to examine overconfidence bias when investors have experienced pessimism and loss of confidence. With this gap, the author attempts to answer a set of research questions; does overconfidence bias impact the G7 countries? contemporary did the outbreak of COVID-19 affect trading activity, and is there any difference between the contemporaneous relationship between market volume, market return, and market liquidity in pre-COVID-19 and during COVID-19 periods?

The study makes use of literature on market mood or optimism. This body of work illustrates that financial market movements are driven by the psychological perception of specific operations or deals, which may result in mispricing and force investors to accept lower returns than anticipated (Kinari, 2016). Prices might differ from economic fundamentals due to changes in sentiment (Kumar & Prince, 2022). Moreover, research by Statman et al. (2006) and Hirshleifer and Shumway (2003) demonstrates that investors need to be more rational. According to these studies, investors must rely on something other than traditional finance theories' rational assumptions. In other words, they are influenced by their emotions and can, as a result, make cognitive errors while making investment decisions (for example, they may be overconfident in their abilities).

The COVID-19 pandemic brought devastation never seen before, including stock markets and investors' sentiments in the stock market (Abdulla & Rabbani, 2021; Dharani et al., 2022; Habeeb et al., 2021; Karim, Rabbani et al., 2022; Naeem et al., 2023). Standard & Poor's 500-stock index dropped 19.4%, while the Dow Jones Industrial Average benchmark sank 8.9%. Technology companies were among the lowest performers, falling around 2 and 66%. % According to Haworth, the effect of COVID-19 on stock markets in 2023 will be far less severe than earlier in the pandemic outbreak (Hassan et al., 2020; Rabbani et al., 2021, 2022). The COVID-19 pandemic has contributed to increased volatility & financial inactivity. The correlation between stock returns and unpredictability has increased throughout the COVID-19 epidemic (Dong et al., 2022; Farid et al., 2022). Interestingly, the market's turmoil and volatility led to an overestimation and overconfidence bias in the stock market. Overconfidence bias frequently causes investors to exaggerate their knowledge about the stock market or particular securities while ignoring facts and professional advice. This frequently leads to inappropriate efforts to predict market movements or establish preponderance in unsafe investments that individuals regard as certainties (Azam & Baig, 2023; Naveed & Taib, 2021; Parhi & Pal, 2022).

The current study emphasizes COVID-19 and overconfidence bias in the G7 countries, which account for roughly 40% of global GDP and have the most significant market capitalization and trading activity (Izzeldin et al., 2021). We present evidence for overconfidence bias and its persistence in G7 pre- and post-COVID-19 subsamples. We investigate overconfidence bias in daily data from January 2015 to December 2021 using vector autoregression and impulse response functions (IRFs). Vector autoregression (VAR) is a mathematical framework that describes the connection among many variables as they evolve over time. It constitutes a stochastic process framework. VAR frameworks extend the single-variable (univariate) self-regressive framework by using multidimensional time series data (Maghyereh et al., 2019; Tabassum et al., 2024). VAR (vector autoregression) is an extension of AR (autoregressive model) for several time-series data that determines the linear connection between them (Huang et al., 2022; Neaime et al., 2018). Impulse response functions (IRFs) are capable of and utilized to investigate the dynamic impact of structural fluctuations on financial parameters. To create IRFs, construct a VAR (vector autoregression) model to determine the structure-specific disruptions that align with the error elements (Apostolakis et al., 2021; Zouaoui & Zoghلامي, 2020).

Only a few studies examine the relationship between COVID-19 and overconfidence bias. Azam et al. (2022) examined the overconfidence bias in 12 cyclical and defensive sectors and compared the COVID and non-COVID periods. Kuranchie-Pong et al. (2022) examined the overconfidence bias and stock market volatility in Ghana. Another study by Shrotryia and Kalra (2023) compared the overconfidence bias in developed, emerging, and frontier markets. Our study offers three unique contributions to the existing strand of literature. First, we examine the overconfidence Bias in pre- and during the COVID-19 period for G-7 countries. Second, we added liquidity as one of the endogenous variables along with market volume and market return, which is only found in some studies that measure overconfidence bias. Third, the sample span included in the study is significant. Most studies have taken only the COVID-19 period to study its impact.

The study finds a highly contemporaneous relationship between market volume and market return is pronounced in the Canadian and Italian stock markets in the pre-COVID-19 period because the relevant coefficients are positive and highly significant for a few lags. During the COVID-19 crisis, there is strong evidence of overconfident behavior in the Italian market. Besides trading volume, overconfidence bias is also driven by market liquidity and follows market return but not vice versa. The results strengthened the case for a positive effect, with high-income people leading to a more prominent feeling of market overconfidence. The COVID-19 illness and its rapid spread appear to have affected people's risk views and behaviors, particularly those of investors. Therefore, effective communication from government agencies and financial regulators is essential for disseminating correct information and minimizing psychological (behavioral) effects.

The remainder of the article is organised as follows: Section 2 represents the literature review, and data and methodology are presented in Section 3. Empirical results and a discussion are included in Sections 4 and 5, which deal with the study's conclusion.

## 2. Review of literature and hypothesis development

### 2.1. Theoretical foundations

Behavioral finance studies investor psychology and its impact on the financial market (Kinari, 2016; Kuranchie-Pong & Forson, 2022; Naveed & Taib, 2021). It examines how investors base their decisions on personal biases and intuitions rather than facts and principles (Hirshleifer, 2015). Many behavioral biases have been found in finance literature, including overconfidence bias, disposition effect, cognitive dissonance, and anchoring (Boussaidi, 2022; Fayyaz Sheikh & Riaz, 2012; Kumar & Prince, 2022; Qasim et al., 2019; Scott et al., 2003). According to scholars such as Ricciardi and Simon (2000) and Thaler (1993), overconfidence bias is the most apparent behavioral bias in the financial market. Overconfidence bias manifests in three ways in the financial market: overplacing, over-precision, and overestimation. Overestimation bias refers to the propensity of market participants to overestimate the outcome despite their competence, success, and level of control (Fayyaz Sheikh & Riaz, 2012). Over precision bias is an overconfidence bias related to extreme confidence in one's knowledge (Campbell & Moore, 2024;

Ferretti et al., 2023). Over placement bias occurs when a market participant has excessive self-confidence and believes they are superior to others (Baker et al., 2022; Han et al., 2022).

According to Nofsinger (2007), Della Vigna (2009), and Johnson and Fowler (2009), overconfidence makes investors overly confident about their abilities and beliefs and unable to give enough weight to other people's viewpoints. According to psychological studies, Overconfidence has a variety of impacts on human behavior (Griffin & Tversky, 1992; Lichtenstein et al., 1982). A widespread cognitive bias in society is overconfidence (Campbell & Moore, 2024; Ferretti et al., 2023). It comes in several forms and can be quantified in various ways. The numerous manifestations of certainty overconfidence, or the illusion of control, occur when investors are confident in their decisions. Overconfidence in predictions is also known as miscalibration. According to Akert and Deaves, a better-than-average effect occurs when people assign probability to favorable and unfavorable outcomes based on past developments, and excessive optimism is prevalent when people believe their knowledge and talents are more significant than average (Blaseg & Schwienbacher, 2024; Ferretti et al., 2023). Three biases, namely the self-attribution, hindsight, and confirmation bias, may be to blame for the persistence of overconfidence (Saraskanrood & Ghafouri, 2022; Talwar et al., 2021; Upashi & Kadakol, 2023).

Prospect Theory is the foundation for the debate on biases in decision-making processes (Kahneman & Tversky, 1984). Investigating psychological prejudices can improve comprehension of investment decision-making procedures (Talwar et al., 2021). These prejudices indicate oversights of assessment during decision-making (Jain et al., 2023) and provide insights into the way shareholders handle the information at their disposal (Campbell & Moore, 2024). Researchers have categorized these prejudices in a number of different ways. Shefrin (2001), divided biases into heuristic-driven and frame-dependent biases. Pompian et al. (2011), classified them into cognitive and emotional biases. Montier (2007), classified biases into self-deception, heuristic simplification, and social interaction. These three groups include approximately 20 prejudices. The self-deception bias refers to optimism, self-attribution, and hindsight bias. Representativeness and anchoring/salience are two examples of intuitive simplifications. In contrast, the final category, social interaction, includes prejudices such as flocking (Talwar et al., 2021; Upashi & Kadakol, 2023).

## 2.2. Overconfidence bias and financial market

According to the studies, gender and age influence people's overconfidence. For example, Barber and Odean (2000) claimed that men trade 45% more than women. Furthermore, Trejos et al. (2019) contend that gender has a significant influence on biased trading behavior. Similarly, Baker et al. discovered that male investors outperform their female counterparts regarding trading knowledge. However, research shows that men and women have equal levels of overconfidence (Biais et al., 2005; Deaves et al., 2003).

One of the critical empirical studies on overconfidence bias at the market level based on the lead-lag relationship (VAR methodology) is the work by Statman et al. (2006). The lead variable (market volume) is linked to the lag variable (market return), which supports the overconfidence hypothesis theory. Zia et al. (2017) use the same econometric model to find comparable results for the Pakistani stock market. Daily observations are used in addition to monthly observations to identify overconfidence bias (Ganesh et al., 2020; Metwally & Darwish, 2015; Prosad et al., 2017). By separating the data into pre-COVID-19 and COVID-19, Shrotiya and Kalra (2023) discover evidence of overconfidence bias in developed, frontier, and emerging markets. According to the study, the Indian market avoids the overconfidence bias in both phases. The COVID-19 epidemic has also caused changes in the world capital markets, including declining prices and index values and a decline in share trading volume. Additionally, Haroon and Rizvi (2020) show an inverse relationship between liquidity and the quantity of COVID-19 instances. Additionally, Talwar et al. (2021) contend that the financial data about COVID-19 represents a profitable chance for numerous investors to buy and sell.

There are only a few studies on the G-7 countries, despite the relevance of overconfidence and its effects on market returns, liquidity, trading volumes, and volatility. Thanks to the digitalization of financial markets, investors can now access global markets with a mouse click. The study aims to analyse the effects of overconfidence-driven trading in the G-7 stock markets in light of the size of market shocks



and their impact on the volume of global market trade. Consequently, the following is the current research's hypothesis:

H1: In the G-7 countries, overconfidence bias was visible both before and during COVID-19.

Trading on the financial markets is driven by liquidity (Karim, Akhtar, et al., 2022; Nyborg & Östberg, 2014; Tripathi et al., 2020). Theoretical explanations for how reasonable investors ought to respond to sudden fluctuations in liquidity do not fully account for the observed scales and trends in trading behavior. A number of studies suggest that overconfidence is the most probable cause. Individuals in the business community often disapprove, each of them claiming their position is right. Overconfidence-based theories suggest that overconfident investors prioritize their personal opinions above, as indicated in the price of an asset. Overconfident traders seek lucrative returns by gambling on their own views (Daniel & Hirshleifer, 2015). The problem of active investing refers to excessive trading among individual investors. Aggressive trading in shares by individual investors typically results in losses, and investors who trade aggressively tend to lose greater sums of money (Aljifri, 2023; Daniel & Hirshleifer, 2015; Podvorec, 2023).

It may change over time depending on market circumstances. Increased trading expenses might occasionally result in decreased liquidity. Since liquidity decreases with market decrement, Hameed et al. (2010) discovered that liquidity dried up during the recession in the 1990s. Market liquidity providers gain confidence as conditions on the market improve and trading activity rises. Ftiti et al. (2021) investigated how fatalities during COVID-19 increased stock market return volatility and decreased stock market liquidity, increasing total stock market risk. Using data from 49 developed and emerging countries, Zaremba et al. (2021) discovered that while government intervention has no effect on market liquidity in developed markets, it causes a moderate loss in liquidity in emerging markets, with yearly turnover falling by 10–13%. According to Ferry et al., a rise in margin requirements during COVID-19 leads to decreased liquidity. The COVID-19 pandemic is an international health emergency that has led to widespread panic and turmoil in the financial sector. This behavior is especially prominent in index stocks, which have a more extensive supply of liquidity provided by high-frequency market makers. As a result, the second hypothesis is:

H2: *The market return, trading volume, and liquidity increased during COVID-19 period as compared to before and after the COVID-19 period.*

### 3. Data and methodology

The data on G7 countries for daily trading volume and closing prices of the indices are obtained from the Bloomberg website. The indexes under consideration are TSX (Canada), CAC-40 (France), DAX (Germany), FTSE MIB (Italy), Nikkei 225 (Japan), FTSE-100 (UK), and S & P 500 (USA). The period for the study is January 2015– December 2021, which is further split into pre-COVID-19 and COVID-19 periods. The pandemic period when the effect of the virus is at its peak and then starts declining is taken as 31st December 2019 to 31st December 2021 (Corbet et al., 2020). The daily return (Mkt return) is calculated as logarithmic differences of closing prices at  $t$  and  $t - 1$ . The trading volume log is taken as market volume. All the trading volumes are stationary at the level using ADF and PP tests except for Japan. The HP filter is used to make the Japanese trading volume stationary, and the detrended log volume is taken for the study, which is found to be stationary. The market volume (Mkt volatility) is taken as a logarithm of the index's high price and low price (Prosad et al., 2017). Further, the price set by the traders impacts the market liquidity (Mkt liquidity). It is calculated as the ratio of absolute market returns over the market volume based on the approach of Amihud (2002).

The study employs the vector autoregression (VAR) model that Statman et al. (2006) developed to explain overconfidence bias in the chosen indices. It is an econometric model applied to capture the interdependencies among the multiple time series that are endogenous and exogenous variables. Here, it is used to capture the interdependencies between market traded volumes, return of the indices, market liquidity, lag values, and volatility. Further, the Impulse response function (IRF) is applied to test how long overconfidence bias persists in the market. The market volume, market return, and market liquidity

are endogenous variables, and market volatility, which is considered a control variable, is an exogenous variable in the VAR model. The VAR structure is as follows:

$$X_t = \alpha + \sum_{l=1}^L A_l X_{t-l} + B_t C_t + \mu_t \quad (1)$$

where  $X_t$  is  $n \times 1$  vector of endogenous variables (market volume, return, and liquidity),  $C_t$  is  $n \times 1$  vector of exogenous variable (market volatility),  $B_t$  estimates the relationship between endogenous and exogenous variables,  $\mu_t$  is residual vector of  $n \times 1$ , which defines the relationship between endogenous and exogenous variables and  $L$  is the number of lags of endogenous variables selected through Akaike Information Criteria (AIC) and Schwartz Information Criteria (SIC). A separate market-wide vector autoregression (M-VAR) is estimated for each of the seven markets.

## 4. Results

### 4.1. Descriptive statistics

Tables B1 and B2 (see Appendix B) present descriptive statistics for the pre-COVID-19 and COVID-19 eras, respectively. The ADF and PP tests indicate that all relevant series are steady for all relevant markets (see Appendix A, Tables A1 and A2). The USA had the greatest average market return of 0.001 in the pre-COVID-19 timeframe. Among the G7 countries, Canada and the United States have the most significant market returns, 0.001, during COVID-19. Furthermore, the Italian stock market has the highest standard deviation (0.014) and mean volatility (0.009) before COVID-19, whereas it has the highest standard deviation (0.018) and average volatility (0.015) during COVID-19. In Table B1, Germany and the USA each record the highest market liquidity of 0.540. While the maximum market liquidity of 0.58 is observed in Germany and the UK. Moving ahead, most distributions are skewed with values that are not equal to zero and are not generally distributed since the kurtosis is higher than 3.

### 4.2. VAR and IRF during the pre-COVID-19 phase

Pre-COVID-19 VAR coefficients and t-statistics for G7 markets are presented in Table C1 (see Appendix C). The table is arranged in rows by market return, liquidity, and volatility, with the names of the nations and their trading volume in columns. The statistical significance is reported at 1, 5, and 10% levels. The first lag has the highest coefficient for practically all stock markets, and the market volume is autocorrelated. Then, it exhibits falling coefficient values at other higher delays. However, out of all the countries, Italy has the most excellent autocorrelation coefficient at the first lag (15.690), while for the other markets, the values range from positive to negative coefficients.

Table C1 shows that market turnover depends on lagged market return for all the markets at various lags. For Canada (lags = 5 and 10 days), France (lag = five days), Italy (lags = 1, 5, 6 and 10 days), Japan (lags = 6 and 7 days), the USA (lags = 2 and 3 days), and the UK (lags = 2 and 5 days), this contemporaneous link is found to be substantial. This implies that investors turn to the market and engage in excessive trading when the market return increases. This result aligns with empirical evidence supporting the overconfidence theory (Chuang & Lee, 2006; Glaser & Weber, 2009; Statman et al., 2006). The pertinent coefficients, however, are statistically negligible for the German stock markets and do not indicate overconfident trading behavior prior to COVID-19.

IRFs have been offered to understand the maximum day's overconfidence bias moving forward. Although the graph for market volume, market return, and liquidity has been plotted for ten days, we have explained the market volume's response to a one-standard-deviation shock to the market return for the sake of conciseness. Figure D1 shows that for the following three days, one standard deviation market return shock causes an increase of 0.002, 0.011, 0.006% for Canada, 0.001, 0.004, 0.012% for France, 0.004, 0.007, 0.001 for Germany, 0.011, 0.012, 0.008% for Italy, 0.005, 0.011, 0.011% for Japan, 0.008, 0.011, 0.012% for the USA, and 0.001, 0.011, 0.007% for the UK. Since the values are close to zero on day one, the market's reaction to the market return shock is not reported. These results indicate



traders' upbeat attitudes and support previously established VAR estimations (Azam & Baig, 2023; Kuranchie-Pong & Forson, 2022).

### 4.3. VAR and IRFs during COVID-19

The COVID-19 VAR estimates for the G7 countries are displayed in Table C2 (see Appendix C). Except for the Canadian stock market, the market volume first appears to be considerably autocorrelated for all markets. The estimates in Table C1 also show that the market volume relationship with the lagged market return is significantly positive for Canada (lags = four days), Germany (lags = one day), Italy (1 and 2 days), the USA (lag = three days), and the UK (lag = 1, 3 and 7 days), while the stock markets of France and Japan are immune to overconfidence bias.

Additionally, IRFs have been plotted to measure overconfidence bias more accurately. According to Figure D2, a one-standard-deviation market shock causes the volume to rise by 0.017, 0.018, and 0.012% for Germany and 0.033, 0.029, and 0.019% for Italy during the following three days. The Canadians' positive response (0.029%) and the Japanese's positive response (0.015%) are both reported on day five. The unfavorable replies appear after the second day for the USA and the UK.

### 4.4. Market volatility and the liquidity effect

The findings about the volatility and liquidity effect are explained in this section. Market volatility, an exogenous variable, has concurrent relationships with endogenous factors. The findings in Tables C1 and C2 demonstrate that for all G7 nations, market trading volume is positively connected with market volatility during the pre-COVID-19 and COVID-19 stages. This result aligns with Statman et al. (2006)'s empirical research. The relationships between market volume, liquidity, and return through VAR are then illustrated (see Appendix C). Market volume in our study's samples highly correlates with the lagged market liquidity. Market liquidity is related to lagged market return and was statistically significant before COVID-19, but the coefficient is very low, with a negative value throughout the COVID-19 period. It suggests that market liquidity providers must receive an adequate market return for trading activity throughout the pandemic. Furthermore, during a crisis like COVID-19, investors feel pessimistic about investing in the stock market. The findings are congruent with those of Hameed et al. (2010), who found that liquidity providers do not generate cash for trading operations during a recession.

## 5. Conclusion

We examine overconfidence bias using vector autoregression and impulse response functions (IRFs) for the daily data from January 2015 to December 2021 in G7 countries. The sample period is split into pre- and during-COVID-19 phases. A highly contemporaneous relationship between market volume and return is pronounced in the Canadian and Italian stock markets in the pre-COVID-19 period because the relevant coefficients are positive and highly significant for a few lags. During the COVID-19 crisis, the study only finds strong evidence of overconfident behavior in the Italian market. Thus, it is a fact that behavioral finance can explain market financial abnormalities caused by the recent COVID-19. It means that in pre-COVID-19, investors were optimistic about trading behavior. Further, the finding of our study suggests that besides overconfidence bias, the markets are also dominated by the disposition effect of the individual stock. Besides trading volume, overconfidence bias is also driven by market liquidity and follows market return but not vice versa. This article has relevant implications for investors, policymakers, and market regulators in market turbulence like the COVID-19 pandemic. The study focuses on one bias; future research can be done on other biases, and its impact can be checked. Finally, losses have occurred repeatedly due to overconfident traders misunderstanding the risks involved in stock investments because of the epidemic. It is, therefore, advised that these investors use their excessive confidence more sensibly and intelligently. Investors should choose competent advisors in this area because their advice and support may reduce risks and create the potential for more significant profits. The study sheds light on the range of COVID-related information entering the market, considering the complexities associated with behavioral bias in stock trading and, potentially, sentiment-based trading. In the face of

exceptional fluctuations in the market, the study explains massive volatility in investor sentiment, volume, and return. Our findings clarify the relationship between investor emotions, market volume, and market returns. Further studies can broaden the scope of the present research to include a worldwide examination of the spillover impact of fluctuations in markets and investor sentiment across the different nations affected.

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## Authors' contributions

Author's contribution: Mustafa Raza- original draft and methodology. Qamar Azam: Data collection, estimation, writing, proofreading, and project administration. Iqbal Hawaldar: Original draft proofreading and funding acquisition. Rashed AlJalahma: Resource acquisition, writing the original draft, and proofreading. Suzan DSouza: Data curation, analysis, revision, and editing.

## Disclosure statement

We do not have any conflict of interest to declare.

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## Data availability statement

The data can be made available on request.

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## Appendix A

**Table A1.** Unit root test for G7 countries (Pre COVID-19).

G-7 countries	Mkt volume		Mkt return		Mkt liquidity		Mkt volatility	
	ADF t-stat	PP t-stat	ADF t-stat	PP t-stat	ADF t-stat	PP t-stat	ADF t-stat	PP t-stat
Canada	−8.670***	−33.180***	−12.960***	−42.680***	−7.872***	−40.754***	−6.460***	−17.740***
France	−7.308***	−26.077***	−35.990***	−36.709***	−21.150***	−35.186***	−6.681***	−30.273***
Germany	−9.889***	−24.915***	−36.661***	−36.883***	−22.093***	−35.635***	−6.385***	−32.234***
Italy	−5.051***	−16.006***	−38.236***	−38.492***	−17.319***	−36.256***	−8.368***	−28.023***
Japan	−8.185***	−21.241***	−43.013***	−44.844***	−14.696***	−33.605***	−5.561***	−27.983***
USA	−12.473***	−27.197***	−36.313***	−36.379***	−13.137***	−37.030***	−8.952***	−23.870***
UK	−12.360***	−24.908***	−19.050***	−34.993***	−16.930***	−35.175***	−8.982***	−31.283***

Source: Computed Data; \*\*\* represents 1% level of significance.

**Table A2.** Unit root test for G7 countries (COVID-19).

G-7 countries	Market volume		Market return		Market Liquidity		Market volatility	
	ADF t-stat	PP t-stat	ADF t-stat	PP t-stat	ADF t-stat	PP t-stat	ADF t-stat	PP t-stat
Canada	−43.78***	−12.908***	15.451***	15.485***	−14.95***	−15.06***	−8.038***	−8.106***
France	−6.496***	−11.033***	−13.582***	−21.854***	−9.724***	−22.000***	−4.539***	−10.574***
Germany	−3.351***	−8.146***	−13.630***	−21.934***	−12.581***	−20.827***	−4.986***	−10.708***
Italy	−5.612***	−9.535***	−13.330***	−23.563***	−20.810***	−21.717***	−4.928***	−11.599***
Japan	−5.163***	−8.771***	−13.596***	−21.552***	−13.031***	−20.093***	−3.879***	−12.585***
USA	−8.166***	−13.631***	−6.716***	−30.542***	−7.435***	−21.518***	−5.260***	−9.085***
UK	−5.103	−12.117***	−8.042***	−21.990***	−13.299***	−22.534***	−4.715***	−11.824***

Source: Computed Data; \*\*\* represents 1% level of significance.



## Appendix B

**Table B1.** Descriptive statistics for G7 countries (Pre COVID-19).

			31st December 2019–December 2021			
December 2019 Parameters	Lags		Mean	Std Dev	Skewness	Kurtosis
Mkt volume	Canada	10	19.178	0.313	0.150	7.085
Mkt return			0.000	0.013	−1.641	31.224
Market liquidity			3.620	0.525	1.171	7.470
Volatility			0.009	0.008	5.396	46.645
Mkt volume	France	6	18.365	0.339	−0.225	5.834
Mkt return			0.000	0.011	−0.843	11.776
Market liquidity			3.597	0.531	1.366	6.169
Volatility			0.012	0.007	2.053	11.122
Mkt volume	Germany	6	18.329	0.278	0.335	5.590
Mkt return			0.000	0.011	−0.654	8.280
Market liquidity			3.580	0.540	1.364	5.887
Volatility			0.013	0.007	1.693	7.823
Mkt volume	Italy	10	20.076	0.392	0.328	2.686
Mkt return			0.000	0.014	−1.192	16.244
Market liquidity			3.511	0.490	1.031	4.738
Volatility			0.015	0.009	3.269	31.471
Mkt volume	Japan	7	20.748	0.394	−0.005	2.391
Mkt return			0.000	0.012	−0.159	7.169
Market liquidity			3.628	0.524	1.156	5.104
Volatility			0.011	0.008	3.644	25.988
Mkt volume	USA	8	18.923	0.260	0.941	6.922
Mkt return			0.001	0.011	−0.439	6.231
Market liquidity			3.644	0.540	1.036	4.931
Volatility			0.012	0.008	2.944	20.524
Mkt volume	UK	6	20.466	0.263	−0.488	10.201
Mkt return			0.000	0.010	−1.247	17.149
Market liquidity			3.671	0.523	1.440	7.352
Volatility			0.011	0.006	3.267	28.363

**Table B2.** Descriptive statistics for G7 countries (COVID-19).

G7	Lags Mean	January 2015–2030		
		Std Dev	Skewness	Kurtosis
4	19.215	0.286	−0.686	9.660
	0.001	0.009	−0.415	3.497
	3.593	0.476	1.226	4.901
	0.007	0.004	1.804	7.432
2	18.260	0.396	0.171	6.214
	0.000	0.017	−1.213	15.956
	3.495	0.543	0.948	4.516
	0.014	0.011	3.151	17.292
2	18.141	0.417	0.839	4.132
	0.000	0.017	−0.877	16.608
	3.513	0.580	1.109	5.143
	0.015	0.011	3.074	16.839
	19.883	0.374	0.694	4.018
	0.000	0.018	−2.825	32.771
	3.495	0.521	0.933	4.437
	0.017	0.015	5.405	45.868
3	20.373	0.290	0.825	4.427
	0.000	0.014	−0.112	9.233
	3.503	0.488	1.152	5.546
	0.013	0.009	3.116	17.169
7	19.098	0.279	1.209	5.453
	0.001	0.018	−0.822	12.308
	3.440	0.526	0.967	4.509
	0.017	0.012	2.485	11.748
	20.465	0.363	0.217	4.956
	0.000	0.016	−1.124	17.580
	3.583	0.580	1.169	5.542
	0.016	0.013	3.272	18.227

This table provides descriptive statistics for G7 countries in pre COVID-19 and during COVID-19 phases with endogenous variables (Mkt volume, Mkt return and Mkt liquidity) and exogenous variable (Mkt volatility). [Table A1](#) reports descriptive statistics for pre COVID-19 period and [Table A2](#) reports descriptive statistics during COVID-19 period.

## Appendix C

Table C1. VAR results: January 2015–30 December 2021 (Pre COVID-19).

Parameters	Canada		France		Germany		Italy		Japan		USA		UK	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Mkt volume(-1)	0.251	9.754***	0.315	12.147***	0.348	12.920***	0.406	15.690***	0.392	14.769***	0.235	8.462***	0.313	11.639***
Mkt volume(-2)	0.085	3.208***	0.077	2.817***	0.036	1.248	0.081	2.860***	0.105	3.648***	0.094	3.298***	0.115	4.080***
Mkt volume(-3)	0.104	3.906***	0.124	4.489***	0.075	2.621**	0.096	3.385***	0.030	1.031	0.041	1.429	0.106	3.696***
Mkt volume(-4)	0.010	0.359	-0.019	-0.672	-0.001	-0.025	-0.015	-0.520	0.042	1.452	-0.016	-0.564	-0.002	-0.076
Mkt volume(-5)	0.075	2.790***	0.140	5.064***	0.128	4.468***	0.149	5.205***	0.087	3.003***	0.086	2.982***	0.087	3.031***
Mkt volume(-6)	0.001	0.037	-0.030	-1.135	-0.036	-1.350	-0.016	-0.574	-0.038	-1.327	-0.034	-1.169	-0.041	-1.516
Mkt volume(-7)	0.005	0.169					0.000	0.006	-0.057	-2.156	-0.022	-0.764		
Mkt volume(-8)	0.035	1.321					0.032	1.100			0.019	0.680		
Mkt volume(-9)	-0.001	-0.046					-0.016	-0.550						
Mkt volume(-10)	0.075	2.926***					0.112	4.343***						
Mkt return(-1)	0.142	0.273	0.107	0.169	0.380	0.654	0.863	2.111**	0.396	0.958	0.747	1.274	0.139	0.229
Mkt return(-2)	0.898	1.669	0.350	0.560	0.598	1.037	0.657	1.618	0.696	1.657	1.091	1.884*	1.061	1.762*
Mkt return(-3)	0.398	0.757	1.044	1.668	-0.076	-0.133	0.281	0.686	0.457	1.088	1.220	2.117**	0.372	0.615
Mkt return(-4)	0.822	1.590	0.280	0.451	-0.276	-0.480	0.201	0.492	0.171	0.409	0.657	1.140	0.266	0.446
Mkt return(-5)	1.138	2.210**	1.311	2.101**	0.949	1.651	1.161	2.849***	0.548	1.315	-0.011	-0.019	1.653	2.759**
Mkt return(-6)	0.215	0.426	0.698	1.130	-0.258	-0.451	0.781	1.906*	0.784	1.868*	0.701	1.241	0.725	1.209
Mkt return(-7)	0.764	1.475					0.139	0.340	0.750	1.858*	0.588	1.042		
Mkt return(-8)	0.601	1.177					0.159	0.390			0.437	0.787		
Mkt return(-9)	0.584	1.138					0.269	0.659						
Mkt return(-10)	1.535	3.026***					0.979	2.432**						
Mkt liquidity(-1)	0.00	-0.29	-0.003	-0.206	0.022	1.818*	0.018	1.489	-0.003	-0.294	-0.006	-0.517	-0.005	-0.445
Mkt liquidity(-2)	0.01	0.57	0.016	1.205	0.016	1.267	-0.009	-0.736	0.025	2.739**	0.012	0.976	0.001	0.095
Mkt liquidity(-3)	0.02	1.25	0.007	0.525	0.013	1.088	0.001	0.122	0.018	1.955*	0.009	0.733	0.005	0.447
Mkt liquidity(-4)	0.00	0.12	-0.006	-0.481	0.007	0.574	0.007	0.589	0.015	1.654	-0.016	-1.324	0.025	2.095**
Mkt liquidity(-5)	-0.01	-0.70	0.017	1.304	0.027	2.178**	0.045	3.724***	0.020	2.219**	0.004	0.362	0.016	1.309
Mkt liquidity(-6)	-0.01	-0.76	0.023	1.741*	0.008	0.626	0.020	1.653	0.017	1.868*	0.020	1.672*	0.045	3.706***
Mkt liquidity(-7)	0.00	0.33					-0.004	-0.291	0.026	2.980***	-0.010	-0.888		
Mkt liquidity(-8)	0.01	0.46					0.032	2.632**			0.029	2.446**		
Mkt liquidity(-9)	0.02	1.86*					0.022	1.844*						
Mkt liquidity(-10)	0.02	1.37					0.042	3.485***						
Constant	6.60	8.24***	6.774	11.340***	7.745	10.548**	2.573	5.282***	-0.551	-6.903	10.981	11.421***	8.169	10.541***
Volatility	12.35	9.59***	20.312	18.276***	15.712	16.325***	15.581	19.956***	11.436	17.802***	14.662	15.796***	14.206	13.701***

Note. This table reports coefficients and t-statistics from M-VAR which contains log volume (Mkt volume), market return (Mkt return), market liquidity (Mkt liquidity) and market volatility (Mkt volatility) with different lags specifications.

\*Denotes significance at 10%.

\*\*Denotes significance at 5%.

\*\*\*Denotes significance at 1%.

Table C2. VAR results: 31 December 2019–December 2021 (COVID-19).

Parameters	Canada		France		Germany		Italy		Japan		USA		UK	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Mkt volume(-1)	0.099	1.575	0.399	9.167***	0.492	11.018***	0.544	12.570***	0.503	11.400***	0.229	5.238***	0.335	7.507***
Mkt volume(-2)	0.121	1.934*	0.167	3.909***	0.163	3.738***	0.137	3.209***	0.002	0.043	0.059	1.316	0.156	3.285***
Mkt volume(-3)	0.067	1.062							0.114	2.615**	0.012	0.259	0.085	1.749*
Mkt volume(-4)	0.275	4.046**									-0.065	-1.452	0.024	0.489
Mkt volume(-5)											0.057	1.282	0.044	0.883
Mkt volume(-6)											-0.030	-0.685	-0.001	-0.026
Mkt volume(-7)											0.030	0.725	0.000	0.006
Mkt volume(-8)													0.013	0.272
Mkt return(-1)	-1.461	-0.843	0.407	0.593	1.116	1.782*	2.089	3.429***	0.079	0.140	0.134	0.241	1.432	2.032**
Mkt return(-2)	0.125	0.073	-0.327	-0.481	0.732	1.181	1.088	1.796*	0.692	1.241	-0.351	-0.614	-0.375	-0.540
Mkt return(-3)	-0.235	-0.140							0.683	1.234	1.086	1.931*	1.331	1.947**
Mkt return(-4)	3.256	1.968									0.480	0.865	0.929	1.360
Mkt return(-5)											-0.018	-0.032	1.061	1.560
Mkt return(-6)											-0.905	-1.645	-0.626	-0.922
Mkt return(-7)											-0.142	-0.269	1.227	1.765*
Mkt return(-8)													-0.330	-0.470
Mkt liquidity(-1)	0.029	0.859	0.068	3.054***	0.050	2.559**	0.038	1.783*	0.039	2.264**	-0.024	-1.260	0.032	1.533
Mkt liquidity(-2)	-0.007	-0.210	0.047	2.092**	0.014	0.725	0.060	2.819**	0.017	0.949	0.006	0.344	0.057	2.748**
Mkt liquidity(-3)	0.041	1.210							-0.009	-0.517	-0.037	-1.968	0.017	0.821
Mkt liquidity(-4)	0.035	1.046									0.016	0.872	0.042	1.985**
Mkt liquidity(-5)											0.023	1.224	0.006	0.267
Mkt liquidity(-6)											-0.039	-2.113	-0.006	-0.311
Mkt liquidity(-7)											0.015	0.777	0.003	0.162
Mkt liquidity(-8)													-0.019	-0.924
Constant	7.879	4.443***	7.311	9.179***	5.864	8.285***	5.872	8.157***	7.451	8.784	13.466	8.713***	6.380	5.398***
Mkt volatility	24.540	5.193***	13.862	10.730***	11.980	10.019***	7.830	9.259***	11.317	10.241	11.977	11.237***	11.052	9.584***

Note. This table reports coefficients and t-statistics from M-VAR which contains log volume (Mkt volume), market return (Mkt return), market liquidity (Mkt liquidity) and market volatility (Mkt volatility) with different lags specifications.

\*Denotes significance at 10%.

\*\*Denotes significance at 5%.

\*\*\*Denotes significance at 1%.

## Appendix D

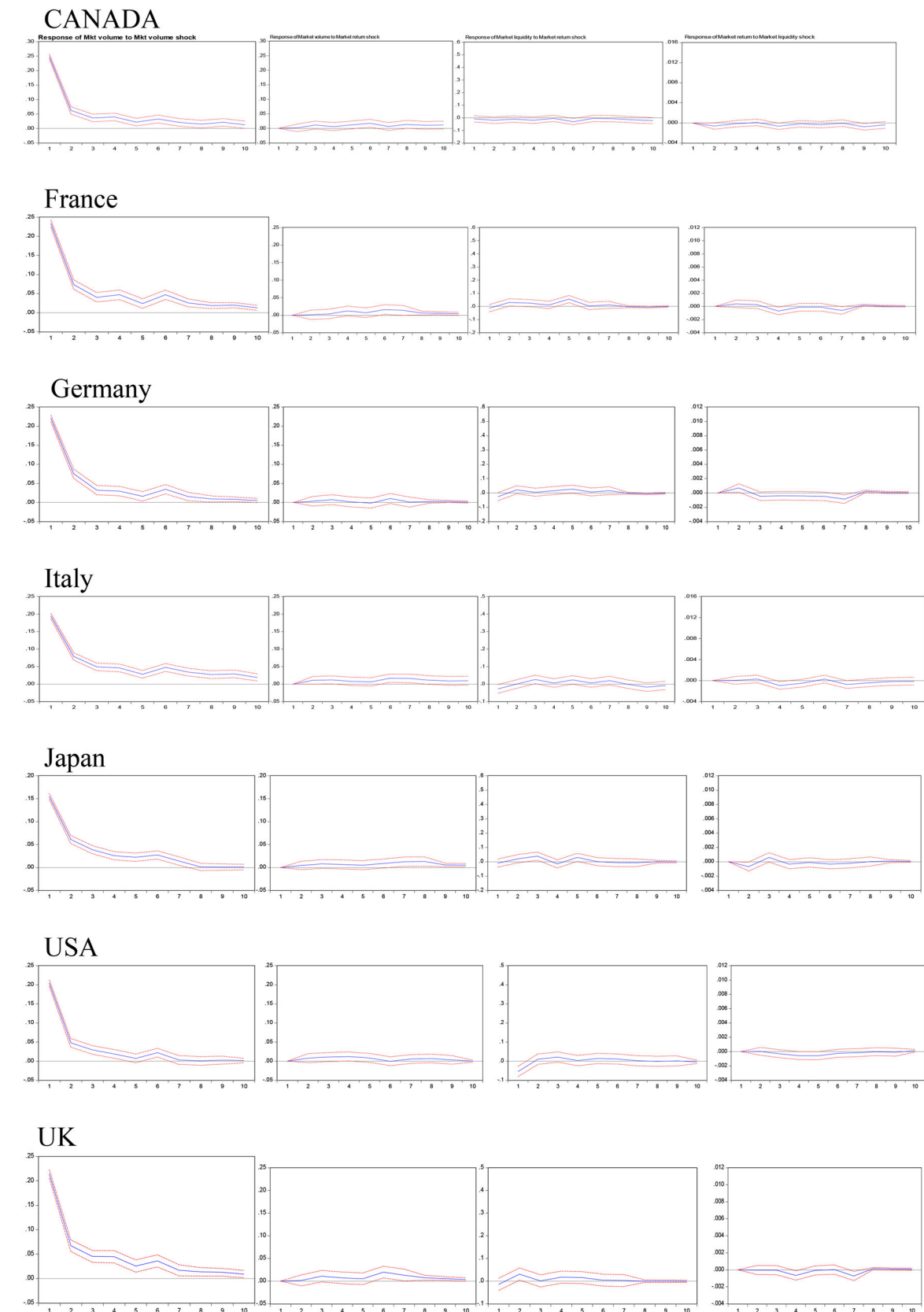
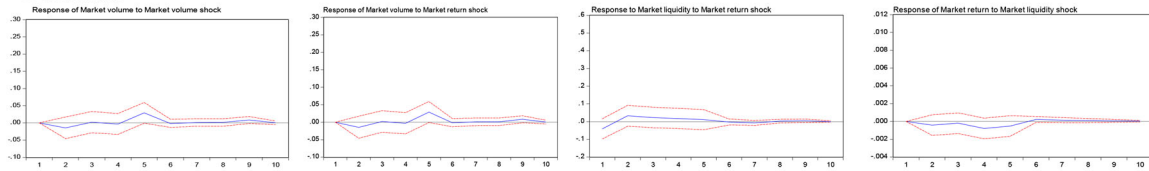
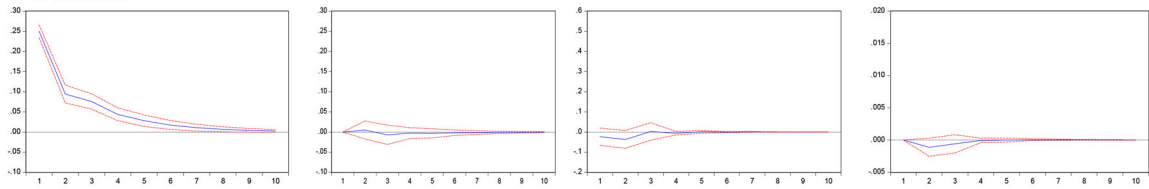


Figure D1. Pre-Covid 19: IRFs for G7 countries.

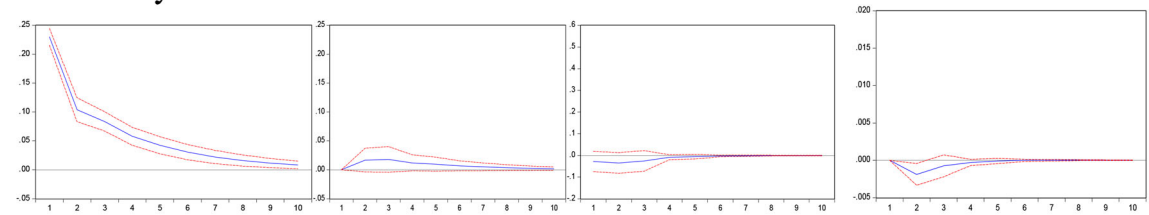
## Canada



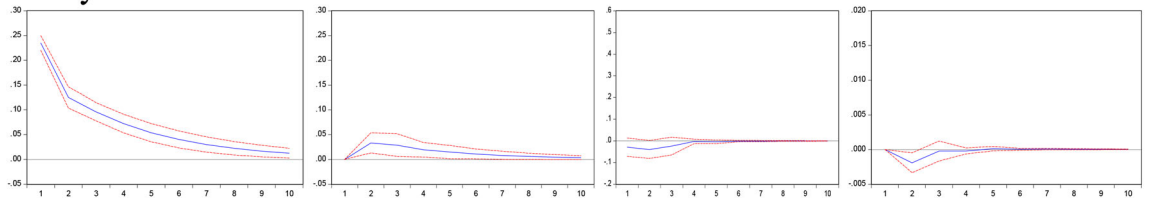
## France



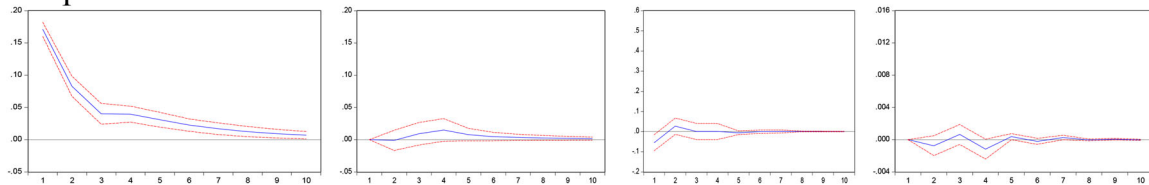
## Germany



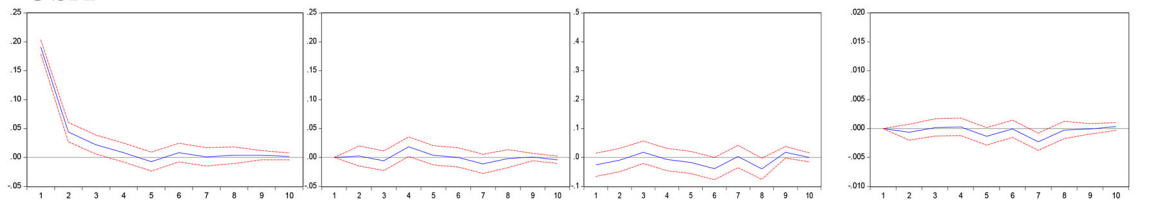
## Italy



## Japan



## USA



## UK

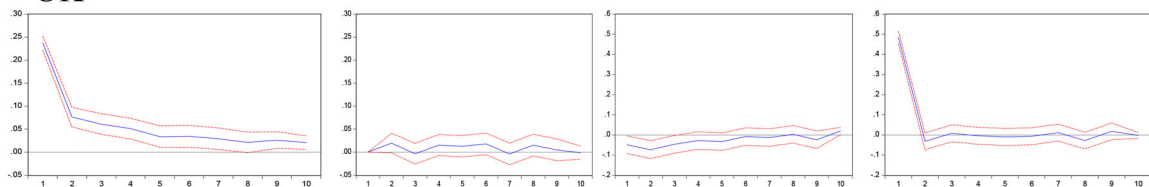


Figure D2. Post COVID-19: IRFs for G7 countries.