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The financial pandemic: COVID-19 and policy interventions on rational and irrational markets.

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The Financial Pandemic:

COVID-19 and Policy Interventions on Rational and Irrational Markets[1]

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Abstract

Financial markets are useful indicators of public beliefs and dispersed knowledge on future outcomes and policy efficiency, especially in periods of uncertainty. 51 national stock markets successfully absorb publicly available information regarding COVID-19 and anticipate policy measures being taken to address the pandemic. The financial markets imply national lockdown policies, as well as monetary or fiscal stimuli, are counterproductive measures while targeted regional lockdowns can be effective. The fundamental effect of the pandemic is relatively low, sentiment and irrational panic play a greater role, while the most significant drivers of negative stock returns are policy interventions.

Keywords: COVID-19, event studies, policy intervention, financial market, efficient market hypothesis, SIR model

JEL codes: E44, E63, G14, G15, G18, I18

[1] The authors are grateful to Scott Ellis for fruitful discussions and helpful comments

Introduction

The rapid spread of COVID-19 and the alarming number of human casualties worldwide have established this disease as a dangerous and a major threat to the global economy. It has spread to more than 2.4 million people in April 2020 alone. There is no medicine available to cure it yet and as vaccine trials are still ongoing in labs around the world, many countries have continued to extend containment measures as the only means of minimising the spread of the disease. Social distancing and lockdowns have turned cities into ghost towns and business closures are triggering a major economic tragedy (Romei, 2020). This has also adversely affected the stock markets globally. In the week commencing 24th February, indices worldwide reported the largest decline since the 2008 financial crisis. Several other major drops in the global financial markets have been reported since then, such as Black Monday I of 9th March, and Black Thursday of 12th March and Black Monday II of 16th March. According to some measurements, March 2020 can be considered the worst month in the history of global stock markets (Gormsen and Koijen, 2020), although the global market has also rallied to move up frequently. While the recoveries are often linked with governments' stimulus announcements (such as central bank rate cuts, business grants and salary schemes) and lockdown measures (Davies, 2020), there is no empirical evidence to suggest the effectiveness of these interventions.

A voluminous body of literature has already emerged trying to analyse, interpret, or forecast the impact of COVID-19 on the global economy and the stock markets and to suggest the optimal policy interventions. Nevertheless, most of the research is based on theoretical estimates (Eichenbaum et al., 2020; Guerreri et al., 2020) or model calibrations informed by past pandemic data, such as SARS (McKibbin and Fernando, 2020) or "Spanish flu" (Barro et al., 2020). The literature is yet to form a consensus around such a recent topic, and as for now, the assertions of recent studies vary tremendously. The GDP decline estimates fluctuate from as low as 0.7% to as high as 17%, depending on various hypothetical disease transmission scenarios and policy stances taken by governments (Barro et al., 2020; Eichenbaum et al., 2020; McKibbin and Fernando, 2020). The justifiable stock market downturn is assessed at 7% (Barro et al., 2020), but the actual drawdowns can reach as high as 60% (Gormsen and Koijen, 2020). Some suspect the market reaction is largely irrational (Corbet et al., 2020), while others reinforcing the forward-looking nature of financial markets (Gormsen and Koijen, 2020).

This study, therefore, embarks on an ambitious endeavour to decompose the financial impact of the COVID-19 pandemic into “rational” and “irrational” while also separating the effect of the disease itself from the consequences of policy interventions. Utilising a sample of 51 national stock markets across 115 days, it demonstrates that the sentiment component of the stock market downturn is material and can be estimated at 6% on average. Nevertheless, the market is decidedly efficient and forward-looking in incorporating new information on COVID-19 fundamental effect and policy interventions. Markets react to innovations in SIR model-forecasted infection peak and anticipate lockdowns and stimulus measures probabilistically, evidencing Bayesian updating and, even more surprisingly, successful application of differential equations by a representative investor, yielding the market-implied estimates of fundamental and policy factors sufficiently reliable.

The economic impact of the infection peak is shown to be statistically significant yet small, the highest estimate obtained being -1.6%. Contrastingly, policy interventions and their anticipation can explain most of the drawdowns, with assessed effects of national lockdowns, monetary stimulus, and fiscal stimulus reaching as much as -11.0%, -14.0%, and -4.7%, respectively, in some of the models. Regional lockdowns and targeted containment policies have no such effects, highlighting the preferability of this policy strategy.

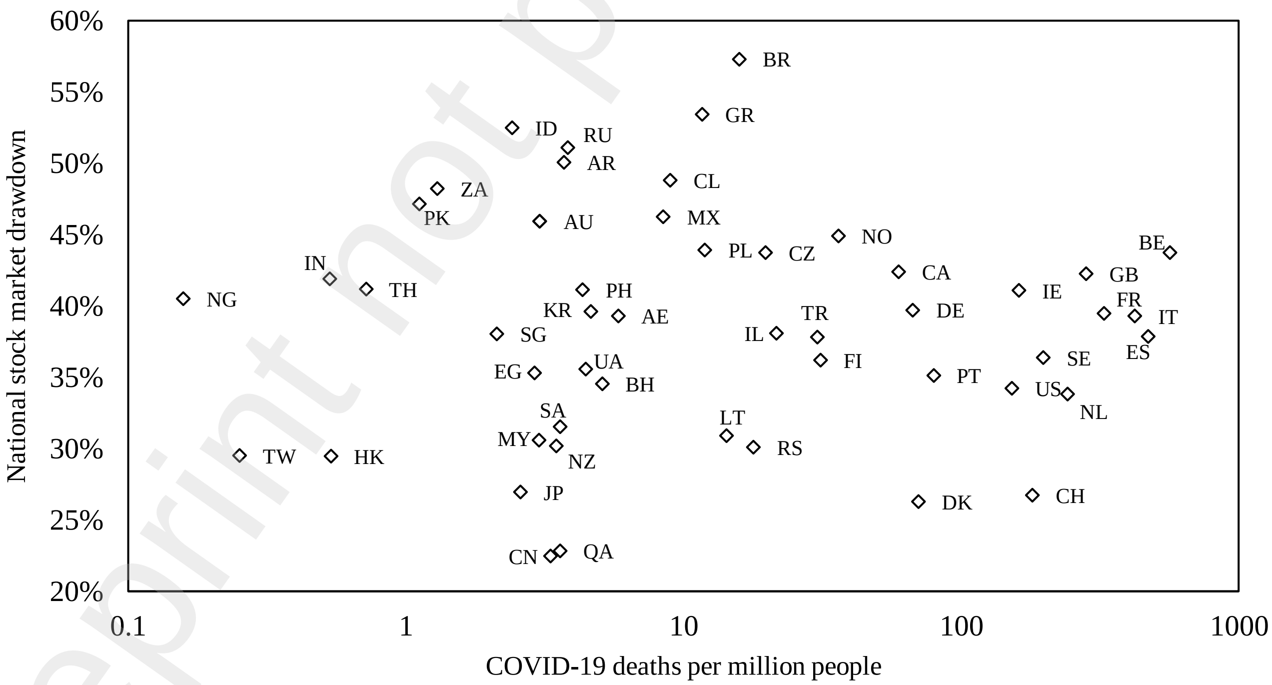
The rest of the paper is organised as follows. First, the data and methods on the assessment of fundamental, policy, and sentiment effects are presented, with relevant literature on epidemiology, macroeconomics, and behavioural finance reviewed consequentially. Next, the empirical results are discussed with respect to the previous studies and existing conjectures and theories on COVID-19, and a set of robustness checks is applied. The last section concludes.

Material and Methods

The study utilises an exhaustive sample of 51 countries that provide reasonably high-quality data both on COVID-19 prevalence as well as stock market performance[2]. National stock market performance is measured using a USD-denominated MSCI country-specific total return index from 31 December 2019 until 23 April 2019. COVID-19 dynamics are studied using daily data on global and national cases, deaths, and recoveries from John Hopkins University. Population data for respective countries in 2019 has been retrieved from World Development Indicators (World Bank).

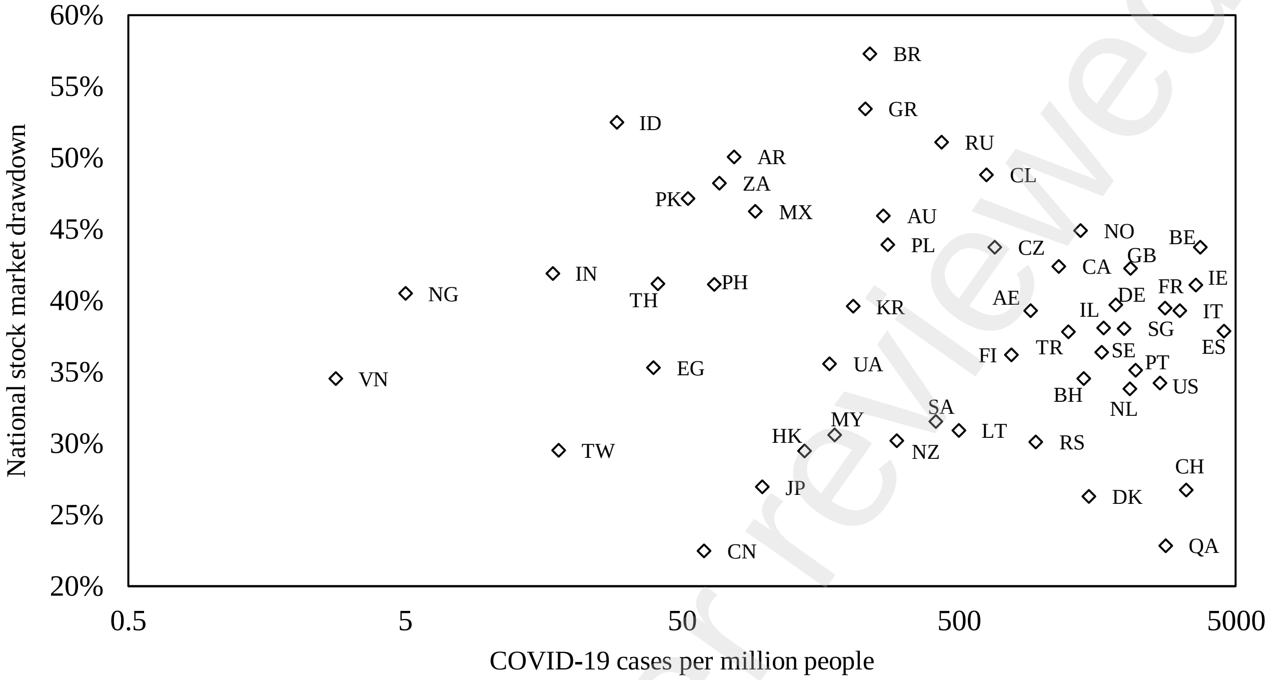
The first stylised fact emerging from the preliminary analysis shows that stock index drawdowns are not directly associated with COVID-19 prevalence measured as either deaths or cases per million people (see Figures 1a and 1b below, respectively).

Figure 1a. COVID-19 prevalence and stock market drawdown - deaths



[2] All countries that have both value-weighted stock market index data from MSCI and COVID-19 data from John Hopkins University have been included into the sample

Figure 1b. COVID-19 prevalence and stock market drawdown – cases



This observation provides some further support to speculations that market responses to the pandemic are mostly attributable to irrational investor panic (Corbet et al., 2020) or to various policy interventions designed to address the virus outbreak (Baker et al., 2020). Past epidemics and pandemics, such as Spanish Flu, Bird Flu, SARS, Swine Flu, MERS, and Ebola, are shown to have a limited, if any, impact on stock markets of affected countries (Nippani and Washer, 2004) and global market volatility (Baker et al., 2020). Furthermore, as the adverse economic effects of COVID-19 are assessed at 2.4%-9.9% of GDP even in the most pessimistic scenarios in DSGE models (McKibbin and Fernando, 2020) and have an upper bound at 6%-8% from the worst-case scenario estimates using "Spanish flu" data (Barro et al,. 2020), drawdowns of 40% and higher observable on most national markets considered are hardly justifiable[3].

The study, therefore, seeks to quantify the impact of all three COVID-19 related factors – *fundamental*, *policy*, and *sentiment* – that could potentially explain such an unprecedented

[3] Barro et al. (2020) provide an estimate of 7% for stock market drawdown for the US.

fall in stock indices. High-quality data on 51 national stock markets as well as notable cross-country variation in COVID-19 spread dynamics and respective policy interventions ensure an ideal environment for such an analysis. As research on the economic and financial effects of the pandemic highlights increasing contagion, spillovers, and interdependencies between financial markets (Ahtaruzzaman et al., 2020; Corbet et al., 2020), identifying notable cross-country differences across the three dimensions outlined above can prove crucial in estimating true magnitudes of COVID-19 impact.

To measure the *fundamental* effect, the study considers a variety of direct channels through which an epidemic can affect an economy. First, and perhaps most clearly, the total number of cases influences both the overall number of casualties (permanent shocks to labour supply and consumption) as well as the total number of working hours forgone as infected individuals have to stay at home or a medical facility recovering and/or isolating. The innovations to this factor can be directly measured as the growth rate of total cases[4] either within a country or in the global context (local case growth and global case growth, respectively), as in Al-Awadhi et al. (in press), since the adverse economic impact of the pandemic in the rest of the world can have important spillover effects (Ahtaruzzaman et al., 2020; McKibbin and Fernando, 2020). Second, the infection peak also has substantial economic implications. The more people are infected at the same time, the higher is the immediate pressure on the healthcare system and the more severe are the disruptions to the functioning of the economy. In epidemiology, this factor is usually of major concern and therefore a variety of compartmental models are used to predict the infection peak (Anderson and May, 1979; Vynnycky and White, 2010). The simplest and most widely used model of this kind is the SIR model. It comprises a set of differential equations:

[4] Death rate growth, either local or global, was insignificant in all estimations which is unsurprising given death count is a backward-looking measure reflecting the ultimate realisation of cases that were already public knowledge for weeks. This is where this study contradicts earlier China-specific findings of Al-Awadhi et al. (in press) for the initial wave of the outbreak.

$$\frac{\partial S}{\partial T} = -rSI$$

$$\frac{\partial I}{\partial T} = rSI - aI$$

$$\frac{\partial R}{\partial T} = aI$$

SIR is a "compartmental" model as it separates the population into three so-called compartments – susceptible, infected, and removed (hence the acronym). The number of infected people grows proportionately to the number of potential interactions between susceptible and infected people and simultaneously decreases proportionately to the number of people infected due to eventual recovery or death of infected individuals. To calibrate the SIR model on historical COVID-19 data, therefore, one can estimate the susceptible population as total population minus the number of identified cases, the removed population as recoveries plus deaths, and the infected population as cases minus deaths and recoveries. Without loss of generality, the total population can be normed to one, by dividing all compartments by total population. The recovery rate a is mostly assumed to be exogenous and specific to a particular disease, while transmission rate r can be influenced by hygiene practices and contact intensity. This has largely been the scientific justification of social distancing measures around the world designed to "flatten the curve" to minimise immediate adverse impact on national healthcare systems (Eichenbaum et al., 2020; Sguazzin et al., 2020).

Hence, the recovery rate can be estimated globally, while the transmission rate should be calculated locally to assess SIR-predicted infection peaks in dynamics, using 7-day estimation windows[5]:

$$a = \left(1 + \frac{(Recoveries_t - Recoveries_{t-7}) + (Deaths_t - Deaths_{t-7})}{Cases_{t-7} - Recoveries_{t-7} - Deaths_{t-7}}\right)^{\frac{1}{7}} - 1$$

[5] The study considered a wide range of other estimation windows without the overall results being affected

$$r = \left(1 + \frac{Cases_t - Cases_{t-7}}{Cases_{t-7} - Recoveries_{t-7} - Deaths_{t-7}}\right)^{\frac{1}{7}} - 1$$

Next, the computed parameters can be used to solve the system of differential equations and obtain the peak value for the infected population:

$$I_{max} = I_0 + S_0 - \frac{a}{r}\left(1 + \ln\frac{r}{a}S_0\right) \approx 1 - \frac{a}{r}\left(1 + \ln\frac{r}{a}\right)$$

As the population is normed to 1, I_{max} is interpretable as a maximum share of the population that is expected to be infected at the same time. Rolling estimates of I_{max} for selected sample countries can be seen in Figures 2a and 2b.

Figure 2a. SIR-predicted infection peak dynamics in selected countries

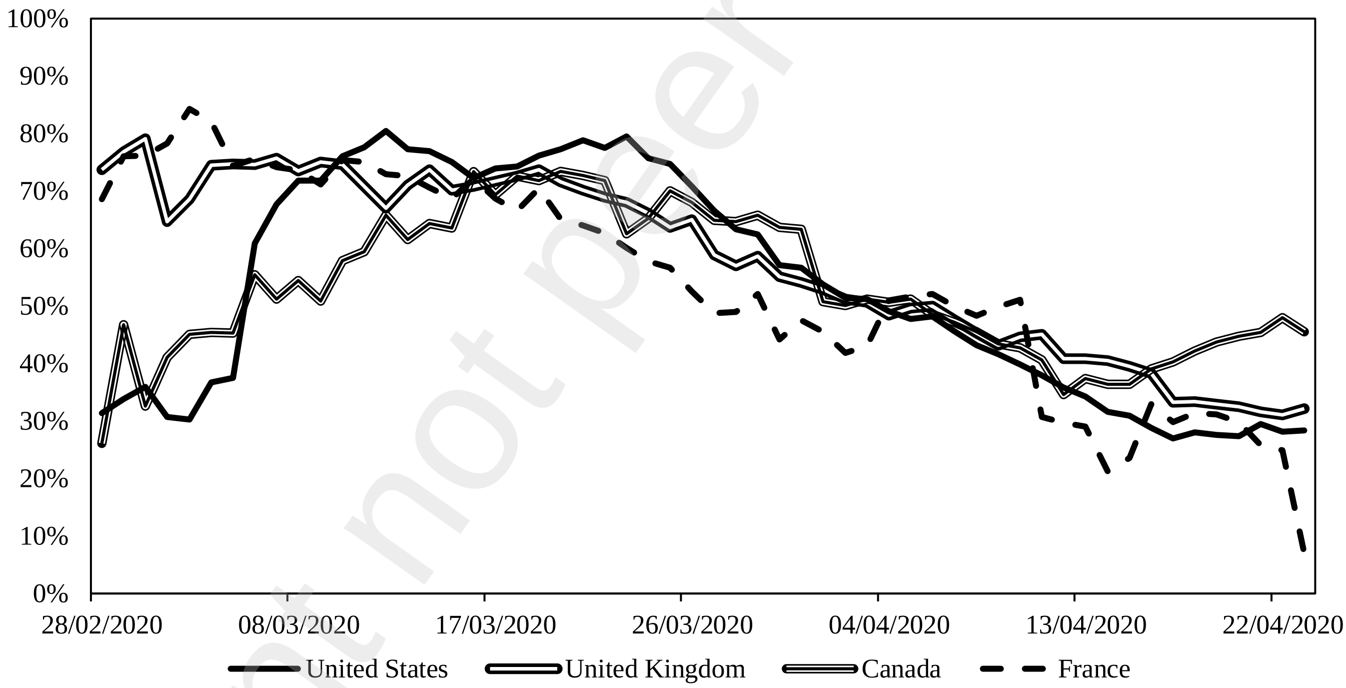
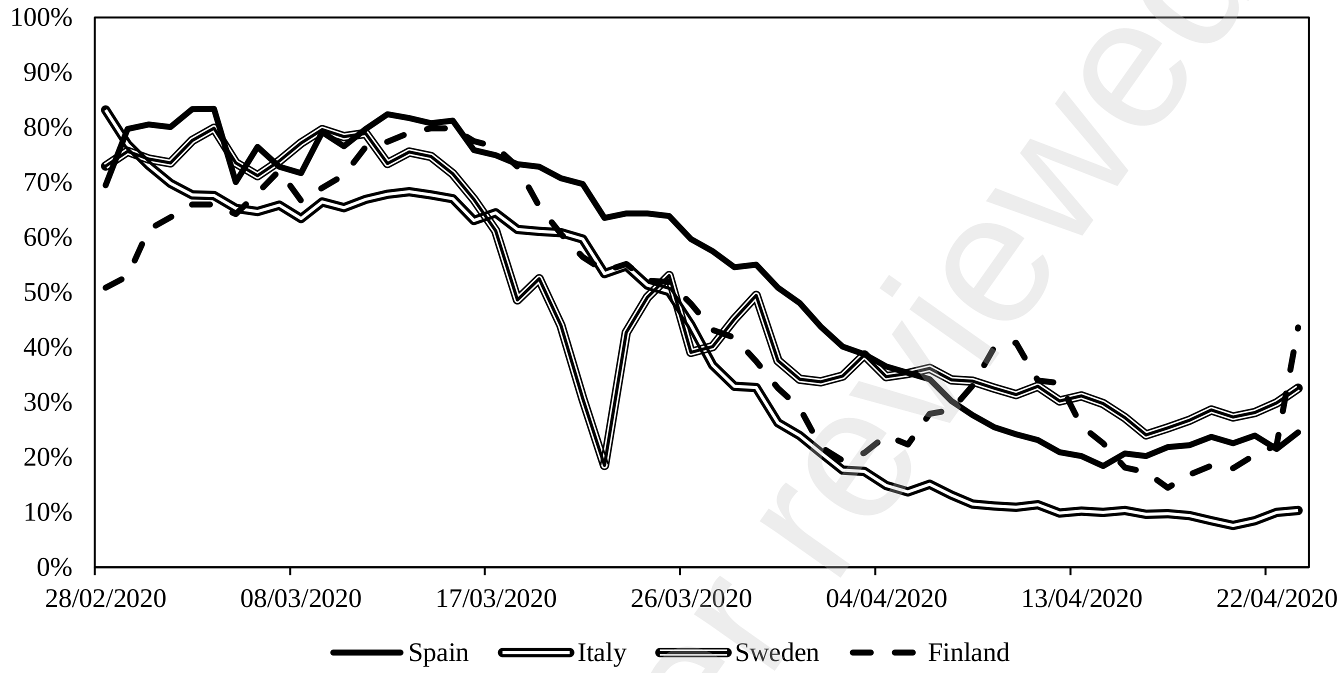


Figure 2b. SIR-predicted infection peak dynamics in selected countries



Evidently, there is some intertemporal as well as cross-sectional variation in I_{max} that can be instrumental in explaining national stock market returns. Moreover, such an analysis can be crucial in testing the efficient market hypothesis and rational versus adaptive expectations. If the stock market reacts to case growth but not the SIR-predicted infection peak, that would imply adaptive expectations and not rational, and vice versa. Putting it plainly, the COVID-19 pandemic can serve as an invaluable test of whether the stock market knows differential equations.

Eichenbaum et al. (2020) are using a modified SIR model with endogenous consumption decisions to show that the economic impact of COVID-19 will be limited to 0.7% of GDP if agents do not react to the pandemic, will increase to 4.7% of GDP in the competitive equilibrium when agents limit social interaction in their self-interest ("bottom-up" lockdowns) and equals 17% of GDP if governments impose optimal lockdown policies to fully internalise the external benefits of isolation. Such an optimal policy would include incremental tightening or relaxation of containment measures as transmission rates increase or decrease. However, Eichenbaum et al. (2020) evidence that real-world lockdown policies are far from optimal, with excessively strict measures that do not adjust quickly enough to the external conditions. Another limitation in the applicability of Eichenbaum et al. (2020) SIR macro-model is that it treats the enforcement of social distancing as a consumption tax that discourages excessive interactions between agents and the proceeds can be redistributed lump-sum to all agents, while in practice lockdowns are supply restrictions that are pure deadweight losses in the economic sense. Hence, the optimal policy that acknowledges the trade-off between economic harm of containment and the benefits from preventing COVID-19 deaths might be even less strict with negative economic effects of lockdowns being even higher than estimated by the SIR macro-model.

Therefore, to address the *policy* channel of COVID-19 economic impact, policy interventions have been classified into two broad groups: lockdown measures and stimulus packages. Lockdowns are policies aimed at minimising contact between susceptible and infectious populations and thus minimising transmission rates and "flattening the curve". Lockdowns are further separated into national (enforced throughout countries) and regional (enforced in specific areas, e.g., Bavaria and Saarland federal lands and the city of Freiburg in Germany). Stimulus packages designed to overcome the recessionary effect of the pandemic are broken down into monetary or fiscal based on the usual characteristics. Hence, the monetary authority rate cuts, quantitative easing, and banking regulation relaxation are considered monetary, while increases in government spending and grants to businesses and households are classified as fiscal. The data on announcement dates for all policy interventions is collected manually from official government and central bank websites as well as from reputed news sources such as Reuters, Bloomberg, BBC, and Financial Times. Table 1 below presents the nature and timing of policy measures taken to address the COVID-19 pandemic in 51 sample countries.

Table 1. COVID-19 policy responses across countries.

Country	Lockdown		Stimulus	
	National	Regional	Monetary	Fiscal
Argentina	19/03/2020	none	20/03/2020	19/03/2020
Australia	23/03/2020	none	03/03/2020	04/03/2020
Bahrain	18/03/2020	none	17/03/2020	17/03/2020
Belgium	18/03/2020	none	12/03/2020*	13/03/2020
Brazil	None	17/03/2020	18/03/2020	16/03/2020
Canada	13/03/2020	none	04/03/2020	18/03/2020
Chile	19/03/2020	none	16/03/2020	19/03/2020
China	None	23/01/2020	03/02/2020	19/03/2020
Czech Republic	16/03/2020	none	16/03/2020	14/03/2020
Denmark	11/03/2020	none	19/03/2020	27/03/2020
Egypt	25/03/2020	none	07/04/2020	07/04/2020
Finland	None	27/03/2020	12/03/2020*	20/03/2020
France	17/03/2020	none	12/03/2020*	17/03/2020
Germany	None	20/03/2020	12/03/2020*	25/03/2020
Greece	23/03/2020	none	12/03/2020*	16/03/2020
Hong Kong	None	none	04/03/2020	26/02/2020
India	25/03/2020	none	27/03/2020	26/03/2020
Indonesia	None	26/03/2020	12/03/2020	25/02/2020
Ireland	12/03/2020	none	12/03/2020*	09/03/2020
Israel	None	02/04/2020	25/03/2020	16/03/2020
Italy	09/03/2020	21/02/2020	12/03/2020*	11/03/2020
Japan	None	07/04/2020	16/03/2020	08/03/2020
Lithuania	16/03/2020	none	12/03/2020*	15/03/2020
Malaysia	17/03/2020	none	03/03/2020	27/02/2020
Mexico	None	none	09/03/2020	05/04/2020
Netherlands	16/03/2020	none	12/03/2020*	17/03/2020
New Zealand	22/03/2020	none	16/03/2020	16/03/2020
Nigeria	None	30/03/2020	16/03/2020	16/03/2020
Norway	12/03/2020	none	13/03/2020	15/03/2020
Pakistan	24/03/2020	none	17/03/2020	24/03/2020
Philippines	None	15/03/2020	19/03/2020	30/03/2020
Poland	13/03/2020	none	17/03/2020	07/04/2020
Portugal	19/03/2020	none	12/03/2020*	26/03/2020
Qatar	None	17/03/2020	16/03/2020	16/03/2020
Russia	None	30/03/2020	20/03/2020	25/03/2020
Saudi Arabia	29/03/2020	08/03/2020	14/03/2020	20/03/2020
Serbia	15/03/2020	none	11/03/2020	31/03/2020
Singapore	07/04/2020	none	14/02/2020	18/02/2020
South Africa	27/03/2020	none	19/03/2020	21/04/2020
South Korea	None	none	16/03/2020	03/03/2020
Spain	14/03/2020	none	12/03/2020*	18/03/2020
Sweden	None	none	13/03/2020	16/03/2020
Switzerland	17/03/2020	none	19/03/2020	13/03/2020
Taiwan	None	none	19/03/2020	25/02/2020
Thailand	25/03/2020	none	05/02/2020	06/03/2020
Turkey	11/04/2020	none	17/03/2020	18/03/2020
Ukraine	17/03/2020	none	14/03/2020	18/03/2020
United Arab Emirates	26/03/2020	12/03/2020	12/03/2020	12/03/2020
United Kingdom	23/03/2020	none	11/03/2020	11/03/2020
United States	None	19/03/2020	03/03/2020	06/03/2020
Vietnam	01/04/2020	none	17/03/2020	03/03/2020

Notes: *European Central Bank monetary stimulus effective throughout Eurozone countries

There is sufficient variation in the timing and the degree to which policy interventions has been implemented. The study can exploit such a dataset in three main ways.

First, the effectiveness of lockdown measures can be directly assessed. If the market expects the benefits of lockdowns (the decrease in infection rates, lower pressure on the healthcare sector, lower permanent shocks to labour supply and consumption) outweigh the costs, the abnormal returns that occur in anticipation and announcement of the measure will be positive and significant, and vice versa.

Second, a wide range of theories related to macroeconomic and stock market effects of monetary and fiscal policy can be explicitly tested in such an event-rich environment. Early research on monetary policy and the stock market sought to illustrate non-neutrality of money and suggested that easing of monetary policy regime has an unconditional positive effect on stock prices (Thorbecke, 1997). Further studies highlighted the importance of anticipation (Bernanke and Kuttner, 2005) and pre-announcement drift (Lucca and Moench, 2015). Bernanke and Kuttner (2005) show that an unanticipated 25 bps Federal funds rate cut results in a positive abnormal return of 1%, while Lucca and Moench (2015) demonstrate significant positive abnormal returns are accumulating 24 hours prior to the scheduled Federal Open Market Committee meetings. Other research focused on the conditionality of responses to monetary policy surprises. As such, Kurov (2010) evidences level and timing surprises have much higher effects on bearish markets and when investor sentiment is low. Nevertheless, all these sources agree on easier monetary policy leading to higher stock returns. Contrastingly, Chevapatrakul (2014, 2015) shows that the impact of monetary policy is heterogeneous across countries, with it being effective only during high-return or low-return periods on different markets, the US notably being the example of the former. The apparent consensus is further challenged by some recent evidence from emerging markets. As such, expansionary policy in terms of repurchase rate cuts in Thailand is shown to impact the national stock market negatively (Vithessonthi and Techarongrojwong, 2012). It is needless to say that the COVID-19 pandemic surrounded by a severe drop of sentiment and expansionary monetary policy environment is a remarkably useful "natural experiment" that can be used to develop further evidence to stress-test the established theories.

For fiscal policy, the research on its stock market implications remains much scarcer (Tavares and Valkanov, 2001). Traditionally, variations in fiscal policy have been used as market inefficiency illustrations, with lagged budget deficits depressing future stock returns in the US (Laopodis, 2009). Alternatively, fiscal policy indicators are highlighted as conditional variables that determine the effectiveness of monetary stimulus or restraint (Jansen et al., 2008). Jansen et al. (2008) show that when governments face fiscal constraints, monetary policy shocks can be much more impactful, however, they do not find any direct informational content in fiscal policy that is priced in the stock indices. Contrastingly, Tavares and Valkanov (2001) show that increases in spending and taxes have material negative stock and bond market effects. However, their analysis has been undertaken on a quarterly basis as conventional data on budgets is only available at a quarterly frequency at best. The prominence of fiscal stimulus announcements in the wake of COVID-19 crisis, on the other hand, presents a unique opportunity to study the immediate or very short-term responses to fiscal policy measures as well as their anticipation effects directly. Furthermore, the interaction between two types of stimulus policy can also be tested with ease and confounding events limitation can be easily avoided.

If monetary policy is indeed more effective during recessions, then the effect of monetary stimulus will be positive, significant, and higher than that of fiscal stimulus. Alternatively, the specificity of the current economic downturn can prove useful at indirectly assessing some other macroeconomic theories related to the origins of recessions and policy effectiveness in crisis times. If the currently looming and widely anticipated recession is demand-side and related to plummeting consumer sentiment or "animal spirits" more broadly, then stimulus might indeed be effective at mitigating it. Otherwise, if the crisis is predominantly supply-side and related to lockdown measures or other interventions, it is widely asserted that both monetary and fiscal policies are counterproductive and can achieve at best a redistributive effect, which is a common concept in the new classical school of macroeconomics (Barro, 1981, 2009). Nevertheless, Guerrieri et al. (2020) show that in a New Keynesian framework, supply shocks that occur from sector-specific factors (such as national lockdowns accompanied by temporary closures of hospitality and other service industries) can induce even larger changes in demand, and a "social insurance" fiscal policy can achieve macroeconomic stabilisation simultaneously aiding the policymaker at fulfilling their public health objectives. Studying market responses to policy interventions might be able to help resolve this theoretical debate. Another testable implication is that fiscal policy can be less detrimental and value-destroying during turbulent times such as wars, famously stated in the concept of the time-varying fiscal multiplier (Barro, 1981, 2009; Auerbach and Gorodnichenko, 2012; Faria-e-Castro, 2018). Barro (1981, 2009) estimates it is at 0.8 for temporary purchases during wartime and at 0.14 for non-temporary purchases during peacetime. Auerbach and Gorodnichenko (2012) report a fiscal multiplier of 0.5 during expansions and 1.2 during recessions, agreeing that temporary spending such as military budgets has the highest effects. As COVID-19 fiscal stimulus measures are undoubtedly temporary and are initiated during almost universal fears of recession, the market responses to fiscal policy announcements can serve as a perfect test for these theories. If assertions of Barro (2009) hold, one can expect both monetary and fiscal stimulus packages having a negative impact on stock prices, however, the magnitude should be lower in case of fiscal measures. A positive reaction, on the other hand, would serve as supporting evidence for Guerreri et al.

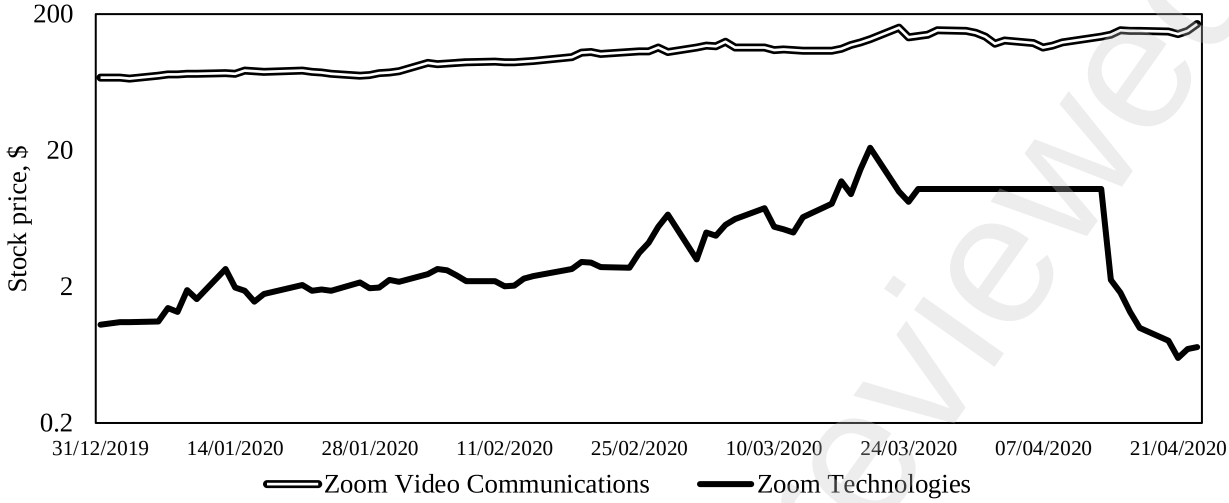
(2020) “Keynesian supply shock” theory and Auerbach and Gorodnichenko (2012) estimates of a greater-than-one fiscal multiplier during recessions.

Third, stock index reactions to policy announcements can serve as yet another market efficiency test – if anticipation and announcement effects are significant and material and adjustment effects are insignificant and negligible, it can serve as another piece of evidence for efficient reflection of relevant information in asset prices and yield market-implied estimates of policy effects more reliable.

Despite some persuasive evidence from dividend futures that the stock market downfall is fully rational and attributable to changes in expected growth rates (Gormsen and Koijen, 2020), the irrational explanation of the pandemic-induced financial crisis can also be plausible. COVID-19 has attracted media attention to an incomparably higher degree than any other epidemic or pandemic in the past. Baker et al. (2020) show the current pandemic attracted 35 times higher media attention during March 2020 than SARS (April-August 2003), 44 times higher than Bird Flu (November 1997 – November 1997), and 29 times higher than coinciding instances of MERS and Ebola (October 2014 – January 2015). The fact that media sentiment can shape market sentiment and cause downward pressure on stock markets has been well-documented in the behavioural finance literature at least since Tetlock (2007). The stock market panic can be further exacerbated by the fact that epidemics and pandemics are shown to decrease the attention span and the forecasting ability of stock analysts and might cause prominent momentum effects on financial markets (Dong and Heo, 2014). The role of media coverage and irrational pessimism has been highlighted in the literature with regards to the Ebola outbreak in 2014-2016 (Del Giudice and Paltrinieri, 2017; Ichev and Marinc, 2018). Currently, research and anecdotal evidence on irrational stock market behaviour during the COVID-19 pandemic has been steadily accumulating. Corbet et al. (2020) show that if a publicly listed company’s name or its product brand name contains “corona”, implicit negative connotations with the word "coronavirus" will cause significant drops in its stock price and increase its exposure to Chinese stock markets. Al-Awadhi et al. (in press) show that during the initial outbreak in China, B-shares (issues that are denominated in US dollars and available for trading to foreign investors on the Shanghai stock exchange), all other things held equal, experienced more pronounced negative returns, which can to some extent also support the sentiment explanation.

But perhaps the clearest instance of irrational and bubble-like market behaviour during the current pandemic is the tale of two Zooms. Zoom Video Communications (ZM US) is a tech company offering an app that has been increasingly used for remote work and virtual meetings by employees urged to work from home during lockdowns. Zoom Video Communications stock price has predictably surged 92% from 31 December 2019 until 20 March 2020. It has continued the rally and is trading 149% higher than year-end as of 23 April 2020 (see Figure 3 below). However, there is another Zoom to consider: Zoom Technologies (ZTNO US) is a penny stock completely unrelated to the video communications Zoom, belonging to a China-domiciled company that has not filed an annual report since 2013. Zoom Technologies skyrocketed 1890% during the same period and the ticker confusion even required SEC to intervene and halt trading in ZTNO US (McGrath, 2020). After the trading resumed, the share price predictably dropped, 31% below year-end as of 23 April 2020, which is comparable to the overall stock market drawdown.

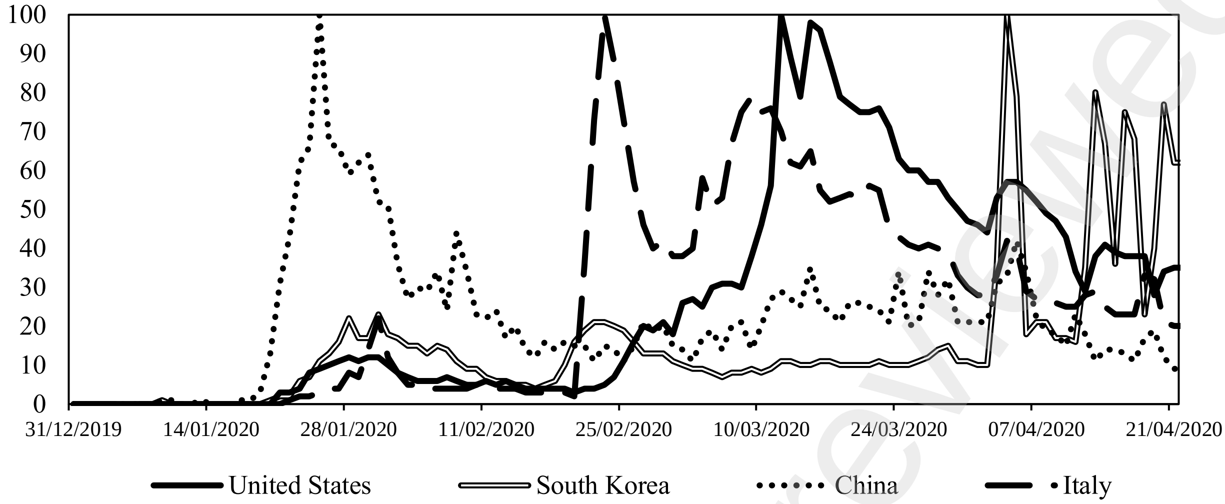
Figure 3. A tale of two Zooms: Market irrationality amid the pandemic



The tale of two Zooms is strikingly similar to the CUBA fund case famously highlighted by Thaler (2016), when the lifting of the US sanctions against Cuba briefly prompted an ETF that had no exposure to Cuba yet had "CUBA" in its market ticker to trade at a 70% premium against its net asset value. Overall, if the level of uncertainty is high and the attention is limited, investors can be tricked into trading based on noisy or completely irrelevant information. Therefore, the sentiment explanation for the COVID-19 financial impact seems very plausible, at least theoretically.

Hence, for the evaluation of *sentiment* effects, the study opts to use country-specific Google trends search volume for COVID-19-related topics that has been collected on a daily frequency from 31 December 2019 until 23 April 2020. The search volume index is normed to a scale from 0 to 100, therefore it is comparable across countries with varying populations and Internet use intensity. Figure 4 below again demonstrates the notable variation in the timing of sentiment peaks for selected countries.

Figure 4. COVID-19 sentiment dynamics (Google trends search volume) in selected countries.



Search volume indices, Google trends in particular, despite being a relatively novel feature, already have a successful track record of their use in finance and economics research, having predictive and explanatory power over macroeconomic variables (Guzman, 2011) and stock returns (Da et al., 2011; Fong, 2017). For the purposes of this study, Google trends search volume indices can serve as a powerful tool to test the irrational pessimism hypothesis with regards to COVID-19 pandemic and directly estimate the degree of irrational selloffs.

To incorporate all three factors into the analysis, the study seeks to estimate a set of panel regression equations, including local case growth, global case growth, innovations to sentiment (first difference in Google trends search volume index), innovations to SIR-predicted infection peak, and four dummies corresponding to announcement dates of respective policy interventions as explanatory variables and daily national stock market return denominated in USD as the dependent variable. The panel comprises 51 cross-sections and 115 daily periods, however, due to national weekend at holiday schedules the panel is unbalanced and comprises 4,415 observations. For local and global case growth variables, when the market reopens after a weekend or holiday, the growth rates are calculated as daily geometric averages since last trading day. The equations are estimated with common and differential slopes for local case growth, global case growth, and sentiment, with standard errors calculated using a panel-corrected cross-sectional heteroskedasticity-consistent covariance matrix (Beck and Katz, 1995). As dummy variable coefficients for policy measures are effectively event study-like estimates of announcement abnormal returns, Beck and Katz (1995) covariance estimates can address potential volatility clustering concerns[6]. Sample coefficients in a differential slopes setting are estimated using a Wald test for the equality of the average slope among cross-sections to zero. The choice between common and differential slopes is reinforced using the results of a redundant variables F-test. Table 2 below presents the results for local case growth, global case growth, and sentiment factors, showing that differential slopes do significantly improve the model's explanatory power in case of local case growth and sentiment and do not for global case growth. Therefore, in all further estimations, the study treats the effects of the former as heterogeneous and the latter as homogenous across countries.

Table 2. Redundant variables F-test for differential slopes

Regressor	F-statistic	p-value
Local case growth	1.4476**	*0.0218*
Global case growth	0.0987	*1.0000*
Sentiment	3.2087***	*0.0000*

[6] The use of ordinary covariance matrix, White (1980) diagonal covariance matrix, Zellner (1962) seemingly unrelated regression (SUR) covariance estimates, or Petersen (2009) two-way clustered standard errors did not impact the statistical significance of the results. For a more detailed discussion of various volatility clustering techniques in event studies estimations, see Shanaev et al. (2020).

Findings and Discussion

Tables 3a and 3b below report regression estimations for common and differential slopes models, respectively. Global case growth is insignificant in all estimations, while measures reflecting national COVID-19 severity (local case growth and SIR-predicted infection peak) are consistently significant. The maximum economic harm from healthcare system overload and overall disruptions due to infection peak is assessed at 1.2-1.6%, whereas irrational drawdown attributable to pandemic-related sentiment is much higher at 5.6-8.2%. Regional lockdowns are demonstrating a positive yet insignificant announcement abnormal return, evidencing a modest success such measures had in countries that adopted them in terms of slowing the virus' spread while avoiding unnecessary economic harm. National lockdowns, on the other hand, are shown to be largely counterproductive, leading to announcement abnormal returns of -1.9% to -2.3%. As the stock market assesses the net impact of lockdown measures, factoring in the potential reduction in cases and the infection peak, gross value destruction might be even larger in magnitude. Even if one would suggest that lockdown announcements do not incorporate the expectations for eventual transmission decline and respective infection peak decreases, its effect still fully counterweighs the worst-case scenario for SIR-implied peak. Surprisingly, the major driver of negative returns in this setting happens to be monetary stimulus – the announcement abnormal losses are in the range of 3.8-4.1%, which contradicts the general intuition as well as most empirical studies. However, it provides some evidence in support of "new classical" and supply-side interpretation of COVID-19 recession, as demand-stimulating policies in such a framework are ineffective, as well as supports Chevapatrakul (2014, 2015) and Vithessonthi and Techarongrojwong (2012) who report negative stock market reactions to expansionary monetary policies. Fiscal stimulus generates negative abnormal returns on the announcement, albeit of a much smaller magnitude (from -0.7% to -0.8%), supporting the time-varying fiscal multiplier hypothesis (Barro, 2009).

Furthermore, the propagating mechanisms of these stimulus policies might also play a role: as monetary policy injects liquidity into the banking sector, it might not be easily transformed into lending when credit risk and the general level of uncertainty is high, with newly injected money being hoarded at banks' balances as cash or reserves. Fiscal stimulus, in turn, can boost consumption more directly and prevent financial distress for vulnerable households. Interestingly, the numerical estimates tend to support this speculation: if the money multiplier in case of high uncertainty is roughly zero, and the fiscal multiplier for autonomous government spending in times of distress is 0.8 (comparable to Barro's estimate of US fiscal multiplier during the Second World War), then the negative effect of fiscal stimulus and monetary stimulus having a ratio of approximately 1:5 is exactly what one would expect. Nevertheless, such a claim undoubtedly requires further testing which is ultimately not the objective of this study.

Table 3a. Model estimation results – common slopes

Regressor	Common slopes (1)	(2)	(3)	(4)
Constant	-0.2549*** (-5.4398) *0.0000*	-0.2578*** (-5.5061) *0.0000*	-0.2406*** (-5.1302) *0.0000*	-0.1887*** (-4.0446) *0.0001*
Local case growth	-0.3617*** (-3.5779) *0.0004*	-0.2916*** (-2.8124) *0.0049*	-0.2821*** (-2.7319) *0.0063*	-0.2498** (-2.4232) *0.0154*
Global case growth	-0.0014 (-0.5448) *0.5859*	-0.0014 (-0.5392) *0.5898*	-0.0015 (-0.5818) *0.5607*	-0.0018 (-0.7322) *0.4641*
Sentiment	-0.0596*** (-11.9710) *0.0000*	-0.0588*** (-11.8292) *0.0000*	-0.0590*** (-11.8680) *0.0000*	-0.0563*** (-11.4469) *0.0000*
SIR-predicted infection peak		-1.5029*** (-3.3286) *0.0009*	-1.5387*** (-3.4103) *0.0007*	-1.6431*** (-3.6738) *0.0000*
National lockdown			-2.2940*** (-4.6457) *0.0000*	-1.9893*** (-4.0469) *0.0001*
Regional lockdown			0.3604 (0.4685) *0.6395*	0.6021 (0.7983) *0.4247*
Monetary stimulus				-4.0809*** (-9.9567) *0.0000*
Fiscal stimulus				-0.7141* (-1.7372) *0.0824*
R^2	0.0419	0.0445	0.0496	0.0745

Notes: all equations estimated using panel OLS with panel-corrected cross-sectional standard errors (PCSE), as in Beck in Katz (1995). T-stats are reported (in parentheses) while corresponding p-values are presented *in italics*. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 3b. Model estimation results – differential slopes

Regressor	Differential slopes (5)	(6)	(7)	(8)
Constant	-0.1819*** (-3.7403) *0.0002*	-0.1917*** (-3.9320) *0.0001*	-0.1777*** (-3.6446) *0.0003*	-0.1411*** (-2.9130) *0.0036*
Local case growth	-1.1757*** (-5.4078) *0.0000*	-1.0280*** (-4.5852) *0.0000*	-0.9882*** (-4.3907) *0.0000*	-0.8243*** (-3.6923) *0.0002*
Global case growth	-0.0019 (-0.7694) *0.4417*	-0.0019 (-0.7541) *0.4508*	-0.0019 (-0.7869) *0.4314*	-0.0022 (-0.8833) *0.3772*
Sentiment	-0.0819*** (-14.8133) *0.0000*	-0.0811*** (-14.6708) *0.0000*	-0.0812*** (-14.7346) *0.0000*	-0.0776*** (-14.1938) *0.0000*
SIR-predicted infection peak		-1.1924** (-2.5750) *0.0101*	-1.2254*** (-2.6431) *0.0082*	-1.3481*** (-2.9241) *0.0035*
National lockdown			-2.2508*** (-4.5285) *0.0000*	-1.8858*** (-3.7993) *0.0001*
Regional lockdown			0.4037 (0.5116) *0.6090*	0.6677 (0.8579) *0.3910*
Monetary stimulus				-3.7222*** (-8.7753) *0.0000*
Fiscal stimulus				-0.8201** (-2.0017) *0.0454*
R^2	0.1042	0.1056	0.1103	0.1300

Notes: all equations estimated using panel OLS with panel-corrected cross-sectional standard errors (PCSE), as in Beck in Katz (1995). Coefficients for local case growth and sentiment in differential slope models are estimated using a Wald test for the equality of the average slope among cross-sections to zero. T-stats are reported (in parentheses) while corresponding p-values are presented *in italics*. *** and ** denote statistical significance at 1% and 5%, respectively.

Overall, the initial estimations provided overwhelming support for several hypotheses identified in the literature yet not explicitly tested prior to this study. Indeed, the major factor distinguishing this pandemic from prior episodes that had limited economic and financial effects (Nippani and Washer, 2004) seems to be the wide-scale policy response initiated by national governments (Baker et al., 2020). The market did partially succumb to irrational panic, and the effect of sentiment is material. However, even in such turbulent times, financial markets show surprising signs of rationality, seemingly incorporating Bayesian updating for SIR-implied infection peaks, which would require the representative investor to know and apply differential equations.

However, at this stage of the study, the story of COVID-19 and the financial markets is far from over. Notably, the intercepts in all equations estimated so far remain negative and significant, suggesting that a large proportion of stock index drawdowns remain unexplained in this setting. To investigate it in greater detail, the study seeks to apply classical event studies techniques (Brown and Warner, 1985; McKinlay, 1997) to policy interventions and assess whether anticipation or adjustment effects can contribute towards a higher explanatory power of the models. As in McKinlay (1997) and Shanaev et al. (2020), an equal-weighted[7] pseudo-portfolio of national stock indices is composed based on policy intervention timings. For example, the return of the pseudo-portfolio at day -30 for national lockdown is computed as the average of abnormal returns for national markets that have implemented national lockdowns 30 days before they announced it. Abnormal returns are estimated as residuals from equation (6) (see Table 3b), therefore fundamental and sentiment factors related to COVID-19 pandemic are being accounted for.

Figure 5 below demonstrates the dynamics of pseudo-portfolio abnormal returns for all four policy interventions. The dynamics are strikingly similar, with stock indices reversing downward around 15 days before the announcement and starting a full-fledged freefall five days prior to the event. Immediately after the event, the markets remain relatively flat, establishing a recognisable positive trend later.

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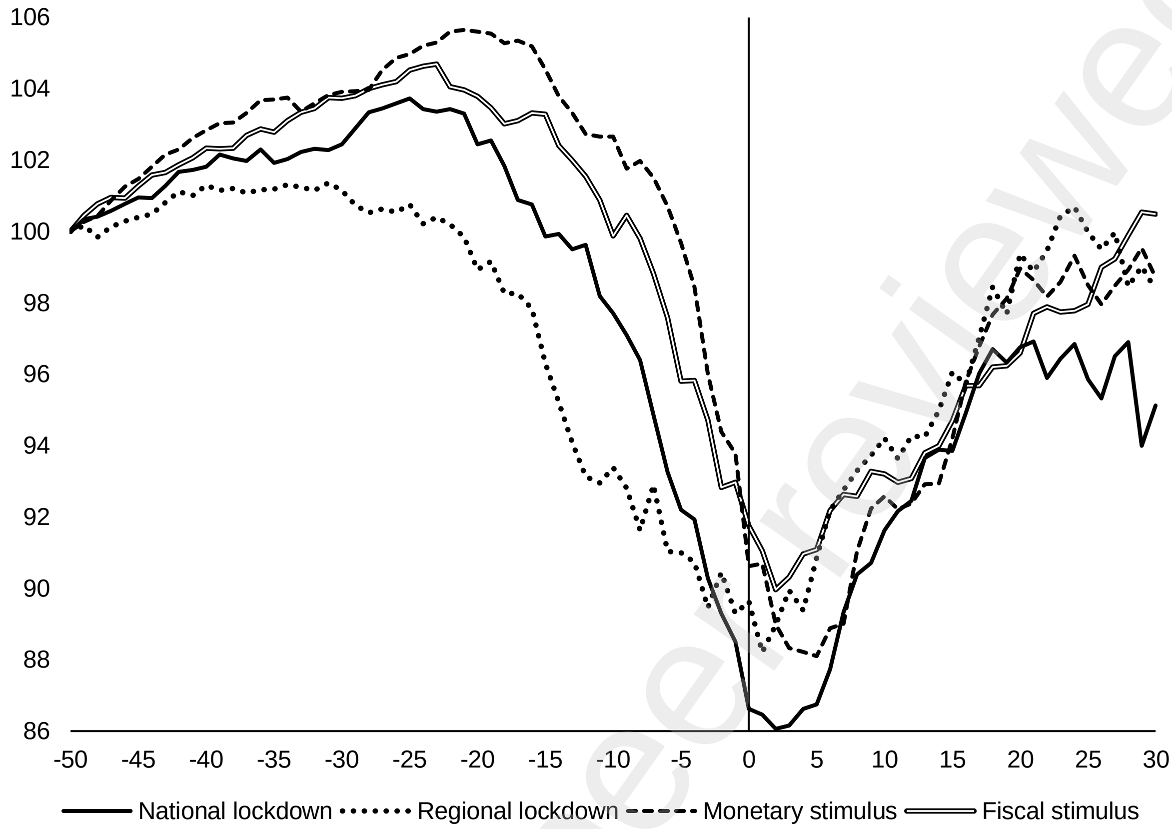
[7] The alternative use of a value-weighted pseudo-portfolio of national stock indices does not change the results

Figure 5. Abnormal return dynamics around policy interventions



Notes: abnormal returns estimated as residuals from the baseline differential slope model (equation 6).

Table 4 below demonstrates announcement abnormal returns as well as anticipation and adjustment effects in terms of cumulative abnormal returns across countries and for the pseudo-portfolio overall. The results are mainly consistent with Tables 3a and 3b estimations and the abnormal return pattern reported in Figure 4. Anticipation effects are greater in magnitude and are almost universally negative, while the announcement effects are more modest, and the adjustment effects are smaller still. The large negative impact of monetary stimulus cannot be attributed to Eurozone alone or to confounding events, as non-Euro countries that announced monetary measures on dates other than 12 March 2020, such as Brazil, Czech Republic, Mexico, Pakistan, Philippines, Taiwan, and Ukraine, also demonstrate significantly negative abnormal returns very similar in magnitude. In some countries, notably Argentina, Australia, Bahrain, Switzerland, and Turkey, the negative effects of both stimulus packages have been fully anticipated by the market. Positive effects of monetary or fiscal policy have been almost solely detected either for markets where stimulus measures have been extremely limited (such as Russia) or where the unconventional relationship between macroeconomic policy and stock markets has been highlighted by previous studies (such as Thailand) (Vithessonthi and Techarongrojwong, 2012).

Table 4. Announcement, anticipation, and adjustment effects for policy interventions

Country	Abnormal return [0; 0]				Cumulative abnormal return [-5; -1]				Cumulative abnormal return [1; 5]			
	National lockdown	Regional lockdown	Monetary stimulus	Fiscal stimulus	National lockdown	Regional lockdown	Monetary stimulus	Fiscal stimulus	National lockdown	Regional lockdown	Monetary stimulus	Fiscal stimulus
Argentina	-2.37%	N/A	-2.80%	-2.37%	-12.95%*	N/A	-15.72%*	-12.95%*	12.00%*	N/A	6.67%	12.00%*
Australia	-1.14%	N/A	2.44%*	-0.63%	-19.19%*	N/A	-4.96%*	-1.17%*	13.78%*	N/A	-4.94%*	-6.63%*
Bahrain	-1.66%*	N/A	3.84%*	3.84%*	-11.15%*	N/A	-14.16%*	-14.16%*	7.15%*	N/A	0.71%	0.71%
Belgium	-2.75%*	N/A	-9.03%*	-0.20%	-17.82%*	N/A	-6.31%*	-15.60%*	13.39%*	N/A	-10.24%*	-3.23%
Brazil	N/A	7.36%*	-11.05%*	-13.51%*	N/A	-2.14%	-3.96%	-1.66%	N/A	-5.40%	12.36%*	-6.51%*
Canada	10.60%*	N/A	2.11%*	-8.97%*	-13.65%*	N/A	-2.43%*	-7.50%*	-21.69%*	N/A	-10.87%*	12.91%*
Chile	8.17%*	N/A	-6.55%*	8.17%*	-20.89%*	N/A	-4.05%*	-20.89%*	7.03%*	N/A	-13.34%*	7.03%*
China	N/A	-1.95%*	0.48%	-0.89%	N/A	0.99%	-3.91%	-12.20%*	N/A	-3.69%	4.69%	10.53%
Czech Republic	-10.06%*	N/A	-10.06%*	-10.06%*	-9.30%*	N/A	-9.30%*	-9.30%*	-10.09%*	N/A	-10.09%*	-10.09%*
Denmark	-0.92%	N/A	-0.66%	0.04%	-1.14%	N/A	-11.95%*	11.54%*	-11.95%*	N/A	11.54%*	4.19%
Egypt	2.12%	N/A	5.27%*	5.27%*	13.36%*	N/A	-1.66%	-1.66%	-2.94%	N/A	9.05%*	9.05%*
Finland	N/A	-2.56%*	-5.45%*	1.49%	N/A	17.05%*	-4.07%*	-4.40%*	N/A	0.58%	-4.40%	13.00%*
France	-1.97%*	N/A	-5.28%*	-1.97%*	-6.80%*	N/A	-9.26%*	-6.80%*	-1.46%	N/A	-10.11%*	-1.46%
Germany	N/A	3.74%*	-11.03%*	2.72%*	N/A	-12.84%*	-8.51%*	3.62%	N/A	9.47%*	-12.84%*	-4.01%
Greece	-8.70%*	N/A	-11.23%*	-13.82%*	-9.25%*	N/A	-6.88%*	-11.54%*	15.12%*	N/A	-10.51%*	-4.13%
Hong Kong	N/A	N/A	0.10%	-0.36%	N/A	N/A	-1.71%	-1.81%	N/A	N/A	-1.90%	-1.24%
India	7.86%*	N/A	0.41%	5.04%*	-5.97%*	N/A	10.23%*	7.19%*	-2.73%	N/A	-2.31%	-7.58%*
Indonesia	N/A	17.05%*	-7.08%*	0.26%	N/A	-19.18%*	-1.89%	-2.29%	N/A	4.13%	-18.20%*	-3.30%
Ireland	-8.83%*	N/A	-8.83%*	-3.87%*	-4.74%*	N/A	-4.74%*	5.59%*	-20.81%*	N/A	-20.81%*	-19.41%*
Israel	N/A	-0.70%	1.14%	-6.72%*	N/A	2.38%	9.93%*	-12.49%*	N/A	11.00%*	2.38%	0.44%
Italy	-8.13%*	2.32%*	-18.07%*	0.21%	-0.73%	0.62%	-16.28%*	-14.14%*	-22.60%*	-8.96%*	0.17%	-18.57%*
Japan	N/A	2.23%*	-0.75%	-2.10%*	N/A	-3.68%*	-16.04%*	0.06%	N/A	4.22%*	2.29%	-14.70%*
Lithuania	-8.68%*	N/A	-7.98%*	-8.68%*	-9.41%*	N/A	-1.90%	-9.41%*	0.16%	N/A	-9.65%*	0.16%
Malaysia	-2.04%*	N/A	1.49%	1.29%	-9.55%*	N/A	0.59%	-3.44%	3.41%	N/A	-0.23%	4.07%
Mexico	N/A	N/A	-10.00%*	4.34%*	N/A	N/A	6.45%*	-2.24%	N/A	N/A	2.40%	9.17%*
Netherlands	-4.99%*	N/A	-5.21%*	-0.90%	-11.05%*	N/A	-5.41%*	-12.48%*	-6.48%*	N/A	-12.16%*	0.67%
New Zealand	-3.84%*	N/A	1.03%	1.03%	-3.08%	N/A	-15.54%*	-15.54%*	11.18%*	N/A	-7.95%*	-7.95%*
Nigeria	N/A	-3.09%*	-0.03%	-0.03%	N/A	-1.63%	-17.71%*	-17.71%*	N/A	-3.86%	-3.75%	-3.75%
Norway	-10.36%*	N/A	1.95%*	-7.72%*	-12.99%*	N/A	-22.25%*	-16.71%*	-6.80%*	N/A	-13.86%*	-7.63%*
Pakistan	-6.51%*	N/A	-4.66%*	-6.51%*	-12.52%*	N/A	-4.73%	-12.52%*	-5.70%*	N/A	-14.24%*	-5.70%*
Philippines	N/A	-7.31%*	-12.59%*	-1.26%	N/A	-8.53%*	-11.02%*	13.83%*	N/A	-2.15%	19.25%*	12.52%*
Poland	4.95%*	N/A	5.95%*	4.44%*	-15.22%*	N/A	-11.70%*	8.50%*	6.56%*	N/A	1.92%	-0.64%
Portugal	-5.35%*	N/A	-11.96%*	2.03%*	-15.69%*	N/A	-13.66%*	9.56%*	16.95%*	N/A	-9.08%*	0.28%
Qatar	N/A	2.12%*	1.75%	1.75%	N/A	-1.89%	-0.80%	-0.80%	N/A	-1.13%	4.24%	4.24%
Russia	N/A	0.78%	2.93%*	2.57%	N/A	7.49%*	-1.17%	9.41%*	N/A	16.58%*	7.49%*	3.87%
Saudi Arabia	0.94%	-6.83%*	0.34%	0.23%	6.10%*	6.81%*	-1.53%	2.28%	7.81%*	-1.53%	2.16%	4.58%
Serbia	-3.65%*	N/A	0.19%	0.26%	-3.10%*	N/A	-4.79%*	8.09%*	-7.33%*	N/A	-9.81%*	4.85%
Singapore	4.56%*	N/A	-0.80%	-1.07%	2.23%	N/A	0.65%	-0.25%	3.47%	N/A	-2.82%	-1.03%
South Africa	-7.38%*	N/A	-3.26%*	-2.89%*	30.10%*	N/A	-19.60%*	-0.80%	-7.06%*	N/A	30.10%*	5.28%
South Korea	N/A	N/A	-4.66%*	1.35%	N/A	N/A	-13.98%*	0.46%	N/A	N/A	-14.28%*	-2.25%
Spain	-11.34%*	N/A	-10.33%*	-4.49%*	-9.60%*	N/A	-6.35%*	-12.57%*	-2.01%	N/A	-7.34%*	10.49%*
Sweden	N/A	N/A	-0.79%	-4.71%*	N/A	N/A	-18.12%*	-16.52%*	N/A	N/A	-10.49%*	-8.93%*
Switzerland	-1.03%	N/A	3.26%*	3.62%	-5.99%*	N/A	-9.95%*	-12.31%*	-0.82%	N/A	5.52%	-4.10%
Taiwan	N/A	N/A	-6.09%*	0.66%	N/A	N/A	-16.09%*	-3.36%	N/A	N/A	11.81%*	0.68%
Thailand	5.90%*	N/A	1.03%	-1.79%	2.32%	N/A	1.09%	1.04%	1.66%	N/A	-0.40%	-16.55%*
Turkey	-1.81%	N/A	1.38%	-2.31%	9.65%*	N/A	-17.97%*	-14.95%*	1.30%	N/A	2.69%	4.98%
Ukraine	0.17%	N/A	-10.82%*	-2.02%	-15.85%*	N/A	-14.69%*	-15.65%*	-6.68%*	N/A	-6.21%*	-0.17%
United Arab Emirates	-3.95%*	-7.78%*	-7.78%*	-7.78%*	18.18%*	-8.11%*	-8.11%*	-8.11%*	-3.41%*	-4.65%*	-4.65%*	-4.65%*
United Kingdom	-2.56%*	N/A	0.29%	0.29%	-8.56%*	N/A	-2.51%	-2.51%	12.45%*	N/A	-13.49%*	-13.49%*
United States	N/A	0.34%	-2.33%*	-1.22%	N/A	-5.67%*	1.02%	4.78%	N/A	6.15%*	2.11%	7.09%*
Vietnam	2.59%*	N/A	-1.35%	0.42%	7.06%*	N/A	-3.39%	-1.74%	12.11%*	N/A	-11.78%*	-2.22%
Average	-2.12%*	0.38%	-3.35%*	-1.32%*	-5.21%*	-1.89%	-7.07%*	-4.79%*	0.15%	1.38%	-2.81%*	-0.73%
% negative	70.59%	46.67%	60.78%	54.90%	76.47%	60.00%	86.27%	72.55%	50.00%	53.33%	60.78%	52.94%

Notes: * denotes statistical significance at 5%.

To better understand the anticipation process for policy interventions, the study estimates binary choice models (probit, logit, and extreme value) for national lockdown, monetary and fiscal stimulus[8]. The probability of policy intervention by date t is regressed on SIR-predicted infection peak, national COVID-19 sentiment, log cases per million people, Polity index, and a federation dummy. The probability of national lockdown implementation is also associated with log population density and whether a regional lockdown is already being enforced. Standard errors are estimated using a Huber-White heteroskedasticity consistent procedure in all equations.

[8] Not enough countries have adopted regional lockdowns to ensure sufficient binary choice model quality

Table 5a. Estimating national lockdown probability

Regressor	Probit	Logit	Extreme value
Constant	-3.0995*** (-7.2040) *0.0000*	-6.9010*** (-6.461) *0.0000*	-1.9489*** (-7.1773) *0.0000*
SIR-predicted infection peak	1.1632*** (2.9372) *0.0033*	2.9043*** (2.8988) *0.0037*	0.7340*** (2.9049) *0.0037*
Sentiment	0.0198*** (5.1922) *0.0000*	0.0429*** (5.0457) *0.0000*	0.0135*** (5.0765) *0.0000*
Log cases per million people	0.1037** (2.0755) *0.0379*	0.2654** (2.3575) *0.0184*	0.0641* (1.8808) *0.0600*
Log population density	-0.1106* (-1.8351) *0.0665*	-0.2079 (-1.5496) *0.1212*	-0.0808** (-1.9791) *0.0478*
Polity index	-0.0276* (-1.8784) *0.0603*	-0.0419 (-1.2666) *0.2053*	-0.0221** (-2.2573) *0.0240*
Federation	-0.1601 (-0.7577) *0.4486*	-0.2829 (-0.6322) *0.5272*	-0.1323 (-0.9037) *0.3661*
Regional lockdown	-0.9306*** (-3.0919) *0.0020*	-2.0020*** (-2.7227) *0.0065*	-0.6246*** (-3.3168) *0.0009*
McFadden R^2	0.3631	0.3575	0.3655

Notes: Binary choice models are estimated with Huber-White heteroskedasticity-consistent standard errors. Z-stats are reported (in parentheses) while corresponding p-values are presented *in italics*. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 5b. Estimating monetary stimulus probability

Regressor	Probit	Logit	Extreme value
Constant	-3.1167*** (-17.4201) *0.0000*	-6.1196*** (-15.2155) *0.0000*	-2.1518*** (-15.8773) *0.0000*
SIR-predicted infection peak	1.3356*** (4.4675) *0.0000*	3.0853*** (4.4779) *0.0000*	0.8893*** (4.3436) *0.0000*
Sentiment	0.0152*** (4.2210) *0.0000*	0.0284*** 3.6968 *0.0002*	0.0123*** (4.5457) *0.0000*
Log cases per million people	0.0245 (0.4144) *0.6786*	0.0370 (0.3170) *0.7512*	0.0218 (0.4631) *0.6433*
Polity index	-0.0086 (-0.6960) *0.4865*	-0.0198 (-0.7667) *0.4433*	-0.0056 (-0.6240) *0.5326*
Federation	0.1298 (0.7204) *0.4713*	0.1328 (0.3440) *0.7309*	0.1636 (1.2346) *0.2170*
National lockdown	-0.0426 (-0.1432) *0.8862*	-0.1040 (-0.1848) *0.8534*	-0.0034 (-0.0137) *0.9891*
Fiscal stimulus	1.0911*** (5.6549) *0.0000*	2.0933*** (5.5063) *0.0000*	0.8686*** (5.3968) *0.0000*
McFadden R^2	0.3953	0.3755	0.4099

Notes: Binary choice models are estimated with Huber-White heteroskedasticity-consistent standard errors. Z-stats are reported (in parentheses) while corresponding p-values are presented *in italics*. *** denotes statistical significance at 1%.

Table 5c. Estimating fiscal stimulus probability

Regressor	Probit	Logit	Extreme value
Constant	-2.8533*** (-19.7397) *0.0000*	-5.7495*** (-16.2626) *0.0000*	-1.8813*** (-20.6788) *0.0000*
SIR-predicted infection peak	0.0495 (0.1609) *0.8722*	0.5039 (0.7378) *0.4606*	-0.0659 (-0.3124) *0.7547*
Sentiment	0.0094*** (2.6558) *0.0079*	0.0181** (2.4345) *0.0149*	0.0069*** (2.7035) *0.0069*
Log cases per million people	0.1453*** (2.6711) *0.0076*	0.2961*** (2.5950) *0.0095*	0.1066*** (2.7301) *0.0063*
Polity index	-0.0043 (-0.3645) *0.7162*	-0.0248 (0.3523) *0.3523*	0.0004 (0.0482) *0.9616*
Federation	0.0781 (0.4769) *0.6334*	0.1772 (0.4962) *0.6198*	0.0502 (0.4589) *0.6463*
National lockdown	0.1564 (0.7626) *0.4457*	0.3705 (0.9396) *0.3474*	0.1161 (0.7156) *0.4742*
Monetary stimulus	0.7996*** (4.4513) *0.0000*	1.7673*** (4.2599) *0.0000*	0.5626*** (4.5456) *0.0000*
McFadden R^2	0.3089	0.3000	0.3161

Notes: Binary choice models are estimated with Huber-White heteroskedasticity-consistent standard errors. Z-stats are reported (in parentheses) while corresponding p-values are presented *in italics*. *** and ** denote statistical significance at 1% and 5%, respectively.

Tables 5a-5c present the estimations of binary choice models. All three policy interventions, especially national lockdowns, are significantly driven by sentiment and likely public or media pressure. SIR-predicted infection peak plays an important role in lockdown and monetary policy decisions but not in fiscal stimulus decisions, while current COVID-19 prevalence (log cases per million people) informs lockdown and fiscal policy yet not monetary policy. Democracies are less willing to impose national lockdowns but are as likely to introduce stimulus measures as authoritarian states. There are no significant differences in policy interventions among federal or unitary states. Population density remarkably decreases lockdown probability, possibly due to the high opportunity cost of isolating a densely packed population. Interestingly, if there has been a regional lockdown imposed, a transition into a national lockdown is less likely, while when a monetary or fiscal stimulus is announced, its counterpart becomes more likely in the near future, potentially reflecting a prominent "whatever it takes" attitude in macroeconomic policy. Relatively high values of McFadden R^2 (0.3-0.4) in all the models suggest that policy interventions could have indeed been predicted in advance by stock market participants and priced in the values of stock indices, at least probabilistically, before their announcement.

To model the anticipation process with greater precision, panel regressions with common and differential slopes – equations (4) and (8) – are estimated with varying anticipation windows (from zero to ten days). Such a framework allows the study to generate a set of plausible estimates of the economic and financial impact of fundamental, policy, and sentiment factors of the COVID-19 pandemic. Anticipation is modelled using a $POLICY_{it+n} - POLICY_{it}$ dummy, where n is the anticipation window length and $POLICY_{it}$ is a dummy variable equal to 1 if a particular intervention has already been announced and 0 otherwise. The total impact of policy measures is computed as $ANN + nANT$, where ANN is the announcement effect, estimated using a $POLICY_{it} - POLICY_{it-1}$ dummy in all estimations, and ANT is the anticipation effect, whereas its statistical significance is assessed using a Wald test for the equality of $ANN + nANT$ to zero.

Tables 6a and 6b below present the estimation results for varying anticipation windows with fixed and differential slopes, respectively, while Figures 6a and 6b plot the estimated total impact of all COVID-19-related factors for different anticipation window assumptions.

Table 6a. Anticipation effects for policy interventions (common slopes estimates).

Regressor	Common slopes										
Anticipation window	0	1	2	3	4	5	6	7	8	9	10
Constant	-0.1887***	-0.1900***	-0.1749***	-0.0837*	-0.0546	-0.0546	-0.0129	0.0396	0.0345	0.0297	0.0428
	(-4.0446)	(-3.9879)	(-3.6125)	(-1.7160)	(-1.0994)	(-1.0836)	(-0.2512)	(0.7617)	(0.6496)	(0.5486)	(0.7742)
	0.0001	*0.0001*	*0.0003*	*0.0862*	*0.2717*	*0.2778*	*0.8017*	*0.4463*	*0.5160*	*0.5833*	*0.4389*
Local case growth	-0.2498**	-0.2378**	-0.2159**	-0.2079**	-0.1846*	-0.1069	-0.0585	-0.0440	-0.0483	-0.0422	-0.0409
	(-2.4232)	(-2.2917)	(-2.0941)	(-2.0352)	(-1.7995)	(-1.0198)	(-0.5568)	(-0.4158)	(-0.4569)	(-0.4023)	(-0.3890)
	0.0154	*0.0220*	*0.0363*	*0.0419*	*0.0720*	*0.3079*	*0.5778*	*0.6776*	*0.6478*	*0.6875*	*0.6973*
Global case growth	-0.0018	-0.0018	-0.0020	-0.0025	-0.0026	-0.0027	-0.0029	-0.0032	-0.0032	-0.0030	-0.0031
	(-0.7322)	(-0.7299)	(-0.7842)	(-0.9969)	(-1.0641)	(-1.0735)	(-1.1715)	(-1.3151)	(-1.2849)	(-1.1200)	(-1.2377)
	0.4641	*0.4655*	*0.4330*	*0.3189*	*0.2874*	*0.2831*	*0.2415*	*0.1886*	*0.1989*	*0.2303*	*0.2159*
Sentiment	-0.0563***	-0.0555***	-0.0543***	-0.0530***	-0.0544***	-0.0538***	-0.0532***	-0.0537***	-0.0538***	-0.0577***	-0.0588***
	(-11.4469)	(-11.2534)	(-10.9715)	(-10.7416)	(-10.7030)	(-10.5414)	(-10.4030)	(-10.4492)	(-10.3277)	(-10.6655)	(-10.7563)
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
SIR-predicted infection peak	-1.6431***	-1.5937***	-1.5974***	-1.4082***	-1.3789***	-1.2845***	-1.2927***	-1.2643***	-1.1816***	-1.0719**	-0.9921**
	(-3.6738)	(-3.5400)	(-3.5456)	(-3.1507)	(-3.0727)	(-2.8577)	(-2.8771)	(-2.8134)	(-2.6056)	(-2.3635)	(-2.1742)
	0.0000	*0.0004*	*0.0004*	*0.0016*	*0.0021*	*0.0043*	*0.0040*	*0.0049*	*0.0092*	*0.0182*	*0.0298*
National lockdown (announcement)	-1.9893***	-2.0184***	-1.7816***	-1.7732***	-1.8481***	-1.8499***	-1.8590***	-1.9304***	-1.9417***	-1.9809***	-1.9947***
	(-4.0469)	(-4.0865)	(-3.5895)	(-3.6110)	(-3.7627)	(-3.7668)	(-3.7806)	(-3.9294)	(-3.8695)	(-3.9533)	(-3.9685)
	0.0001	*0.0000*	*0.0003*	*0.0003*	*0.0002*	*0.0002*	*0.0002*	*0.0001*	*0.0001*	*0.0001*	*0.0001*
Regional lockdown (announcement)	0.6021	0.7008	0.7319	0.7016	0.6559	0.5928	0.6127	0.6047	0.5720	0.5807	0.6069
	(0.7983)	(0.9272)	(0.9647)	(0.9297)	(0.8660)	(0.7831)	(0.8112)	(0.8043)	(0.7580)	(0.7685)	(0.7991)
	0.4247	*0.3539*	*0.3348*	*0.3526*	*0.3866*	*0.4366*	*0.4173*	*0.4213*	*0.4485*	*0.4422*	*0.4243*
Monetary stimulus (announcement)	-4.0809***	-4.1086***	-4.0139***	-4.0297***	-4.1091***	-4.0077***	-3.9487***	-3.8889***	-3.8329***	-3.9057***	-3.8427***
	(-9.9567)	(-9.9422)	(-9.6689)	(-9.7395)	(-9.8887)	(-9.6544)	(-9.4792)	(-9.3596)	(-9.1814)	(-9.3443)	(-9.1249)
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Fiscal stimulus (announcement)	-0.7141*	-0.5976	-0.6446	-0.4968	-0.4900	-0.4458	-0.5008	-0.5489	-0.5841	-0.5266	-0.5575
	(-1.7372)	(-1.4498)	(-1.5610)	(-1.2073)	(-1.1876)	(-1.0809)	(-1.2142)	(-1.3329)	(-1.4099)	(-1.2692)	(-1.3369)
	0.0824	*0.1472*	*0.1186*	*0.2274*	*0.2351*	*0.2798*	*0.2247*	*0.1827*	*0.1587*	*0.2044*	*0.1813*
National lockdown (anticipation)		-1.0149**	-0.7659**	-0.9913***	-0.8184***	-0.8253***	-0.9169***	-1.0284***	-0.9754***	-0.9565***	-0.9003***
		(-2.0551)	(-2.1578)	(-3.3795)	(-3.1561)	(-3.4955)	(-4.1881)	(-5.0107)	(-4.9939)	(-5.1181)	(-4.9930)
		0.0399	*0.0310*	*0.0007*	*0.0016*	*0.0005*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Regional lockdown (anticipation)		-1.0524	0.2537	-0.3376	-0.3028	-0.2889	-0.4910	-0.3226	-0.4840*	-0.4414*	-0.3029
		(-1.3911)	(0.4720)	(-0.7727)	(-0.7962)	(-0.8459)	(-1.5739)	(-1.1188)	(-1.7795)	(-1.7120)	(-1.2258)

		*0.1643***	*0.6370****	*0.4397****	*0.4259****	*0.3977****	*0.1156****	*0.2633****	*0.0752****	*0.0870****	*0.2203****
Monetary stimulus (anticipation)		-0.8521	-1.3443	-1.8597	-1.8563	-1.6515	-1.5279	-1.3131	-1.0272	-1.1180	-0.9921
		(-2.0816)	(-4.5489)	(-7.6188)	(-8.5119)	(-8.2379)	(-8.0966)	(-7.2895)	(-5.8967)	(-6.6357)	(-6.0020)
		0.0374	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Fiscal stimulus (anticipation)		0.6667	-0.2750	-0.2103	0.0003	-0.2842	-0.3508*	-0.4508**	-0.5142***	-0.2736	-0.3700**
		(1.6070)	(-0.9122)	(-0.8430)	(0.0014)	(-1.4038)	(-1.8483)	(-2.5074)	(-2.9732)	(-1.6410)	(-2.2776)
		0.1081	*0.3617*	*0.3933*	*0.9989*	*0.1605*	*0.0646*	*0.0122*	*0.0030*	*0.1009*	*0.0228*
R^2	0.0745	0.0773	0.0817	0.0977	0.1028	0.1066	0.1129	0.1180	0.1136	0.1169	0.1167
National lockdown	-1.99***	-3.03***	-3.31***	-4.75***	-5.12***	-5.98***	-7.36***	-9.13***	-9.74***	-10.56***	-11.00***
	(-4.0469)	(-4.3032)	(-3.7669)	(-4.6298)	(-4.3913)	(-4.5957)	(-5.1621)	(-5.9181)	(-5.8461)	(-5.9459)	(-5.7924)
	0.0001	*0.0000*	*0.0002*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Regional lockdown	0.60	-0.36	1.24	-0.31	-0.56	-0.85	-2.33	-1.65	-3.30	-3.39	-2.42
	(0.7983)	(-0.3280)	(0.9395)	(-0.2050)	(-0.3258)	(-0.4537)	(-1.1497)	(-0.7632)	(-1.4240)	(-1.3812)	(-0.9313)
	0.4247	*0.7429*	*0.3475*	*0.8376*	*0.7446*	*0.6501*	*0.2503*	*0.4454*	*0.1545*	*0.1673*	*0.3517*
Monetary stimulus	-4.08***	-4.96***	-6.70***	-9.61***	-11.53***	-12.27***	-13.12***	-13.08***	-12.05***	-13.97***	-13.76***
	(-9.9567)	(-8.3777)	(-9.0597)	(-11.0744)	(-11.5271)	(-10.8972)	(-10.4612)	(-9.4869)	(-7.9894)	(-8.5718)	(-7.7816)
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Fiscal stimulus	-0.71*	0.07	-1.19	-1.13	-0.49	-1.87*	-2.61**	-3.70***	-4.70***	-2.99*	-4.26**
	(-1.7372)	(0.1158)	(-1.5986)	(-1.2860)	(-0.4855)	(-1.6604)	(-2.0959)	(-2.7261)	(-3.1737)	(-1.8745)	(-2.4770)
	0.0824	*0.9078*	*0.1100*	*0.1985*	*0.6247*	*0.0969*	*0.0362*	*0.0064*	*0.0015*	*0.0609*	*0.0133*
Infection peak (SIR)	-1.64***	-1.59***	-1.60***	-1.41***	-1.38***	-1.28***	-1.29***	-1.26***	-1.18***	-1.07**	-0.99**
	(-3.6738)	(-3.5400)	(-3.5456)	(-3.1507)	(-3.0727)	(-2.8577)	(-2.8771)	(-2.8134)	(-2.6056)	(-2.3635)	(-2.1742)
	0.0000	*0.0004*	*0.0004*	*0.0016*	*0.0021*	*0.0043*	*0.0040*	*0.0049*	*0.0092*	*0.0182*	*0.0298*
Sentiment	-5.63***	-5.55***	-5.43***	-5.30***	-5.44***	-5.38***	-5.32***	-5.37***	-5.38***	-5.77***	-5.88***
	(-11.4469)	(-11.2534)	(-10.9715)	(-10.7416)	(-10.7030)	(-10.5414)	(-10.4030)	(-10.4492)	(-10.3277)	(-10.6655)	(-10.7563)
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Notes: all equations estimated using panel OLS with panel-corrected cross-sectional standard errors (PCSE), as in Beck in Katz (1995). Total impact of COVID-19-related factors is estimated using Wald test for the sum of announcement and anticipation (when present) effects. T-stats are reported (in parentheses) while corresponding p-values are presented *in italics*. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 6b. Anticipation effects for policy interventions (differential slopes estimates)

Regressor	Differential slopes										
Anticipation window	0	1	2	3	4	5	6	7	8	9	10
Constant	-0.1411***	-0.1496***	-0.1415***	-0.0589	-0.0356	-0.0431	-0.0070	0.0395	0.0300	0.0251	0.0387
	(-2.9130)	(-3.0406)	(-2.8347)	(-1.1733)	(-0.6988)	(-0.8350)	(-0.1341)	(0.7451)	(0.5543)	(0.4559)	(0.6902)
	0.0036	*0.0024*	*0.0046*	*0.2407*	*0.4847*	*0.4038*	*0.8934*	*0.4562*	*0.5794*	*0.6485*	*0.4901*
Local case growth	-0.8243***	-0.7345***	-0.6433***	-0.5320**	-0.4911**	-0.3703	-0.2578	-0.2381	-0.2189	-0.1581	-0.1752
	(-3.6923)	(-3.2462)	(-2.8231)	(-2.3467)	(-2.1461)	(-1.6074)	(-1.1169)	(-1.0269)	(-0.9359)	(-0.6712)	(-0.7373)
	0.0002	*0.0012*	*0.0048*	*0.0190*	*0.0319*	*0.1081*	*0.2641*	*0.3046*	*0.3494*	*0.5022*	*0.4610*
Global case growth	-0.0022	-0.0021	-0.0022	-0.0027	-0.0028	-0.0028	-0.0030	-0.0034	-0.0033	-0.0031	-0.0032
	(-0.8833)	(-0.8690)	(-0.8934)	(-1.0980)	(-1.1562)	(-1.1522)	(-1.2461)	(-1.3780)	(-1.3421)	(-1.2569)	(-1.2946)
	0.3772	*0.3849*	*0.3717*	*0.2723*	*0.2477*	*0.2493*	*0.2128*	*0.1683*	*0.1797*	*0.2089*	*0.1956*
Sentiment	-0.0776***	-0.0768***	-0.0750***	-0.0732***	-0.0748***	-0.0735***	-0.0727***	-0.0732***	-0.0752***	-0.0775***	-0.0786***
	(-14.1938)	(-13.9921)	(-13.6099)	(-13.3140)	(-13.2196)	(-12.8788)	(-12.6460)	(-12.7078)	(-12.6081)	(-12.6516)	(-12.7264)
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
SIR-predicted infection peak	-1.3481***	-1.3257***	-1.3611***	-1.2198***	-1.1826**	-1.0837**	-1.1182**	-1.0648**	-0.9783**	-0.8949*	-0.8160*
	(-2.9241)	(-2.8577)	(-2.9294)	(-2.6507)	(-2.5569)	(-2.3369)	(-2.4107)	(-2.2920)	(-2.0865)	(-1.9058)	(-1.7278)
	0.0035	*0.0043*	*0.0034*	*0.0081*	*0.0106*	*0.0195*	*0.0160*	*0.0220*	*0.0370*	*0.0568*	*0.0841*
National lockdown (announcement)	-1.8858***	-1.9454***	-1.7108***	-1.6936***	-1.7565***	-1.7523***	-1.8012***	-1.8798***	-1.8878***	-1.9379***	-1.9623***
	(-3.7993)	(-3.8960)	(-3.4131)	(-3.4141)	(-3.5371)	(-3.5275)	(-3.6173)	(-3.7766)	(-3.7086)	(-3.8041)	(3.8361)
	0.0001	*0.0001*	*0.0006*	*0.0006*	*0.0004*	*0.0004*	*0.0003*	*0.0002*	*0.0002*	*0.0001*	*0.0001*
Regional lockdown (announcement)	0.6677	0.7686	0.8224	0.7592	0.70307	0.6790	0.6730	0.6950	0.6289	0.6074	0.6356
	(0.8579)	(0.9849)	(1.0471)	(0.9697)	(0.8954)	(0.8652)	(0.8607)	(0.8924)	(0.8047)	(0.7757)	(0.8078)
	0.3910	*0.3247*	*0.2951*	*0.3322*	*0.3706*	*0.3870*	*0.3895*	*0.3722*	*0.4211*	*0.4380*	*0.4193*
Monetary stimulus (announcement)	-3.7222***	-3.7722***	-3.7191***	-3.8048***	-3.9046***	-3.8348***	-3.7660***	-3.7349***	-3.6663***	-3.7764***	-3.6970***
	(-8.7753)	(-8.8155)	(-8.6266)	(-8.8573)	(-9.0431)	(-8.8802)	(-8.6934)	(-8.6475)	(-8.4550)	(-8.6948)	(-8.4319)
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Fiscal stimulus (announcement)	-0.8201**	-0.7002*	-0.7610*	-0.6007	-0.6125	-0.5829	-0.6378	-0.7037*	-0.7500*	-0.6958*	-0.7322*
	(-2.0017)	(-1.7036)	(-1.8469)	(-1.4629)	(-1.4868)	(-1.4133)	(-1.5464)	(-1.7091)	(-1.8108)	(-1.6769)	(-1.7553)
	0.0454	*0.0885*	*0.0648*	*0.1436*	*0.1372*	*0.1577*	*0.1221*	*0.0875*	*0.0703*	*0.0936*	*0.0793*
National lockdown (anticipation)		-0.9496*	-0.7532**	-1.0019***	-0.7520***	-0.6964***	-0.8707***	-0.9612***	-0.9142***	-0.9267***	-0.8693***
		(-1.8941)	(-2.0671)	(-3.2507)	(-2.7440)	(-2.7927)	(-3.7782)	(-4.4370)	(-4.4523)	(-4.6812)	(-4.5131)
		0.0583	*0.0388*	*0.0012*	*0.0061*	*0.0053*	*0.0002*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Regional lockdown (anticipation)		-0.9870*	0.2831	-0.2442	-0.2787	-0.2036	-0.4375	-0.1115	-0.2574	-0.2236	-0.0704
		(-1.8941)	(0.5144)	(-0.5380)	(-0.7077)	(-0.5713)	(-1.3488)	(-0.3736)	(-0.8994)	(-0.8171)	(-0.2693)

		0.0583	*0.6070*	*0.5906*	*0.4792*	*0.5679*	*0.1775*	*0.7087*	*0.3685*	*0.4139*	*0.7877*
Monetary stimulus (anticipation)		-0.8642	-1.2472***	-1.7651***	-1.7801***	-1.5957***	-1.4463***	-1.2962***	-1.0316***	-1.1298***	-0.9956***
		(-2.0917)	(-4.1580)	(-7.1106)	(-8.0322)	(-7.7903)	(-7.5115)	(-7.0590)	(-5.7722)	(-6.5337)	(-5.8366)
		0.0365	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Fiscal stimulus (anticipation)		0.7576*	-0.2640	-0.2216	0.0786	-0.2277	-0.2807	-0.3567*	-0.4215**	-0.1911	-0.3106*
		(1.8311)	(-0.8696)	(-0.8768)	(0.3482)	(-1.1087)	(-1.4601)	(-1.9556)	(-2.3935)	(-1.1222)	(-1.8712)
		0.0672	*0.3846*	*0.3806*	*0.7277*	*0.2676*	*0.1443*	*0.0506*	*0.0167*	*0.2619*	*0.0614*
R^2	0.1300	0.1329	0.1366	0.1518	0.1570	0.1598	0.1654	0.1707	0.1675	0.1712	0.1720
National lockdown	-1.89***	-2.90***	-3.22***	-4.70***	-4.76***	-5.23***	-7.03***	-8.61***	-9.20***	-10.28***	-10.66***
	(-3.7993)	(-3.9911)	(-3.5561)	(-4.3795)	(-3.8823)	(-3.8224)	(-4.6915)	(-5.2921)	(-5.2547)	(-5.4457)	(-5.2391)
	0.0001	*0.0001*	*0.0004*	*0.0000*	*0.0000*	*0.0001*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Regional lockdown	0.67	-0.22	1.39	0.03	-0.41	-0.34	-1.95	-0.09	-1.43	-1.41	-0.07
	(0.8579)	(-0.1991)	(1.0066)	(0.0167)	(-0.2289)	(-0.1710)	(-0.9158)	(-0.0377)	(-0.5816)	(-0.5351)	(-0.0248)
	0.3910	*0.8422*	*0.3142*	*0.9867*	*0.8190*	*0.8642*	*0.3598*	*0.9699*	*0.5608*	*0.5926*	*0.9802*
Monetary stimulus	-3.72***	-4.64***	-6.21***	-9.10***	-11.02***	-11.81***	-12.44***	-12.81***	-11.92***	-13.95***	-13.65***
	(-8.7753)	(-7.5615)	(-8.0790)	(-10.0998)	(-10.6746)	(-10.1365)	(-9.6384)	(-9.0599)	(-7.6798)	(-8.3142)	(-7.4565)
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Fiscal stimulus	-0.82**	0.06	-1.29*	-1.27	-0.30	-1.72	-2.32*	-3.20**	-4.12***	-2.42	-3.84**
	(-2.0017)	(0.0962)	(-1.7118)	(-1.4244)	(-0.2918)	(-1.5097)	(-1.8439)	(-2.3214)	(-2.7369)	(-1.4847)	(-2.1854)
	0.0454	*0.9234*	*0.0870*	*0.1544*	*0.7705*	*0.1312*	*0.0653*	*0.0203*	*0.0062*	*0.1377*	*0.0289*
Infection peak (SIR)	-1.35***	-1.33***	-1.36***	-1.22***	-1.18**	-1.08**	-1.12**	-1.06**	-0.98**	-0.89*	-0.82*
	(-2.9241)	(-2.8577)	(-2.9294)	(-2.6507)	(-2.5569)	(-2.3369)	(-2.4107)	(-2.2920)	(-2.0865)	(-1.9058)	(-1.7278)
	0.0035	*0.0043*	*0.0034*	*0.0081*	*0.0106*	*0.0195*	*0.0160*	*0.0220*	*0.0370*	*0.0568*	*0.0841*
Sentiment	-7.76***	-7.68***	-7.50***	-7.32***	-7.48***	-7.35***	-7.27***	-7.32***	-7.52***	-7.75***	-7.86***
	(-14.1938)	(-13.9921)	(-13.6099)	(-13.3140)	(-13.2196)	(-12.8788)	(-12.6460)	(-12.7078)	(-12.6081)	(-12.6516)	(-12.7264)
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Notes: all equations estimated using panel OLS with panel-corrected cross-sectional standard errors (PCSE), as in Beck in Katz (1995). Coefficients for local case growth and sentiment in differential slope models are estimated using a Wald test for the equality of the average slope among cross-sections to zero. Total impact of COVID-19-related factors is estimated using Wald test for the sum of announcement and anticipation (when present) effects. T-stats are reported (in parentheses) while corresponding p-values are presented *in italics*. ***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively.

Figure 6a. Decomposing the financial effect of the pandemic (common slopes estimates)

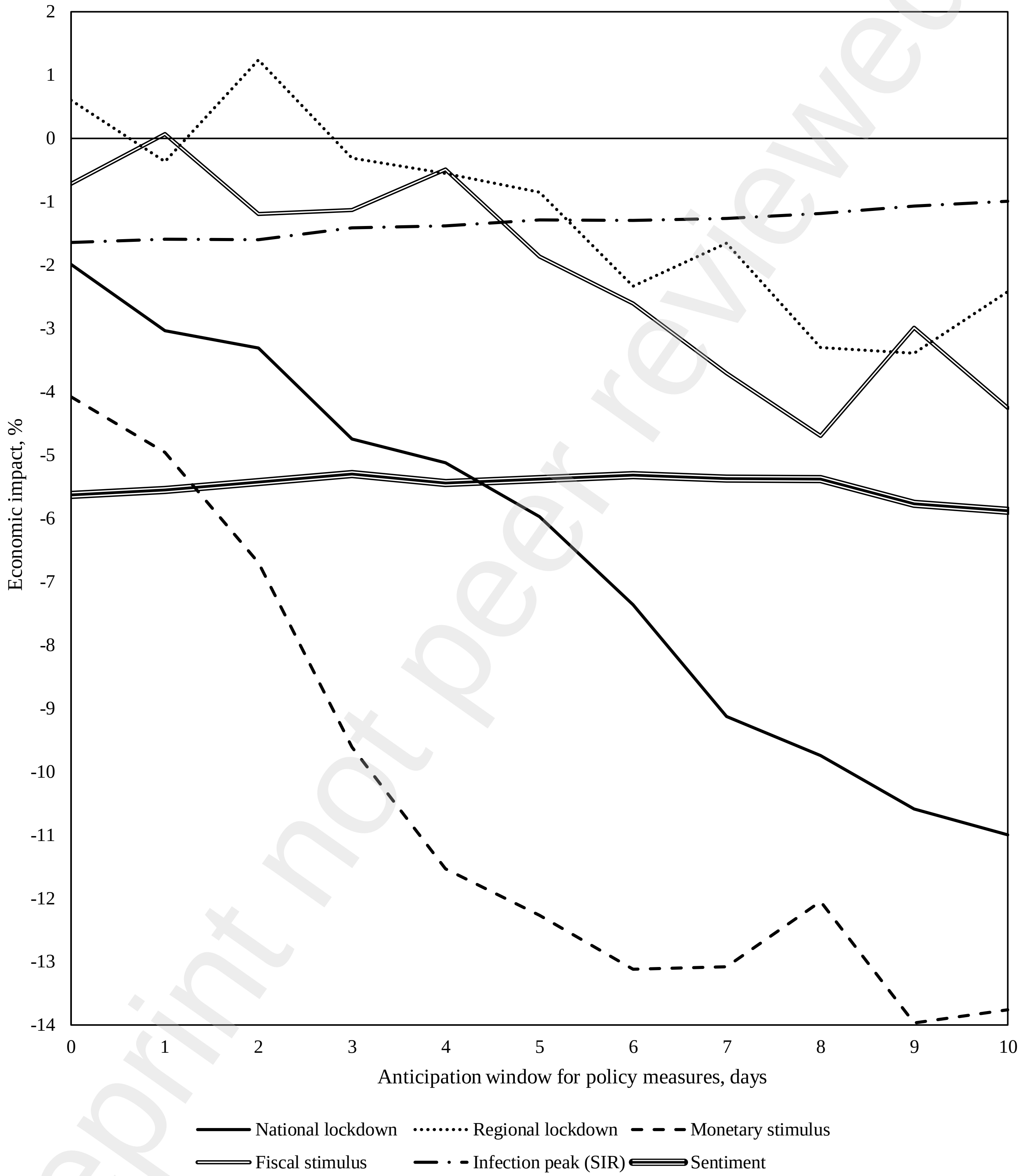
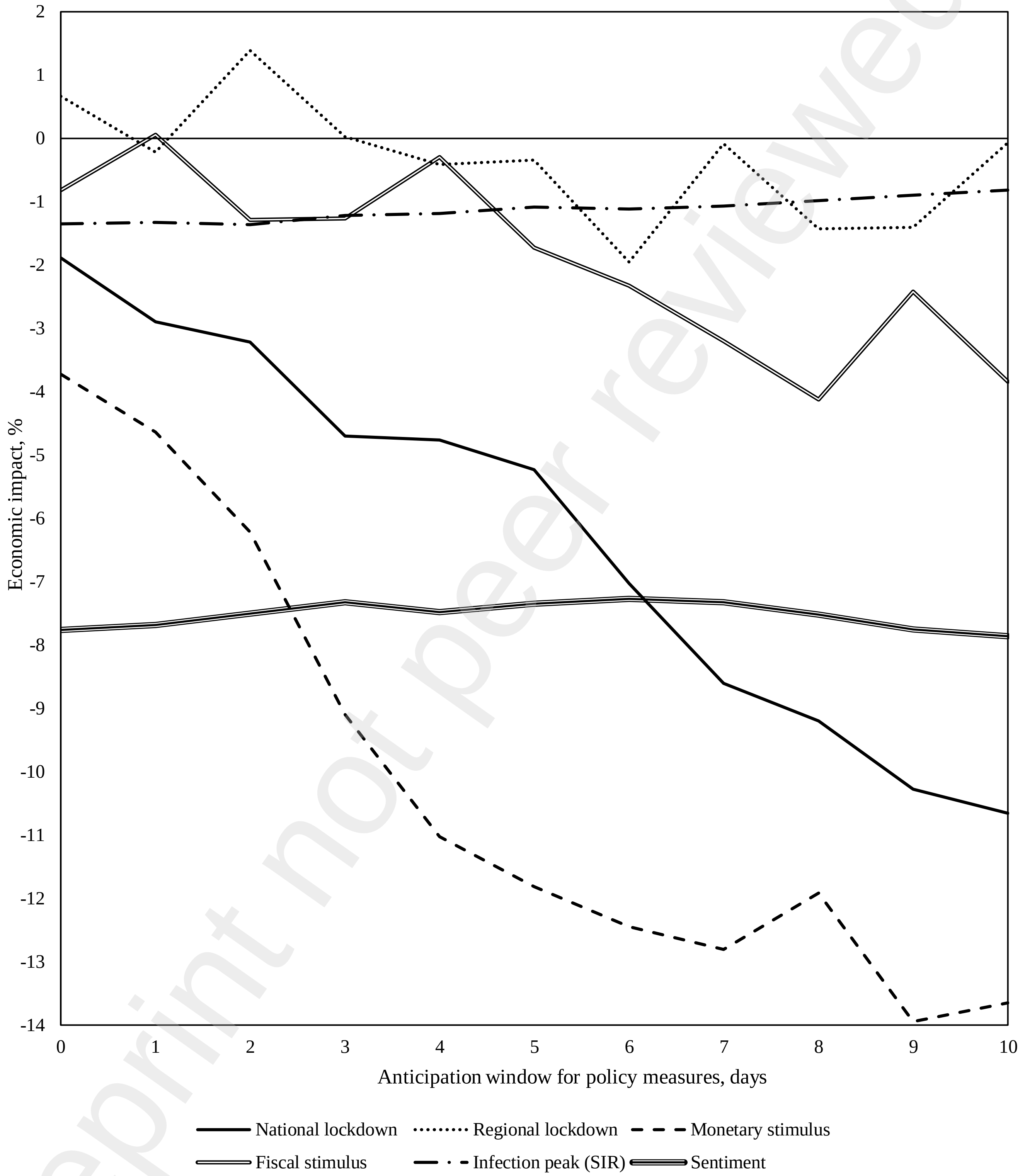


Figure 6b. Decomposing the financial effect of the pandemic (differential slopes estimates)



Tables 6a and 6b decidedly support the anticipation hypothesis and show that the total impact of national lockdowns and stimulus measures is much larger than the initial estimates suggested by announcement abnormal returns alone. Intercepts cease to be significant for anticipation windows of four days or higher and turn positive when it is extended to seven days, evidencing the drawdown of the market can be fully explained by the fundamental, policy, and sentiment factors accounted for in the regression models. Local case growth ceases to be significant when at least five days of policy intervention anticipation is allowed for. However, SIR-predicted infection peak and sentiment have a robust negative effect (-0.8% to -1.6% and -5.3% to -7.9%, respectively) in all the estimations, the latter even slightly increasing in magnitude for longer anticipation windows. Interestingly, the average estimates for fundamental and sentiment effect in total arrive at a figure that is remarkably close to 7% provided by Barro et al. (2020) from a "Spanish flu"-based scenario. Regional lockdowns consistently show to have no adverse economic impact priced on the financial markets, reinforcing the relative success of this strategy, while the adverse effect of national lockdowns increases substantially (from 1.9-2.3% to 8.6-9.1%). The total impact of monetary stimulus is also shown to be much higher at 12.8-13.1% (compared to 3.7-4.1% in initial estimations). The results for fiscal stimulus are less prominent and more volatile, the anticipation effect being significant only if five days of anticipation are allowed. Nevertheless, it is consistently significant for long anticipation windows and can with reasonable accuracy be assessed as at 3.2-3.7%.

Finally, to account for the anticipation process using a less assumption-sensitive framework, the study also considers equations (4) and (8) with innovations to policy intervention probabilities from binary choice models reported in Tables 5a-c instead of announcement dummies. The probability of a national lockdown or a stimulus policy is set at 1 if the measure has been announced and is calculated using the extreme value binary choice model[9] if it has not been announced yet. Table 7 reports the probabilistic responses to policy interventions (apart from regional lockdowns, where it is estimated using an announcement dummy).

Table 7. Probabilistic responses to policy interventions

Regressor	Common slopes	Differential slopes
Constant	-0.1762*** (-3.7163) *0.0002*	-0.1352*** (-2.7462) *0.0061*
Local case growth	-0.2383** (-2.2917) *0.0220*	-0.7663*** (-3.4002) *0.0007*
Global case growth	-0.0019 (-0.7565) *0.4494*	-0.0022 (-0.8959) *0.3704*
Sentiment	-0.0554*** (-11.2087) *0.0000*	-0.0762*** (-13.8293) *0.0000*
SIR-predicted infection peak	-1.6503*** (-3.6689) *0.0002*	-1.3763*** (-2.9647) *0.0030*
National lockdown	-2.3907*** (-4.4767) *0.0000*	-2.2056*** (-4.0872) *0.0000*
Regional lockdown	0.5929 (0.7822) *0.4341*	0.6388 (0.8154) *0.4149*
Monetary stimulus	-4.8739*** (-10.5940) *0.0000*	-4.3760*** (-9.1709) *0.0000*
Fiscal stimulus	-1.0621** (-2.3476) *0.0189*	-1.0757** (-2.3784) *0.0174*
R^2	0.0774	0.1307

Notes: all equations estimated using panel OLS with panel-corrected cross-sectional standard errors (PCSE), as in Beck in Katz (1995). Coefficients for local case growth and sentiment in differential slope models are estimated using a Wald test for the equality of the average slope among cross-sections to zero. T-stats are reported (in parentheses) while corresponding p-values are presented *in italics*. *** and ** denote statistical significance at 1% and 5%, respectively.

[9] The use of forecasted probabilities from logit and probit models does not qualitatively change the results. Extreme value estimates have been chosen as extreme value binary choice model has the highest McFadden R^2 in all three cases.

The market reaction to innovations in policy probabilities is negative and significant, reinforcing the prior findings of the study. It is larger in magnitude than announcement effects from initial estimations but smaller than the total impact calculated from a seven-day anticipation window. It suggests that the anticipation process is more sophisticated than the one incorporated in a binary choice regression, with investors using latent variables or private information ahead of policy intervention announcement.

Conclusion

This study has highlighted the importance of fundamental, policy, and sentiment components of the COVID-19 impact on 51 national financial markets from 31 December 2019 until 23 April 2020, providing empirical evidence to support or reject multiple speculations and conjectures posed in the literature and the media (Baker et al., 2020; Corbet et al., 2020; Guerrieri et al., 2020). Although all three factors are statistically significant, their magnitude and economic significance varies substantially. The fundamental effect of the pandemic can mainly be explained by the expected infection peak that depresses the stock markets by at most 1.6%, while local case growth ceases to be significant in some estimations. The irrational panic surrounding COVID-19 does have a material effect, with sentiment-driven selloffs triggering a temporary stock market downturn of 5.3%-7.9%. The major driving force behind the global stock market drawdown, however, is found to be policy interventions. National lockdown policies are estimated to have a net negative effect of 8.6%-9.1%, while regional lockdowns do not have any material impact on the markets, highlighting the relative success of this containment strategy that avoids unnecessary economic harm. The monetary and fiscal stimulus also appear to be counterproductive, leading to value destruction of 12.8%-13.1% and 3.2%-3.7%, respectively. The effects are relatively stable across countries and cannot be attributed to confounding events.

The pandemic has triggered a wide array of rational and irrational responses across the markets. While sentiment does play a crucial role in explaining the economic and financial implications of the pandemic, supporting the assertions of prior research (Del Giudice and Paltrinieri, 2017; Ichev and Marinc, 2018; Corbet et al., 2020), the market reaction to fundamental and policy factors has been incredibly rational. The markets are shown to reflect the information on policy interventions probabilistically, anticipating them at least five trading days in advance and reacting to innovations to implied probabilities of various measures. Even more surprisingly, stock indices incorporate the dynamics of infection peak calculated using the SIR model, effectively suggesting that a representative investor knows and successfully applies differential equations.

The implications of the study to various stakeholder groups are innumerable. The findings suggest the "whatever it takes" response to macroeconomic stabilisation taken by governments all over the world with regards to fiscal and monetary stimulus is remarkably counterproductive and value-destroying. It is strongly evidenced that national lockdowns are excessive measures leading to unnecessary economic harm and targeted regional lockdowns could be a better containment strategy. The investors could leverage the findings of the study by incorporating the fundamental, policy, and sentimental aspects of COVID-19 financial impact into their forecasting and trading strategies. As for the broad corpus of academic knowledge, the study has established several original market efficiency tests as well as provided additional evidence for the voluminous literature on stock market implications of macroeconomic policy.

Further research can build upon the findings of this study and achieve better estimates of the effects in question by using sector-level or stock-level data. For example, the effects of regional lockdowns can be assessed with greater precision by exploiting the variations of stock returns of companies headquartered or operating in affected or unaffected regions. Earlier findings on sectoral heterogeneity of pandemic effects (Ichey and Marinc, 2018; Ramelli and Wagner, 2020) can also be examined in an international setting. As more data becomes available on future policy interventions or their gradual relaxation, an out-of-sample test of this study can be performed.

The markets have overwhelmingly suggested that in case of COVID-19, the policy "cure" has been much worse than the disease, the virus itself actually having a rather modest fundamental economic impact, consistent with the past literature on epidemics and financial markets (Nippani and Washer, 2004; Baker et al., 2020). Overall, looking at the markets even during such turbulent times can be a source of valuable information and, perhaps surprisingly, of much-needed optimism.

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