

Article

COVID-19 Outbreak and CO₂ Emissions: Macro-Financial Linkages

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Abstract: In the Dynamic Conditional Correlation with Mixed Data Sampling (DCC-MIDAS) framework, we scrutinize the correlations between the macro-financial environment and CO₂ emissions in the aftermath of the COVID-19 diffusion. The main original idea is that the economy's lock-down will alleviate part of the greenhouse gases' burden that human activity induces on the environment. We capture the time-varying correlations between U.S. COVID-19 confirmed cases, deaths, and recovered cases that were recorded by the Johns Hopkins Coronavirus Center, on the one hand; U.S. Total Industrial Production Index and Total Fossil Fuels CO₂ emissions from the U.S. Energy Information Administration on the other hand. High-frequency data for U.S. stock markets are included with five-minute realized volatility from the Oxford-Man Institute of Quantitative Finance. The DCC-MIDAS approach indicates that COVID-19 confirmed cases and deaths negatively influence the macro-financial variables and CO₂ emissions. We quantify the time-varying correlations of CO₂ emissions with either COVID-19 confirmed cases or COVID-19 deaths to sharply decrease by -15% to -30% . The main takeaway is that we track correlations and reveal a recessionary outlook against the background of the pandemic.

Keywords: COVID-19; CO₂ emissions; time-varying correlations; macroeconomy; stock markets; DCC MIDAS



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1. Introduction

With the quarantine in action in most industrialized countries since mid-March 2020, market observers predict a deep recession for 2021–2022. As [Carlsson-Szlezak et al. \(2020\)](#) put it, “COVID-19 risks have been priced so aggressively across various asset classes that some fear a recession in the global economy” (p. 2). Stock markets plunged in March–April 2020 as a direct consequence of the Coronavirus's shocking news spreading around the world. Indeed, [Baker et al. \(2020\)](#) report that the U.S. stock market reacted so much more forcefully to COVID-19 than to previous pandemics, such as the Spanish Flu. Investor managers already document that the stock-bond correlation has been negatively affected by the COVID-19 outbreak ([Papadamou et al. 2020](#)).

A burgeoning literature is emerging on the COVID-19's financial outcomes, whereby the role of fear and uncertainty plays a central role ([Lyócsa and Molnár 2020](#)). [Baig et al. \(2020\)](#) link COVID-19 cases/deaths, stock market volatility, and illiquidity. In the U.S., [Albulescu \(2020\)](#) demonstrates that the sanitary crisis enhanced the S&P 500 realized volatility. While using an Infectious Disease Equity Market Volatility Tracker (EMV-ID), [Bai et al. \(2020\)](#) further investigate the effects of infectious disease pandemic on the volatility of the U.S., China, U.K., and Japan stock markets. [Rizwan et al. \(2020\)](#) investigate how COVID-19 impacted the systemic risk in eight countries' banking sectors (including China). [Azimli \(2020\)](#) focuses on the Google Search Index for Coronavirus (GSIC) and the risk-return dependence structure. [Topcu and Gulal \(2020\)](#) document the negative impact of the pandemic on emerging stock markets. [Gharib et al. \(2020\)](#) reveal the bilateral contagion effect of bubbles in oil and gold markets during the recent COVID-19 outbreak. Last but not least, [Mazur et al. \(2020\)](#) find that natural gas, food, healthcare, and software stocks earn high positive returns; whereas,

equity values in petroleum, real estate, entertainment, and hospitality sectors fall dramatically. Similarly to the years 2007–2008, which provided an experience that most economists, practitioners, and policymakers never thought they would witness (Melvin and Taylor 2009), the year 2020 brought along the COVID-19 sanitary crisis. To some extent, this most recent phenomenon can be compared to the two previous financial crises, inherited, respectively, from the U.S. sub-primes defaults and the European debt hazards¹.

Kamin and DeMarco (2012) underline the failure of the banking industry in the wake of the Lehman Brothers' collapse. Realizing that financial firms around the world were pursuing similar (flawed) business models² was a hard hit on the banker's consciousness and payroll. Similarly, governments and policymakers were underprepared to deal with a pandemic (such as respiratory equipment in hospitals or the mass production of disposable masks), as the World Health Organization rang the bell (Sohrabi et al. 2020).

Gruppe et al. (2017) review the literature on interest rate convergence and the European debt crisis with a particular focus on the fiscal problems of some countries (such as Greece) in Europe. Moro (2014) further details how the European economic and financial Great Crisis spread quickly among closely integrated economies, either through the trade channel or the financial channel. In that latter case, the solution would be found in a more effective political integration. This is precisely what the EU-27 is aiming at with the simultaneous distribution of the Pfizer-BioNTech COVID-19 and Moderna vaccines across the member countries as early as 27 December 2020 as well as in the early days of 2021 (National Academies of Sciences 2020).

In the meantime, the issue of decreasing CO₂ emissions is attached to the lockdown, with the dramatic reduction in international trade and tourism that followed shipping routes' and airports' closure. The sanitary crisis and its associated uncertainty determine an economic contraction through direct (real) or indirect (financial) channels. Consequently, the CO₂ emissions slowdown. In this paper, we aim at quantifying the correlations between epidemiological (daily) cases, macro- (monthly) financial (intra-daily) factors, and (monthly) CO₂ emissions in the Dynamic Conditional Correlation with Mixed Data Sampling (DCC-MIDAS) framework (Colacito et al. 2011). Introduced by Ghysels et al. (2004), this technique allows mixing the data frequencies by resorting to lag polynomials and dedicated weight functions. Empirical studies relying on the DCC-MIDAS in the finance literature include to cite few, Asgharian et al. (2016) for the long-run stock-bond correlation, Conrad et al. (2014) for long-term correlations in U.S. stock and crude oil markets, or Xu et al. (2018) for measuring the systemic risk of the Chinese banking industry.

To our best knowledge, this piece of research is the first to study the correlations between COVID-19 epidemiological cases, macro-financial factors, and CO₂ emissions. Our article's interest is to visualize the correlations with the macro-financial environment due to COVID-19 clinical cases' multiplication. U.S. cases of confirmed, dead, and recovered patients of COVID-19 are sourced from the Johns Hopkins Coronavirus Center³. U.S. macroeconomic indicators and CO₂ emissions are sourced from the U.S. Energy Information Administration⁴. Tick-by-tick data for U.S. stock markets are accessed from the Oxford-Man Institute for Quantitative Finance⁵.

¹ Academically, it is interesting to investigate whether the two crisis events are connected to each other. As argued by Gómez-Puig and Sosvilla-Rivero (2016), the European sovereign debt crisis is preceded by contagion episodes with causal links that stem from the Global Financial Crisis's outburst. Wegener et al. (2019) challenge the view that the arising sovereign credit risk in the EMU has been triggered by the U.S. subprime crunch. On the contrary, they conclude that the severe fiscal problems in peripheral countries are homemade, rather than imported from the U.S. Thus, no definitive conclusion seems to be reached based on quantitative analysis.

² Such as the excessive dependence on short-term funding; or vicious cycles of mark-to-market losses driving fire sales of mortgage-backed securities.

³ <https://coronavirus.jhu.edu>

⁴ <https://www.eia.gov>

⁵ <https://realized.oxford-man.ox.ac.uk>

Extant literature on the link between CO₂ emissions and the macroeconomy includes Chevallier (2011a, 2011b), who described the joint dynamics of industrial production and carbon prices by means of regime threshold vector error-correction and Markov-switching VAR models. Regarding correlations, more specifically, Chevallier (2012) documents time-varying correlations between energy markets (oil and gas) and CO₂. Lutz et al. (2013) examined the nonlinear relation between the E.U. carbon price and its fundamentals (such as energy prices, macroeconomic risk factors, and weather conditions) in a Markov regime-switching GARCH. Fell (2010) examines the dynamic relationship with Nordic wholesale electricity prices. Hintermann (2010) and Aatola et al. (2013) completed the analysis of CO₂ price fundamentals based on structural modelling, Instrumental Variables, and Vector Auto-Regressive models.

Through the lens of correlations, we establish that COVID-19 confirmed cases and deaths have a negative and statistically significant influence on the macro-financial environment and CO₂ emissions, i.e., there is a counter-cyclical business cycle pattern here. This result is precisely documented by the parameter governing the lag polynomials in MIDAS regressions and by the plots of long-run correlations. In the short run, we especially identify spikes in the stock market. Time-varying correlations between the COVID-19 and CO₂ emissions are documented to drop dramatically by -15% to -30% depending on the underlying instrumental variable (i.e., COVID-19 confirmed cases or COVID-19 deaths). When introducing the number of COVID-19 recovered patients in the dynamic system of equations, we record, on the contrary, a positive sign for the MIDAS coefficient, which suggests that, with more patients healing, the U.S. economy is on track for a recovery. This latter result is only visible for one panel interacting COVID-19 recovered cases with industrial production, whereas correlations that stem from stock markets and CO₂ emissions still paint a recessionary outlook.

The remainder of the article is structured, as follows. Section 2 presents the data. Section 3 details the model. Section 4 contains the estimation results. Finally, Section 5 concludes.

2. Data

As a proteiform disease, COVID-19 is drowning the macro-financial environment into a recession that it is too early to foreshadow. Our study's primary variable of interest is the U.S. growth rate of CO₂ emissions, which is expected to decrease due to the pandemic. In order to fix ideas, we show our intuition in Figure 1, which extracts data from the U.S. Energy Information Administration and the Federal Reserve Bank of St. Louis. Year-on-year, it is visible that macroeconomic (as proxied by industrial production) and financial (as proxied by the S&P 500) factors took a severe blow since mid-March 2020.

2.1. U.S. COVID-19 Cases

For epidemiological cases, the U.S. time-series that were extracted from the Johns Hopkins Repository on 5 May 2020 are of ($3\times$) kinds:

1. confirmed cases,
2. deaths, and
3. recovered cases.

with a daily frequency. One-by-one, these variables will be considered in correlation models combining the CO₂ emissions and macro-financial factors. At the time of writing, the USA totaled 1,309,550 confirmed cases; 78,795 deaths; and, 212,534 recovered cases. Because of data availability, we focus our article on the USA as a representative of the world. Indeed, for other countries, data on CO₂ emissions dates back to the year 2017 at best. A snapshot of the U.S. time-series is given in Figure 2, revealing the worrying trend behind the pandemic.

Each panel displays Generalized Linear Models (GLM). The dispersion parameter for the "Poisson" family is set to 1. Fisher Scoring is the iteration measure used to fit the model.

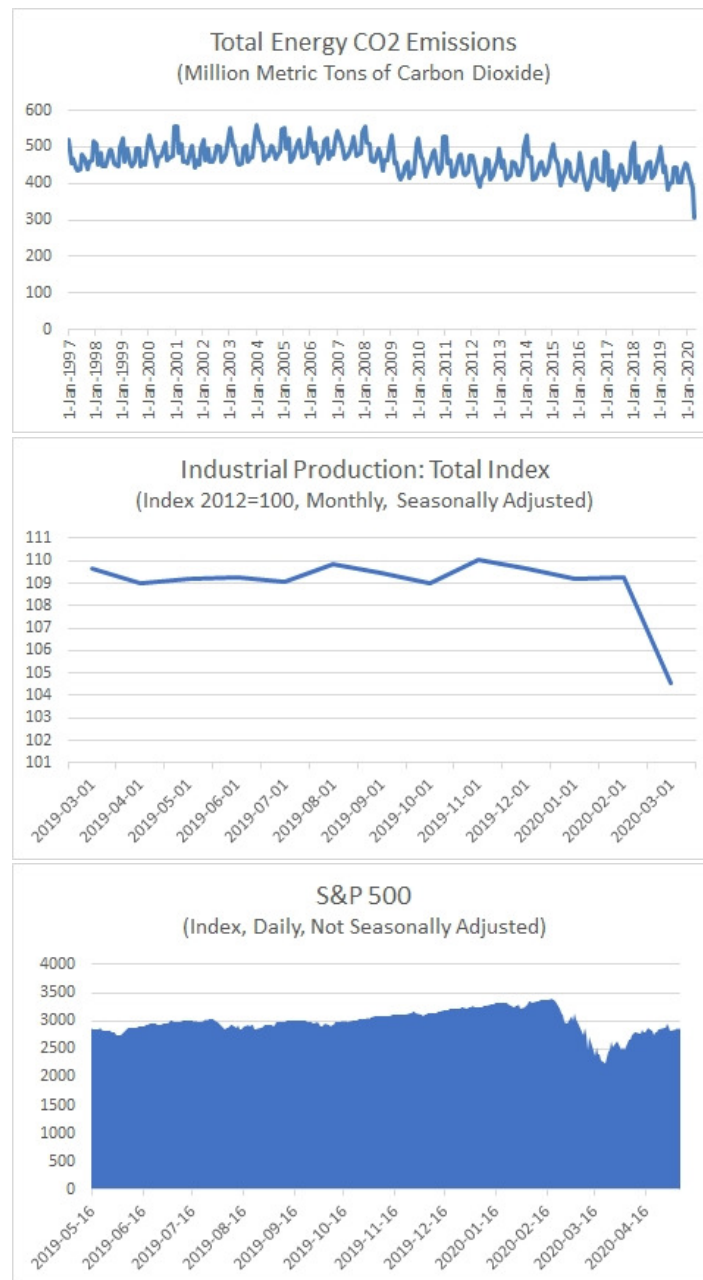


Figure 1. Monthly U.S. Total Fossil Fuel CO₂ emissions (**top**), Monthly U.S. Industrial Production Index Seasonally Adjusted (**middle**) and S&P 500 Index (**bottom**) daily close. Note: CO₂ emissions are sourced from U.S. Energy Information Administration. Industrial production and S&P 500 are sourced from the Federal Reserve Bank of St. Louis.

2.2. U.S. Macroeconomic Indicators and CO₂ Emissions

Another category of explanatory variables is contained in the U.S. Energy Information Administration database⁶ released in May 2020 (as part of the Short-Term Energy Outlook) monthly. This database contains the growth rate of CO₂ emissions, as well as business cycle indicators that are linked to the state of the U.S. economy (see Table 1).

⁶ Precisely, the EIA’s Table 9a accessed from <https://www.eia.gov/totalenergy/data/browser/>.

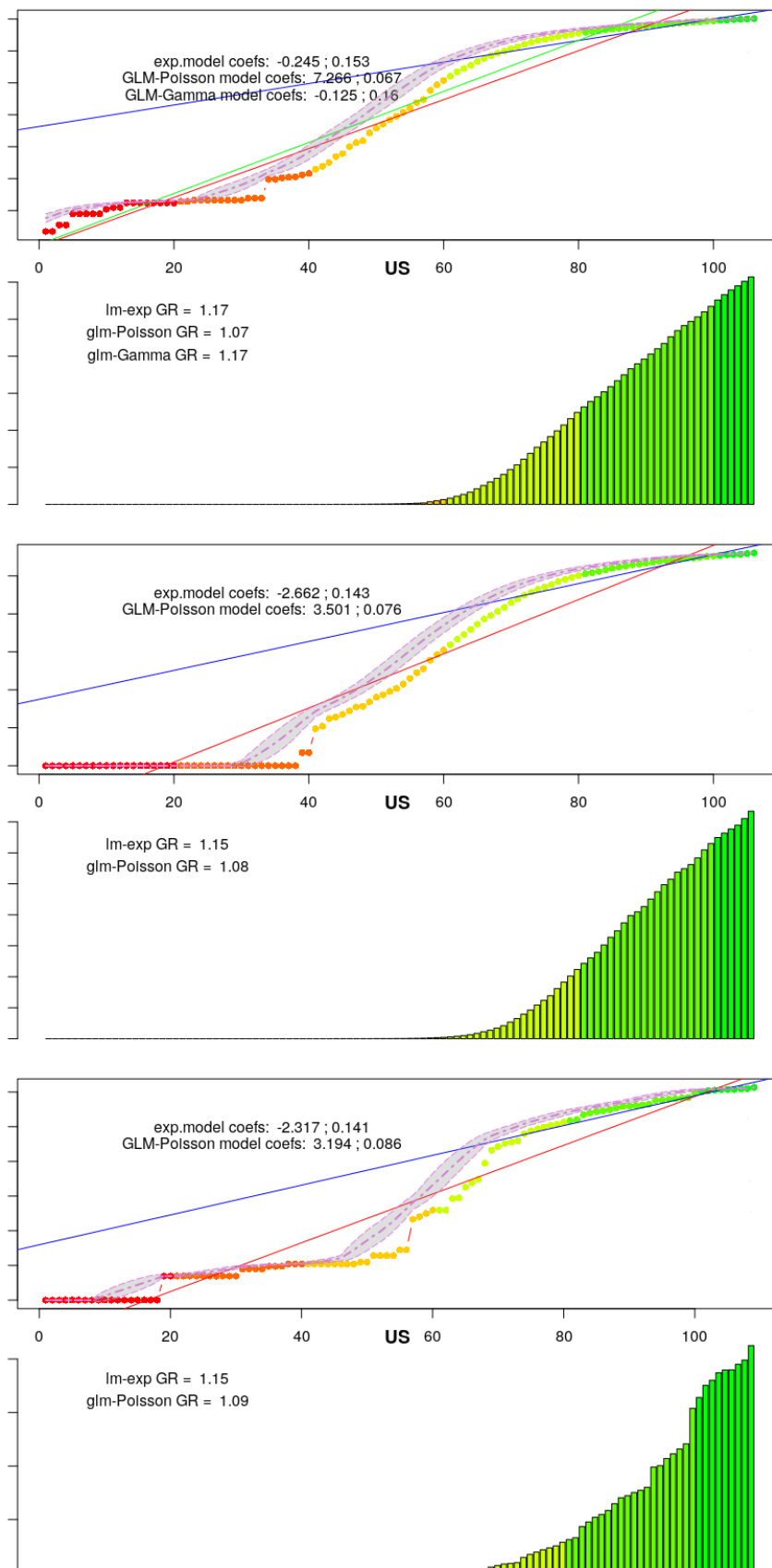


Figure 2. U.S. COVID-19 confirmed cases (**top**), deaths (**middle**), and recovered cases (**bottom**) extracted from the Johns Hopkins Repository on 5 May 2020.

Table 1. U.S. EIA database on Macroeconomic indicators and CO₂ emissions.

<i>Macroeconomic</i>
Real Gross Domestic Product
Real Personal Consumption Expenditures
Real Private Fixed Investment
Business Inventory Change
Real Government Expenditures
Real Exports of Goods & Services
Real Imports of Goods & Services
Real Disposable Personal Income
Non-Farm Employment
Civilian Unemployment Rate
Housing Starts
<i>Manufacturing Production Indices</i>
Total Industrial Production Index
Manufacturing Production Index
Food Production Index (NAICS 311)
Paper Production Index (NAICS 322)
Petroleum and Coal Products Production Index (NAICS 324)
Chemicals Production Index (NAICS 325)
Resins and Synthetic Products Production Index (NAICS 3252)
Agricultural Chemicals Production Index
Nonmetallic Mineral Products Production Index
Primary Metals Production Index (NAICS 311)
Coal-weighted Manufacturing Production Index
Distillate-weighted Manufacturing Production Index
Electricity-weighted Manufacturing Production Index
Natural Gas-weighted Manufacturing Production Index
<i>Price Indexes</i>
Consumer Price Index (all urban consumers)
Producer Price Index: All Commodities
Producer Price Index: Petroleum
GDP Implicit Price Deflator
<i>Miscellaneous</i>
Vehicle Miles Traveled
Air Travel Capacity
Aircraft Utilization
Airline Ticket Price Index
Raw Steel Production
<i>Carbon Dioxide (CO₂) Emissions</i>
Petroleum CO ₂ Emissions
Natural Gas CO ₂ Emissions
Coal CO ₂ Emissions
Total Fossil Fuels CO ₂ Emissions

The indicators are listed according to the following sub-categories: macroeconomic indicators (11×), manufacturing production indices (14×), price indexes (4×), miscellaneous (5×), and, finally, CO₂ emissions (4×).

This article chooses to work with the Total Industrial Production Index (that is representative of the macroeconomic factor) and the Total Fossil Fuels CO₂ emissions variable. Additional specifications are discussed in the sensitivity analysis (Section 4.5).

2.3. U.S. Stock Markets

Finally, we encompass U.S. stock markets' closing returns that are based on the Oxford 'Realized Library' with an intra-daily frequency. Tick-by-tick data are sampled over the 5-min. horizon in order to avoid microstructure noise⁷. These variables are included to proxy for the financial markets' downward trend and its correlation with CO₂ emissions. Following the same logic as decreasing industrial production (e.g., freezing global economy) due to the COVID-19 pandemic, stock markets (such as the NYSE) briefly halted from trading in March 2020, and they have not recovered yet from the crash that ensued.

Table 2 details the list of assets.

Table 2. Oxford-Man's Realized Library: U.S. stock markets.

Symbol	Name	Earliest Available	Latest Available
.DJI	Dow Jones Industrial Average	3 January 2000	8 May 2020
.IXIC	Nasdaq 100	3 January 2000	8 May 2020
.SPX	S&P 500 Index	3 January 2000	8 May 2020

In the main text, we run the estimates with S&P 500 as the financial factor. Other indexes can be included for robustness checks (Section 4.5).

2.4. Series' Transformation

In order to ensure stationarity of the time-series, we use $\Delta\text{CO}_{2,it}$ the growth rate of CO₂ emissions indicator i at time t , $\text{diff}_{\text{COVID},it}$ the first-difference of the COVID-19 case type i , ΔMacro_{it} the growth rate of the macroeconomic indicator i , and $R_{\text{Finance},it}$ the log-returns on the stock market i .⁸

3. Model

We consider the DCC-MIDAS by Colacito et al. (2011) in order to assess the time-varying correlations between COVID-19 epidemiological cases, macro-financial factors, and CO₂ emissions. This class of Dynamic Conditional Correlation models obeys a DCC scheme by Engle and Sheppard (2001) for the daily dynamics, with, additionally, the correlations moving around a long-run component:

$$q_{i,j,t} - \bar{\rho}_{i,j,t} = a(\delta_{i,t-1}\delta_{j,t-1} - \bar{\rho}_{i,j,t}) + b(q_{i,j,t-1} - \bar{\rho}_{i,j,t}) \tag{1}$$

$$\bar{\rho}_{i,j,t} = \sum_{l=1}^{K_c^{ij}} \varphi_l \left(\omega_r^{ij} \right) c_{i,j,t-l} \tag{2}$$

$$c_{i,j,t} = \frac{\sum_{k=t-N_c^{ij}}^t \zeta_{i,k} \zeta_{j,k}}{\sum_{k=t-N_c^{ij}}^t \zeta_{i,k}^2 \sqrt{\sum_{k=t-N_c^{ij}}^t \zeta_{j,k}^2}} \tag{3}$$

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}} \tag{4}$$

with $q_{i,j,t}$ the short-run correlation between assets i and j , $\bar{\rho}_{i,j,t}$ the slowly moving long-run correlation, $c_{i,j,t}$ a normalization of cross-products for the standardized residuals $\zeta_{i,t}$, $\rho_{i,j,t}$ the computation of correlations, $\mathbf{r}_t = \mu + H_t^{\frac{1}{2}} \zeta_t$, and $\zeta_t \sim i.i.d \mathcal{N}(0, I_n)$. \mathbf{r}_t is the

⁷ See Barndorff-Nielsen et al. (2008) for the theory.

⁸ Upon reasonable request, we can transmit (unformatted) unit root tests in order to show that, thus transformed, the series are indeed $I(1)$.

vector of returns. μ is the vector of unconditional means. H_t is the conditional covariance matrix. N_v^i is the number of days that the long-run component m_i (e.g., monthly macroeconomic variables) is held as fixed. The weighting scheme is similar to the GARCH-MIDAS (Engle et al. 2013):

$$\varphi_l(\omega_v^i) = \frac{\left(1 - \frac{l}{K_v^i}\right)^{\omega_v^i - 1}}{\sum_{j=1}^{K_v^i} \left(1 - \frac{j}{K_v^i}\right)^{\omega_v^i - 1}} \tag{5}$$

with K_v^i the number of lag polynomials of the MIDAS component, and ω_v^i the decay pattern across various series.

Equation (5) is known as the beta function weighting scheme. This procedure allows for estimating the number of lags for both the daily and monthly returns within MIDAS optimally. The setting of the MIDAS lags is detailed in the Appendix A for the interested reader. Ghysels et al. (2007) document that the beta function is a better choice than the exponential Almon when dealing with high-frequency data, as in our setting. It can produce various lag structures for past returns, such as monotonically increasing/decreasing or hump-shapes.

As is looked after by the researcher, the econometric system that is composed of Equations (1)–(5) can accommodate weights $\omega_r^{i,j}$, lag lengths $N_c^{i,j}$, and span lengths of historical correlations $K_c^{i,j}$ to differ across any pair of series.

The DCC-MIDAS is estimated by Two-Step Quasi Maximum Likelihood:

$$\begin{aligned} \text{QL}(\Psi, \Xi) &= \text{QL}_1(\Psi) + \text{QL}_2(\Psi, \Xi) \\ &\equiv - \sum_{t=1}^T \left(n \log(2\pi) + 2 \log|D_t| + \mathbf{r}_t' D_t^{-2} \mathbf{r}_t \right) \\ &\quad - \sum_{t=1}^T \left(\log|R_t| + \zeta_t' R_t^{-1} \zeta_t + \zeta_t' \zeta_t \right) \end{aligned} \tag{6}$$

with the parameters of the conditional volatility being collected in a vector Ψ , and that of the conditional correlation into a vector Ξ . Splitting the log-likelihood function allows for first estimating the parameters of the conditional volatility Ψ while using $\text{QL}_1(\Psi)$, and second the DCC-MIDAS parameters with the standardized residuals $\hat{\xi}_t = \hat{D}_t^{-1}(\mathbf{r}_t - \hat{\mu})$ using $\text{QL}_2(\Psi, \Xi)$.

4. Results

4.1. Baseline Correlations (without COVID-19 Cases)

In this setting, we consider the Total Fossil Fuels CO₂ emissions (*TETCCO2*), the Total Industrial Production Index (*ZOTOIUS*), and the 5-min. Realized Volatility of the S&P 500 Index (*SPX – RV5*) from 2000 to present.

GARCH-MIDAS and DCC-MIDAS parameter estimates are reproduced in Table 3, which reports the estimated parameters, standard errors, and the associated maximized log-likelihood values for the model under consideration.

Table 3. Dynamic Conditional Correlation with Mixed Data Sampling (DCC-MIDAS) estimates for the baseline specification including Total Fossil Fuels CO₂ emissions, Total Industrial Production Index, and S&P 500 Index.

	μ	α	β	θ	ω	m
TETCCO2	0.2797 *** (0.0001)	0.0469 *** (0.0002)	0.5986 *** (0.0013)	0.1000 *** (0.0003)	5.7068 *** (0.0005)	7.7439 *** (0.0001)
ZOTOIUS	−0.1181 (0.1101)	0.0142 *** (0.0004)	0.9858 *** (0.0004)	0.1368 (9.9118)	1.001 0 (13.4850)	32.3250 *** (3.6880)
SPX-RV5	0.0015 (0.0090)	0.2344 *** (0.0245)	0.0556 (0.0574)	0.1939 *** (0.0142)	6.4697 *** (2.0287)	0.3568 *** (0.0678)
	a	b	ω			
DCC-MIDAS	0.0171 (0.0204)	0.8000 (0.6090)	1.001 *** (0.2088)			
Logarithmic likelihood:	−6430.57					
Akaike info criterion:	12867.1					
Bayesian info criterion:	12886.7					
Sample size:	5103					

Note: *** indicates statistical significance at the 1% level. The sample covers 3 January 2020 to 8 May 2020. TETCCO2 is the Total Fossil Fuels CO₂ emissions. ZOTOIUS is the Total Industrial Production Index. SPX-RV5 is the five-minute Realized Volatility of the S&P 500 Index. Equations (1)–(5) detail the conditional correlation. The conditional volatility is specified as a GARCH-MIDAS:

$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{(r_{i,t-1} - \mu_i)^2}{m_{i,\tau}} + \beta_i g_{i,t-1},$$

$$m_{i,\tau} = \bar{m}_i + \theta_i \sum_{l=1}^{K_i^v} \varphi_l(\omega_v^i) RV_{i,\tau-l}$$

with $g_{i,t}$ the daily time scale, α_i and β_i the classic ARCH and GARCH parameters, $m_{i,\tau}$ the monthly MIDAS component for the time scale τ that changes every N_i^v days as a weighted sum of K_i^v lags, and θ_i the main MIDAS parameter of various lag polynomials for parsimony.

In Table 3, for the GARCH-MIDAS part, α and β capture the short-term volatility dynamics, as in the ARCH and GARCH framework. We verify that they are statistically significant and positive. Plots of conditional variance have been saved to disk.⁹ The sum of $\alpha + \beta$ is noticeably less than 1, i.e., the MIDAS-GARCH parameter is smaller than what is usually observed for conventional GARCH models.

Most of all, θ is strongly significant. In the baseline specification, a positive sign implies a positive relationship between the series at stake. In the context of the year 2020, we may interpret it as such: when industrial production decreases, the CO₂ emissions decrease, and stock markets decline. Recall that, in a MIDAS regression, the lag polynomial coefficients are captured by a known function (e.g., the beta function in our case) of a few parameters that are summarized in a vector θ . The parameter θ determines the sign of the effect of the lagged X_t on the long-term components.

The same logic applies to the DCC component’s comments, although the parameter ω here indicates the correlation level. Figure 3 shows the DCC-MIDAS conditional correlations (in blue) and long-run conditional correlations (in green) for the baseline specification. As a sign of financial contagion, the graphs pick up correlation increases near the end of the study period. This is all linked to a macro-financial recessionary outlook against the broader background of the COVID-19 pandemic, precisely the next empirical sections’ purpose.

⁹ To save space, conditional variances not shown here and they can be transmitted upon request to the interested reader.

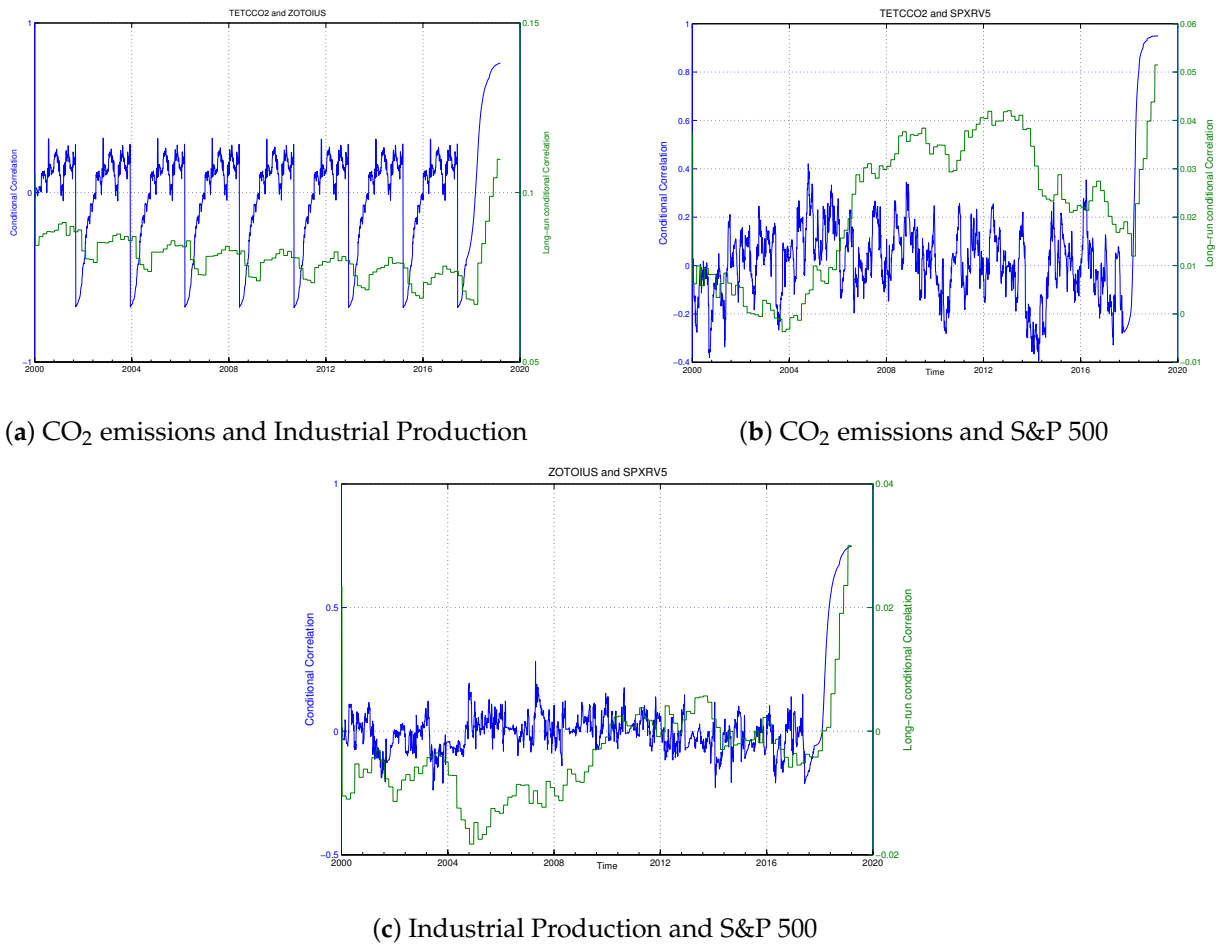


Figure 3. Conditional correlation (blue) and Long-run conditional correlation (green) for the baseline specification.

4.2. Introducing COVID-19 Confirmed Cases

For the introduction of the COVID-19 confirmed cases into the baseline specification, we restrict the estimation window to the sample that was accessed from the Johns Hopkins Coronavirus Center, e.g., 22 January 2020 to 8 May 2020.

In Table 4, the same comments apply to the baseline specification regarding the GARCH-MIDAS. We focus our attention primarily on the parameter estimate of θ for *TS – CONFIRMED – US*, which is -28.49 with a standard error of 6.84 (therefore, highly significant).

The negative sign for θ recorded here means that sharp increases of COVID-19 confirmed that cases in the U.S. had negatively influenced all other macro-financial and CO₂ emissions variables. This is the first time, to our knowledge, that such a statement can be made from statistical expertise.

Figure 4 shows that all U.S. macro-financial factors and fossil fuels CO₂ emissions depict a decreasing long-run trend (in orange) when associated with COVID-19 confirmed cases. Panel (c) shows a peak in stock market volatility (in blue).

Table 4. Dynamic Conditional Correlation with Mixed Data Sampling (DCC-MIDAS) estimates when introducing COVID-19 confirmed cases to the baseline that is composed of Total Fossil Fuels CO₂ emissions, Total Industrial Production Index, and S&P 500 Index.

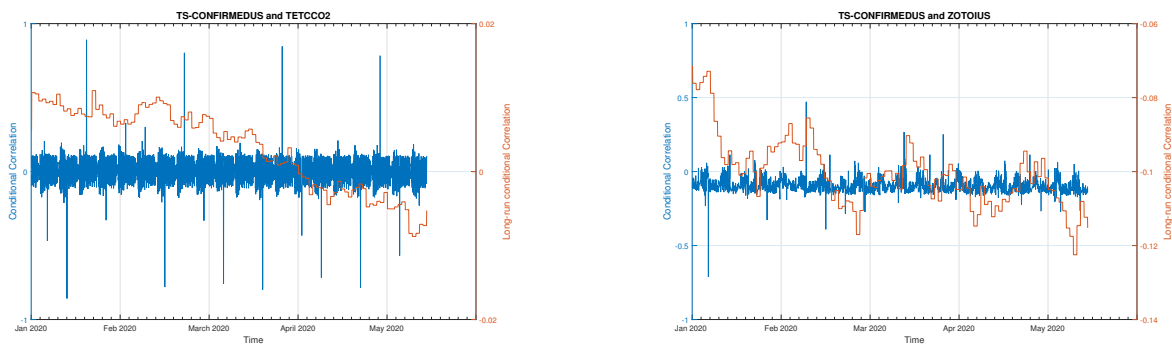
	μ	α	β	θ	ω	m
TS-CONFIRMED-US	12969.7920 (12085)	0.9999 *** (0.3189)	0.0001 *** (0.0001)	−28.4962 *** (6.8426)	1.0830 *** (0.1688)	0.0100 *** (0.0005)
TETCCO2	0.2796 *** (0.0001)	0.0468 *** (0.0001)	0.5980 *** (0.0001)	0.1000 *** (0.0001)	5.7067 *** (0.0001)	7.7438 *** (0.0001)
ZOTOIUS	−0.1180 (0.1103)	0.0141 *** (0.0004)	0.9857 *** (0.0004)	0.1368 (9.9118)	1.001 (13.4850)	32.3246 *** (3.688)
SPX-RV5	0.0015 (0.0090)	0.2344 *** (0.0245)	0.0556 (0.0574)	0.1938 *** (0.0142)	6.4696 *** (2.0287)	0.3567 *** (0.0678)
	a	b	ω			
DCC-MIDAS	0.0178 (0.0291)	0.6012 (0.8847)	1.001 *** (0.4317)			
Logarithmic likelihood:	−6334.08					
Akaike info criterion:	12674.2					
Bayesian info criterion:	12693.8					
Adjusted sample size:	1503					

Note: *** indicates statistical significance at the 1% level. The sample covers 22 January 2020 to 8 May 2020. TS-CONFIRMED-US is the number of COVID-19 confirmed cases in the USA. TETCCO2 is the Total Fossil Fuels CO₂ emissions. ZOTOIUS is the Total Industrial Production Index. SPX-RV5 is the 5-minute Realized Volatility of the S&P 500 Index. Equations (1)–(5) detail the conditional correlation. The conditional volatility is specified as a GARCH-MIDAS:

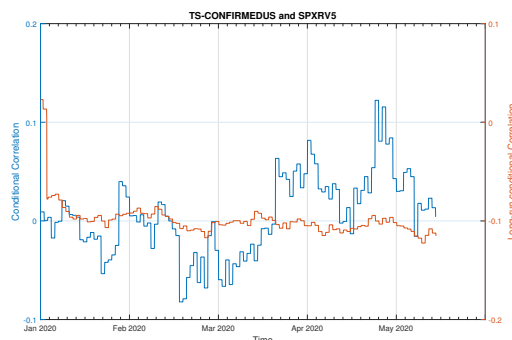
$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{(r_{i,t-1} - \mu_i)^2}{m_{i,\tau}} + \beta_i g_{i,t-1},$$

$$m_{i,\tau} = \bar{m}_i + \theta_i \sum_{l=1}^{K_l^i} \varphi_l (\omega_l^i) RV_{i,\tau-l}$$

with $g_{i,t}$ the daily time scale, α_i and β_i the classic ARCH and GARCH parameters, $m_{i,\tau}$ the monthly MIDAS component for the time scale τ that changes every N_i^v days as a weighted sum of K_l^i lags, and θ_i the main MIDAS parameter of various lag polynomials for parsimony.



(a) COVID-19 confirmed cases and CO₂ emissions (b) COVID-19 confirmed cases and Industrial Production



(c) COVID-19 confirmed cases and S&P 500

Figure 4. Conditional correlation (blue) and Long-run conditional correlation (orange) when introducing COVID-19 confirmed cases in the baseline specification.

4.3. Introducing COVID-19 Deaths

Next, we conduct another experiment by introducing the time-series of U.S. COVID-19 deaths into the baseline specification. Table 5 contains the estimation results.

Table 5. Dynamic Conditional Correlation with Mixed Data Sampling (DCC-MIDAS) estimates when introducing COVID-19 deaths to the baseline composed of Total Fossil Fuels CO₂ emissions, Total Industrial Production Index, and S&P 500 Index.

	μ	α	β	θ	ω	m
TS-DEATHS-US	760.71748 (633.73)	0.9999 *** (0.3178)	0.0001 *** (0.0001)	−46.2930 *** (2.9142)	1.0836 *** (0.1697)	0.0100 *** (0.0005)
TETCCO2	0.2799 *** (0.0001)	0.0468 *** (0.0001)	0.5986 *** (0.0001)	0.1000 *** (0.0001)	5.7068 *** (0.0001)	7.7439 *** (0.0001)
ZOTOIUS	−0.1181 (0.1137)	0.0146 *** (0.0004)	0.9859 *** (0.0004)	0.1366 (9.9118)	1.0010 (13.4850)	32.3250 *** (3.6880)
SPX-RV5	0.0016 (0.0091)	0.2343 *** (0.0246)	0.0557 (0.0577)	0.1939 *** (0.0141)	6.4697 *** (2.0287)	0.3577 *** (0.0688)
	a	b	ω			
DCC-MIDAS	0.0163 (0.0272)	0.6430 (0.8376)	1.001 *** (0.4335)			
Logarithmic likelihood:	−6334.93					
Akaike info criterion:	12677					
Bayesian info criterion:	12696.6					
Adjusted sample size:	1503					

Note: *** indicates statistical significance at the 1% level. The sample covers 22 January 2020 to 8 May 2020. TS-DEATHS-US is the number of COVID-19 deaths in the USA. TETCCO2 is the Total Fossil Fuels CO₂ emissions. ZOTOIUS is the Total Industrial Production Index. SPX-RV5 is the 5-min. Realized Volatility of the S&P 500 Index. Equations (1)–(5) detail the conditional correlation. The conditional volatility is specified as a GARCH-MIDAS:

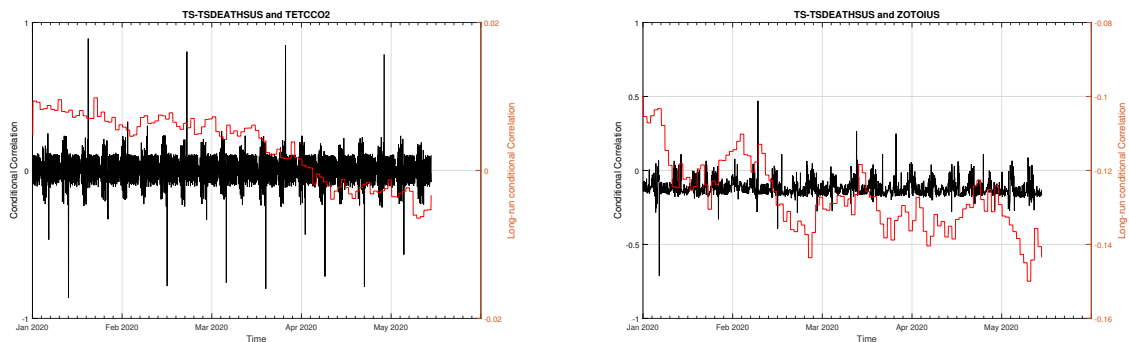
$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{(r_{i,t-1} - \mu_i)^2}{m_{i,\tau}} + \beta_i g_{i,t-1},$$

$$m_{i,\tau} = \bar{m}_i + \theta_i \sum_{l=1}^{K_v^i} \varphi_l (\omega_v^i)^l RV_{i,\tau-l}$$

with $g_{i,t}$ the daily time scale, α_i and β_i the classic ARCH and GARCH parameters, $m_{i,\tau}$ the monthly MIDAS component for the time scale τ that changes every N_v^i days as a weighted sum of K_v^i lags, and θ_i the main MIDAS parameter of various lag polynomials for parsimony.

Looking at the *TS – DEATHS – US* variable, we estimate a statistically significant parameter $\hat{\theta} = -46.29$, with a standard error of 2.91. When the number of deaths in the U.S. associated with the Coronavirus increases, the long-term macro-financial environment (and the associated fossil fuels CO₂ emissions) decreases as a by-product.

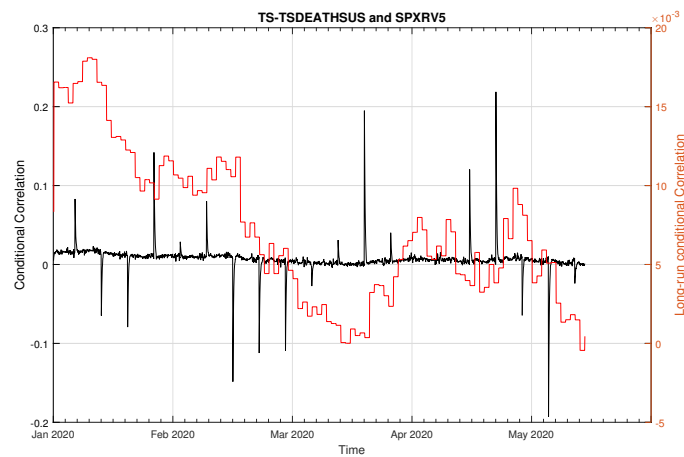
In Figure 5, macro-financial factors and CO₂ emissions exhibit a decreasing long-run trend (in red) when interacting in the dynamic system of equations with COVID-19 deaths. In panel (c), we remark the volatility spikes (in black) agitating the stock market during the year 2020.



(a) COVID-19 deaths and CO₂ emissions

(b) COVID-19 deaths and Industrial Production

Figure 5. Cont.



(c) COVID-19 deaths and S&P 500

Figure 5. Conditional correlation (black) and Long-run conditional correlation (red) when introducing COVID-19 deaths in the baseline specification.

4.4. Introducing COVID-19 Recovered Cases

Last but not least, we turn to the number of COVID-19 recovered cases, which should be taken as a piece of “good” news for the U.S. economy. The estimation results are reproduced in Table 6.

Table 6. Dynamic Conditional Correlation with Mixed Data Sampling (DCC-MIDAS) estimates when introducing COVID-19 recovered cases to the baseline composed of Total Fossil Fuels CO₂ emissions, Total Industrial Production Index, and S&P 500 Index.

	μ	α	β	θ	ω	m
TS-RECOVERED-US	-2567.0739 ** (1041.40)	0.6144 *** (0.0354)	0.3778 *** (0.0328)	1.8502 *** (0.1576)	1.0876 *** (0.2205)	0.0100 (0.0006)
TETCCO2	0.2769 *** (0.0001)	0.0488 *** (0.0001)	0.5980 *** (0.0001)	0.1000 *** (0.0001)	5.7068 *** (0.0001)	7.7439 *** (0.0001)
ZOTOIUS	-0.1189 (0.1137)	0.0147 *** (0.0004)	0.9857 *** (0.0004)	0.1368 (9.9118)	1.0010 (13.4850)	32.3250 *** (3.6880)
SPX-RV5	0.0015 (0.0090)	0.2344 *** (0.0245)	0.0557 (0.0574)	0.1938 *** (0.0142)	6.4697 *** (2.0287)	0.3568 *** (0.0675)
DCC-MIDAS	a 0.0278 (0.0383)	b 0.6170 *** (0.0813)	ω 1.001 *** (0.3917)			
Logarithmic likelihood:	-6492.48					
Akaike info criterion:	12991					
Bayesian info criterion:	13010.6					
Adjusted sample size:	1503					

Note: *** (**) indicates statistical significance at the 1% (5%) level. The sample covers 22 January 2020 to 8 May 2020. TS-RECOVEREDUS is the number of COVID-19 recovered cases in the USA. TETCCO2 is the Total Fossil Fuels CO₂ emissions. ZOTOIUS is the Total Industrial Production Index. SPX-RV5 is the 5-minute Realized Volatility of the S&P 500 Index. Equations (1)–(5) detail the conditional correlation. The conditional volatility is specified as a GARCH-MIDAS:

$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{(r_{i,t-1} - \mu_i)^2}{m_{i,\tau}} + \beta_i g_{i,t-1},$$

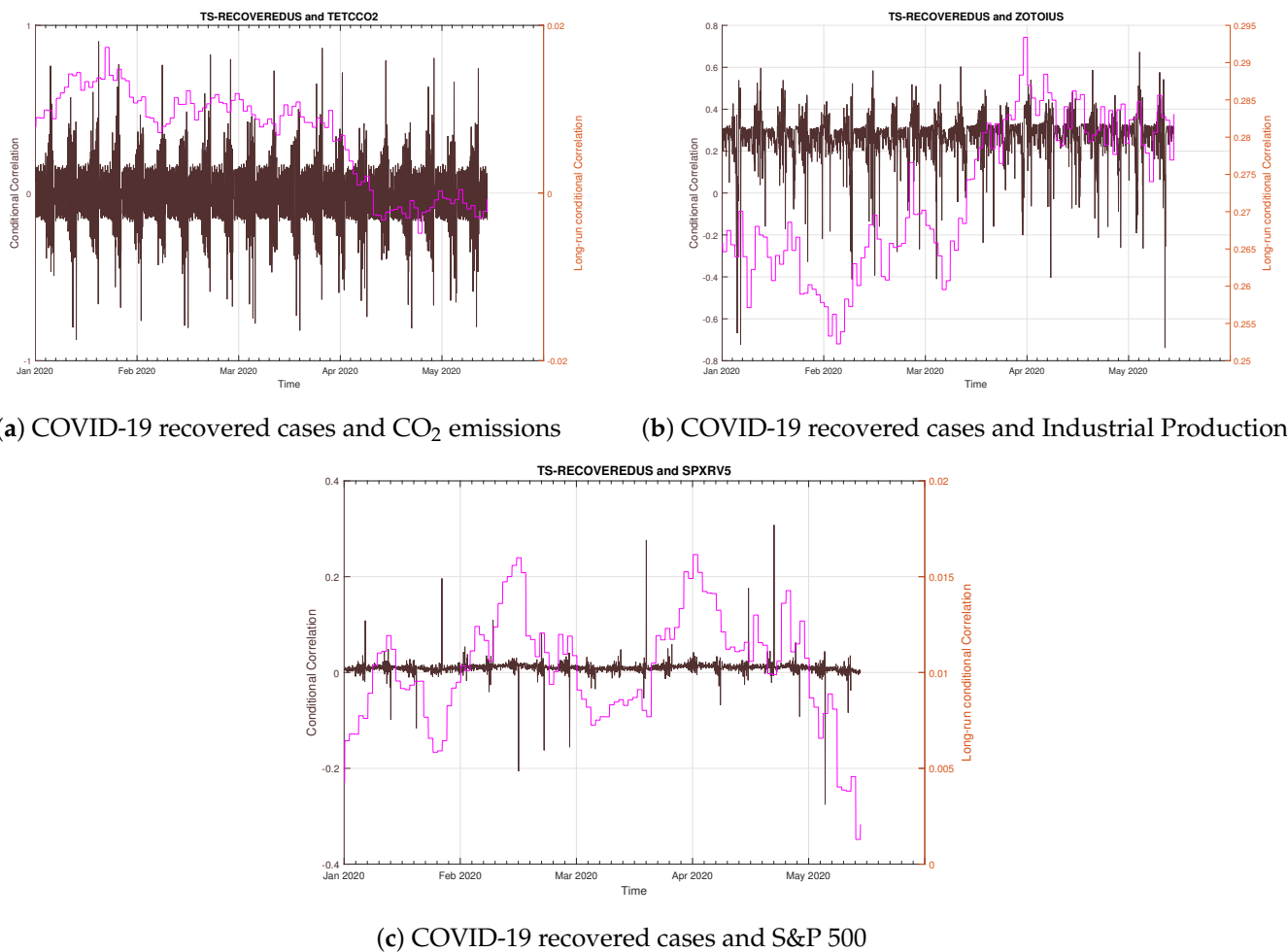
$$m_{i,\tau} = \bar{m}_i + \theta_i \sum_{l=1}^{K_l^i} \varphi_l(\omega_l^i) RV_{i,\tau-l}$$

with $g_{i,t}$ the daily time scale, α_i and β_i the classic ARCH and GARCH parameters, $m_{i,\tau}$ the monthly MIDAS component for the time scale τ that changes every N_i^v days as a weighted sum of K_l^i lags, and θ_i the main MIDAS parameter of various lag polynomials for parsimony.

Interestingly, the parameter estimate of θ for $TS - RECOVERED - US$ is statistically significant and positive, being equal to 1.85 with a standard error of 0.15. Hence, increases in the number of patients recovering from the COVID-19 should end the recession and re-start the economy (cyclical pattern).

All in all, we find that the COVID-19 variables are logically interacting with the set of macro-financial and CO₂ emissions variables selected. The bad news (such as the multiplication of COVID-19 confirmed cases or deaths) degrades the business environment and production cycle. Recovery from the disease instills the hope of a better future "in the world after" the pandemic and the catching-up of economic growth.

When looking at the panel (b) of Figure 6, we notice an increase in the long-run correlation (in pink color) between the COVID-19 recovered cases and industrial production, which might be subsumed as a piece of "good" news: when more people heal, the economy picks up.



(a) COVID-19 recovered cases and CO₂ emissions (b) COVID-19 recovered cases and Industrial Production

(c) COVID-19 recovered cases and S&P 500

Figure 6. Conditional correlation (black) and Long-run conditional correlation (red) when introducing COVID-19 recovered cases in the baseline specification.

However, we are not out of the economic recession cycle yet (not even by a small margin): in Figure 6, both long-run trends are decreasing when interacting COVID-19 recovered cases with either Total Fossil Fuel CO₂ emissions or the S&P 500. Moreover, we again detect volatility spikes in panel (c) for the stock market (in brown color).

4.5. Sensitivity

In the present work, we have detailed estimation output from specifications, including the (3×) kinds of COVID-19 epidemiological cases, the Total Industrial Production Index

(as a proxy of economic activity), the Total Fossil Fuels CO₂ emissions, and the S&P 500 (as a proxy of the U.S. stock market). First, notice that the stability of parameters estimated for the variables *TETCCO2*, *ZOTOIUS*, and *SPX – RV5* across Tables 3–6 serves as a first kind of robustness check.

For further tests, we programmed a loop in order to estimate DCC-MIDAS with the remaining variables (i) (11 ×) macroeconomic indicators, (13 ×) manufacturing production indices, (four ×) price indexes, (five ×) miscellaneous and (ii) the (two ×) stock market indexes that are listed in Tables 1 and 2. By browsing the log of results, we found that the paper’s main message is qualitatively unchanged.¹⁰ Namely, all of the parameter estimates keep their statistical significance, whilst the sign conforms to expected relationships.

5. Conclusions

The 45-day lock-down implemented during mid-March 2020 in most industrialized countries is expected to affect the real economy severely. In the meantime, it will alleviate part of the greenhouse gases’ burden that human activity induces on the environment. In this paper, we track both short- and long-run correlations in the Dynamic Conditional Correlation with Mixed Data Sampling (DCC-MIDAS) time-varying framework that enables data inputs from various (e.g., intra-daily, daily, and monthly) frequencies. The main variables of interest are the U.S. Total Fossil Fuel CO₂ emissions, Total Industrial Production, and the S&P stock market. When we introduced the epidemiological cases of COVID-19, we uncovered two kinds of effects. On the one hand, the multiplication of COVID-19 confirmed cases and deaths seems to negatively influence the macro-financial environment (and associated CO₂ emissions), as visible through MIDAS coefficients and long-run correlations. On the other hand, the increase in the number of patients healing from COVID-19 might be inferred as a good piece of news for the U.S. economy, being evident through the long-run correlation with industrial production. Other than that, we depict a recessionary macroeconomic outlook in the years to come, which is based on the identification of frequent spikes on stock markets against the pandemic background.

We may compare our results with previous studies in other fields, such as climate science. [Zheng et al. \(2020\)](#) use satellite observations together with bottom-up information to track the daily dynamics of CO₂ emissions during the pandemic. The authors document that China’s CO₂ emissions fell by 11.5% as compared to the same period in 2019. [Le Quéré et al. \(2020\)](#) estimate the decrease in CO₂ emissions during forced confinements. According to them, the daily global CO₂ emissions decreased by –17% by early April 2020 when compared with the mean 2019 levels. [Liu et al. \(2020\)](#) present the daily estimates of country-level CO₂ emissions based on near-real-time activity data. The key result is an abrupt 8.8% decrease in global CO₂ emissions in the first half of 2020 compared to the same period in 2019. These three scientific works relate to our estimates in the DCC-MIDAS model well. We quantified the time-varying correlations of CO₂ emissions with either COVID-19 cases or COVID-19 deaths to sharply decrease by –15% to –30% as well.¹¹

The present study is limited in its scope, to the extent that the data on CO₂ emissions accessed only concern the start of the COVID-19 recession (aka, March 2020). Some economists (see, e.g., [Diebold 2020](#)) have already predicted that this sanitary crisis will turn into a “Pandemic Recession” in the years 2021–22 (for contagion effect to asset markets, see [Chevallier 2020](#)). Therefore, future research will be beneficial to assert the severity of the recession and the ultimate quantitative impact on CO₂ emissions. Further studies in the fields of international production logistics and worldwide tourism, but not limited to them, would be promising areas to document this historical crisis better.

¹⁰ Upon a reasonable request, we can transmit (unformatted) logs of DCC-MIDAS estimates. The computational burden induced by the loop (e.g., $\binom{n \times (n-1)}{2}$ combinations) can create memory usage bottlenecks on lower-end computers.

¹¹ This comment is achieved by looking more precisely at panel (a) COVID-19 confirmed cases and CO₂ emissions of Figure 4, or panel (a) COVID-19 deaths and CO₂ emissions in Figure 5.

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Data Availability Statement: Publicly available datasets were analyzed in this study. This data can be found here: <https://coronavirus.jhu.edu>; <https://www.eia.gov>; and <https://realized.oxford-man.ox.ac.uk>.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Setting the MIDAS Lags

The setting of the MIDAS lags is data-driven. Indeed, to accommodate various frequencies within the same methodological framework, the parameters $\omega_r^{i,j}$, $N_c^{i,j}$, and $K_c^{i,j}$ are not necessarily the same for all series (i.e., they differ depending on the monthly or daily frequency considered).

Ghysels et al. (2007) underline that most MIDAS regressors involve polynomials putting hardly any weight on longer lags. Engle et al. (2013) show that the optimal weights decay to 0 around thirty months of lags, regardless of the choice of t and length of MIDAS lag year.

This paper chooses 36 MIDAS lags for the conditional volatility process and 144 for the conditional correlation. This is similar to the original setting of Colacito et al. (2011) in their empirical application to stocks and bonds.

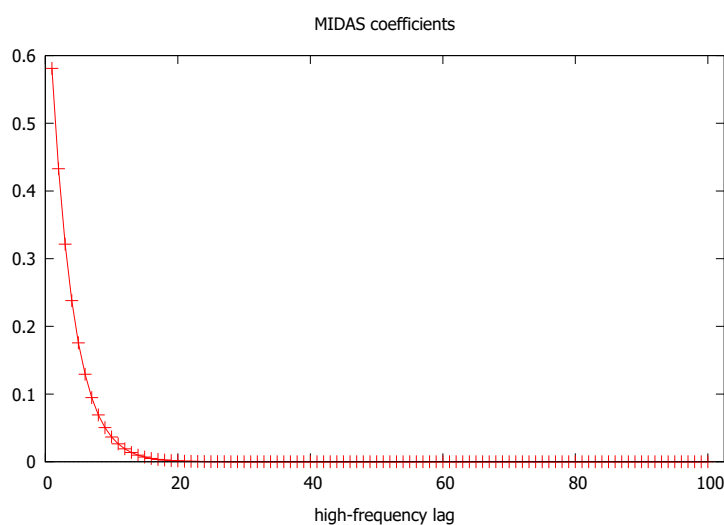


Figure A1. MIDAS lags for the baseline specification.

An example of how this lag setting fares to the data is given in Figure A1 for the baseline specification. We notice that past 20 lags indeed, no further information is gained from the optimal weighting function. Hence, our setting of 36 lags for the conditional volatility process appears as a conservative choice.¹²

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¹² Upon request, a similar analysis can be produced for the 144 lag settings of the conditional correlation. It is not shown for brevity.

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