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Corona, Crisis and Conditional Heteroscedasticity

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Corona, Crisis and Conditional Heteroscedasticity*

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Abstract

In this paper, we illustrate the macroeconomic risk associated with the early stage of the corona-virus outbreak. Using monthly data ranging from July 1991 to March 2020 on a recently developed coincidence indicator of global output growth, we estimate an autoregressive model with GARCH effects and non-Gaussian disturbances. Our results indicate that *i)* accounting for conditional heteroscedasticity is important and *ii)* risk, measured as the volatility of the shocks to the process, is at a very high level – largely on par with that experienced around the financial crisis of 2008-2009.

JEL Classification: C22, E32, E37

Keywords: GARCH, Non-Gaussianity

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1. Introduction

In light of the corona-virus outbreak, businesses, financial market actors, policy makers and other economic agents grapple with how to assess the economic effects. For many, this includes quantifying the amount of risk with which the outbreak is associated. In financial markets, such calculations tend to be standard practice. There is, however, also a need to quantify risks from a macroeconomic perspective. For instance, institutions such as the Bank of England, the IMF and Sveriges Riksbank, which regularly publish density forecasts – or so-called *fan charts* – of key variables have to address this issue.

Admittedly, the methods for quantifying macroeconomic risks are typically less sophisticated than those employed in financial markets. It can, for example, be noted that the Riksbank relies on a method where the historical forecast errors are used to calibrate normal distributions when generating density forecasts for various macroeconomic variables; see Sveriges Riksbank (2007) for details. This implies that the communicated uncertainty of the Riksbank's forecasts will always be based on the historical average at that point in time – an assumption which does not seem unproblematic given that it is reasonable to believe that forecast uncertainty can change rather dramatically in just a short period of time.[1]

In this paper, we provide an estimate of macroeconomic risk at the global level. We estimate an autoregressive (AR) model with GARCH(1,1) disturbances for the recently developed coincidence indicator of global output growth developed by Abberger *et al.* (2020). In line with the research pointing to the importance non-Gaussianity when modelling macroeconomic time series – see, for example, Fagiolo *et al.* (2008) and Chiu *et al.* (2017) – we abandon the traditional assumption of disturbances being drawn from a normal distribution and instead employ a *t*-distribution. Both the use of GARCH effects and non-Gaussian disturbances find support in our empirical analysis.

Our results indicate that the uncertainty around global output growth has increased drastically in conjunction with the outbreak of the corona crisis. The conditional variance of innovations driving the coincidence indicator has jumped to a level approximately 4.5 times higher than its unconditional counterpart (and six times higher than in the previous month). Furthermore, volatility is expected to remain high for several quarters; the half-life of the variance is approximately 13 months. This means that not only short-term forecasts, but also forecasts one or two years ahead are substantially more uncertain than in normal times.

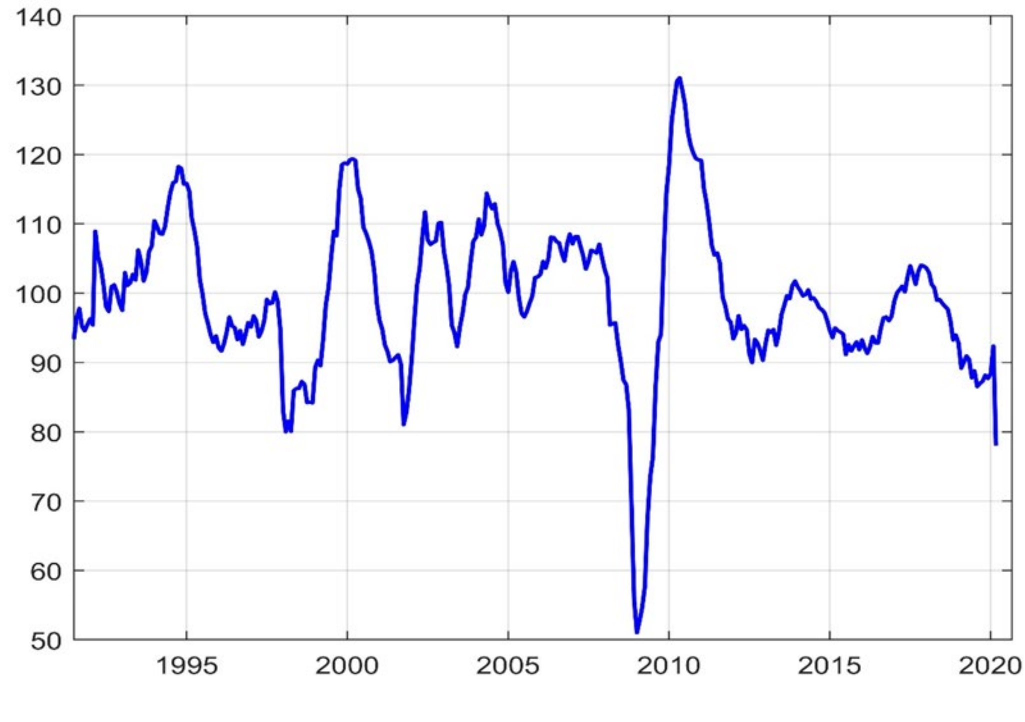
[1] The Bank of England and the IMF instead employ methods that explicitly aim to account for time-variation in uncertainty; see Britton *et al.* (1998) and IMF (2009) for details.

2. Data and empirical analysis

We use monthly data on the recently developed coincident composite indicator for the world business cycle of Abberger *et al.* (2020). The indicator – which is based on a very large number of consumer, business and expert tendency survey data series from all over the world – is intended to target global output growth and is constructed in such a way that it has a mean of 100 and a standard deviation of 10 over the sample.[2]

Data are shown in Figure 1 and as can be seen, there was a dramatic fall in the series in March 2020 when the indicator dropped from its February value of 92.4 to 78.0. While the level of the indicator has not reached the extreme levels of the financial crisis of 2008-2009, it is nevertheless the case that the fall in March 2020 is the largest movement in a single month in the sample. A substantial decline in global growth is accordingly implied by the indicator. It should be noted though that the March value was published in early March, after which there has been plenty of additional negative news.

Figure 1. Data.



Note: The coincident composite indicator for the world business cycle of Abberger *et al*. (2020) is given in index units.

[2] Abberger *et al.* (2020) also provide a leading composite indicator for global output growth. Unreported analysis (available on request) based on the leading indicator yields very similar results.

To account for the large jump and the associated uncertainty, we abandon the traditional assumption of a homoscedastic and Gaussian innovation when modelling and forecasting the indicator.[3] In particular, we estimate an AR(4) model with GARCH(1,1) disturbances:[4,5]

$$y_t = \gamma_0 + \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + \gamma_3 y_{t-3} + \gamma_4 y_{t-4} + \epsilon_t \qquad (1)$$

$$\epsilon_t = \sigma_t v_t \qquad (2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \qquad (3)$$

where v_t is assumed to be an *iid* error distributed according to a *t*-distribution with κ degrees of freedom. We also contrast this with forecasts from an AR(4) model which is assumed to be homoscedastic and based on disturbances drawn from a normal distribution. That is, we modify the model in equations (1) and (2) such that σ_t is a constant and assume that $v_t \sim NID(0,1)$.

Estimation results are collected in Table 1. They show that parameters on conditional volatility are highly significant and the test for conditional heteroscedasticity (Engle, 1982) shows that the GARCH(1,1) specification takes care of conditional heteroscedasticity well. However, even after filtering out time-varying volatility, innovations remain heavy-tailed, as indicated by the low degrees of freedom of the *t*-distribution (3.84); this is also reflected in the strong rejection of normality by the Jarque-Bera (1980) test. Looking at the homoscedastic AR(4) model, we find that the equation for the conditional mean is fairly similar to that of the model with GARCH disturbances. However, as the test statistics suggest, the residuals are heteroscedastic (and non-normal) in this case.

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[3] For a fairly long time, the issue of time-varying volatility of the shocks hitting the economy has received a somewhat stepmotherly treatment in macroeconomics. While important contributions have been made by for example Stock and Watson (2002), Cogley and Sargent (2005) and Hamilton (2010), the vast majority of models being used assume that shocks are homoscedastic.

[4] Lag length was determined by applying the Schwarz (1979) information criterion to AR models assumed to be homoscedastic.

[5] The choice of a GARCH(1,1) specification was based on its robust usefulness in empirical work; see, for example, Hansen and Lunde (2005). The GARCH(1,1) specification also seems to be appropriate when looking at the estimation results and ARCH test shown in Table 1.

Table 1. Estimated key parameters.

	AR(4)-GARCH(1,1)	AR(4)
γ_0	6.19	6.39
	(1.19)	(1.28)
γ_1	1.25	1.29
	(0.05)	(0.03)
γ_2	-0.27	-0.30
	(0.08)	(0.08)
γ_3	0.20	0.17
	(0.09)	(0.10)
γ_4	-0.24	-0.24
	(0.05)	(0.05)
α_0	0.35	-
	(0.24)	
α_1	0.10	-
	(0.05)	
α_2	0.85	-
	(0.07)	
κ	3.84	-
	(0.63)	
Jarque-Bera	2311.05	1151.70
	[0.00]	[0.00]
ARCH(6)	2.49	19.90
	[0.87]	[0.00]

Note: Standard errors in parentheses (). p-values in brackets []. ARCH(6) is the test statistic from Engle's (1982) LM test for conditional heteroscedasticity conducted with six lags.

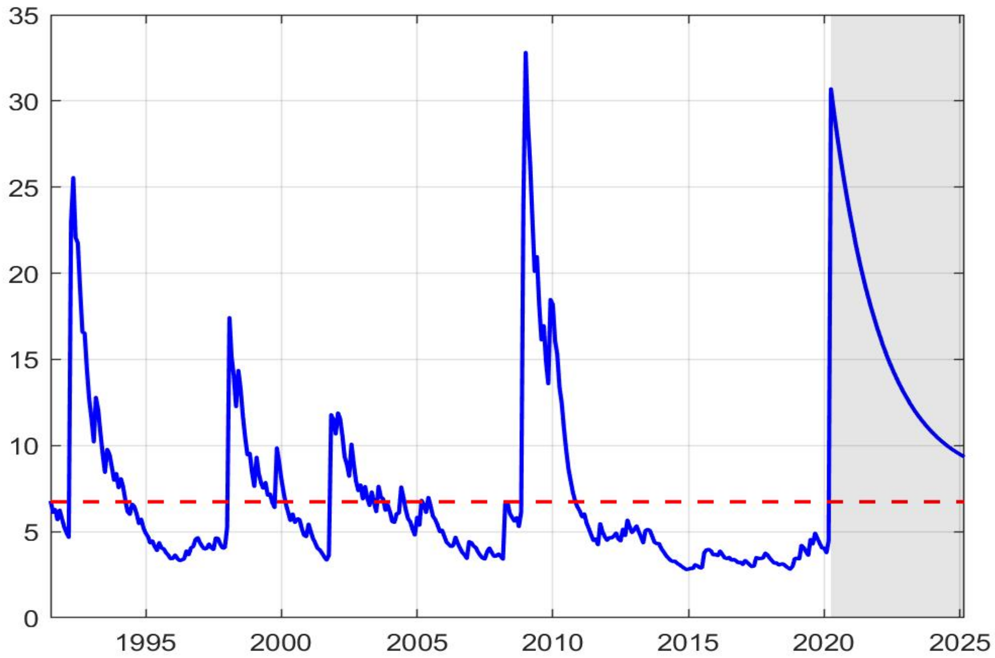
Figure 2 shows the implied conditional variance of the disturbances from the AR(4)-GARCH(1,1) model, including the forecast. Going from March 2020 to April 2020, this variance increases roughly six-fold, from approximately 5 to 30. Since the variance is fairly persistent – the half-life of the variance process is approximately 13 months – this jump implies that the increased uncertainty regarding global output growth will remain quite a long time.[6]

This jump in the disturbances' variance has clear implications for the variance of the forecast error. As can be seen in the left panel of Figure 3, the confidence band around the point forecast widens

[6] An estimate of the half-life can be calculated as $\frac{\ln(0.5)}{\ln(\hat{\alpha}_1+\hat{\alpha}_2)}$.

substantially in the beginning of the forecast horizon. Scenarios as bad as the deepest points of the financial crisis – when the indicator took on values only slightly above 50 – are now in the 95 percent confidence band from basically the middle of 2020 up until the beginning of 2022. This stands in sharp contrast with the results of the homoscedastic model, where financial-crisis-like scenarios are well outside the confidence band at any point in time. It should also be kept in mind that – as pointed out above – there has been plenty of negative news since the March value of the indicator was published. Hence, a substantial drop in the indicator also in April is likely, which means that the conditional variance going forward might be even higher than indicated in Figure 2.

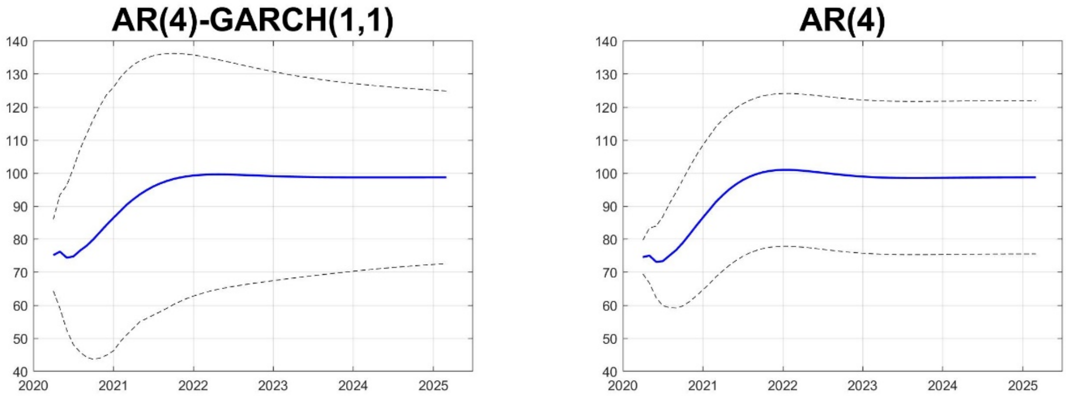
Figure 2. Estimated variance of shocks.



Note: Index units on vertical axis. Shaded area indicates forecasted values. Solid (dashed) line shows the conditional variance of the innovation from the heteroscedastic (homoscedastic) model.

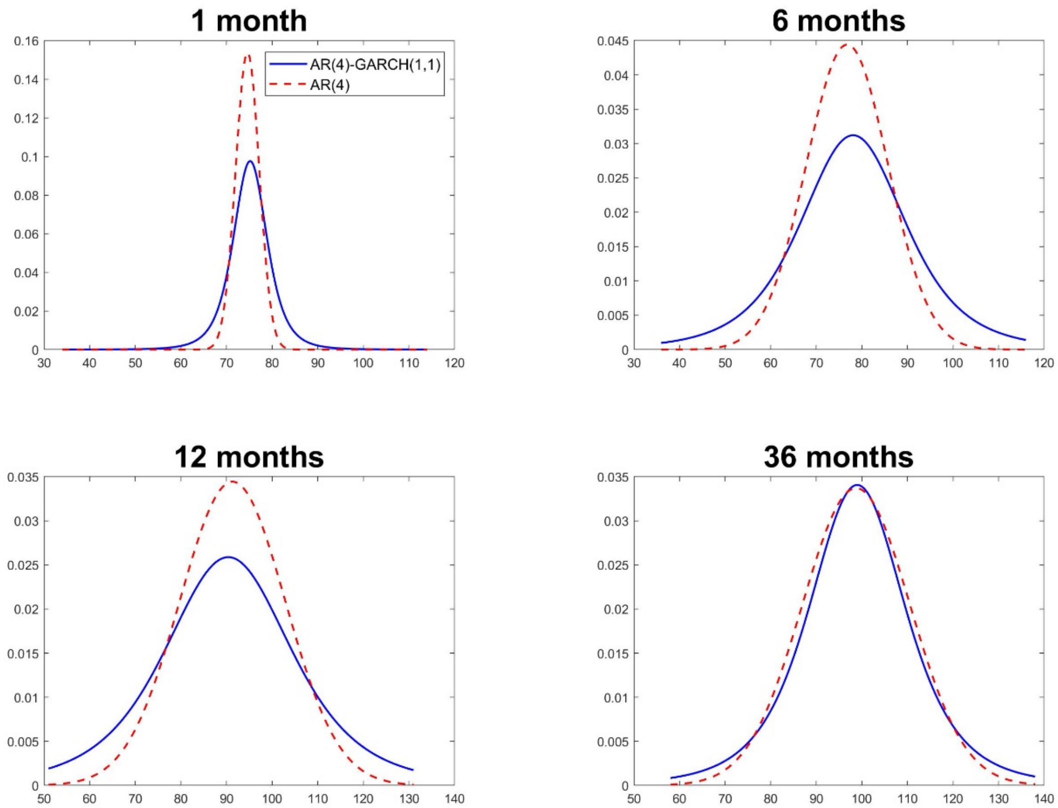
This effect of time-varying volatility is also illustrated in the four density forecasts for selected horizons shown in Figure 4. At the one-month horizon, the homoscedastic AR(4) model is much more concentrated around the point forecast compared to the AR(4)-GARCH(1,1) specification. This difference decreases with the horizon, but even at the 36-month horizon, the AR(4)-GARCH(1,1) model – which also accounts for non-Gaussianity – implies heavier tails (and hence wider confidence intervals) than the homoscedastic model.

Figure 3. Point forecasts and 95 percent confidence intervals for the AR(4)-GARCH(1,1) and AR(4) models.



Note: Index units on vertical axis.

Figure 4. Density forecasts at different horizons.



Note: Index units on horizontal axes.

3. Conclusions

By mid-/late-March 2020, it is clear that the outbreak of the corona virus will have large economic consequences globally. Governments are taking the largest actions since the global financial crisis to mitigate this dramatic negative shock. For the effectiveness of these measures – and for economic policy in general – there is an urgent need to have access to quantitative assessments related to various aspects of the economy. We contribute to this by modelling an indicator for global output growth where we have abandoned the traditional assumptions of homoscedasticity and non-Gaussianity of error terms. We find that forecast uncertainty has increased dramatically within just one month.

That uncertainty is high at the moment is evident; for example, financial markets have very clearly shown this by being subject to extreme volatility during the first half of March 2020. However, an important message from our analysis is that we are also likely to face heightened macroeconomic risk for quite some time in the future – a piece of information that should be of utmost importance to policy makers, both when considering policy actions and when communicating with the surrounding society, for example using fan charts.

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