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The bond market impact of the South African Reserve Bank bond purchase programme

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Abstract

We use a unique dataset comprising over a million trades and quotes to assess the impact of the unexpected announcement of a bond purchase programme by the South African Reserve Bank on intraday market liquidity, yields and pricing volatility. Our dataset details the timing and order details of individual bonds purchased by the South African Reserve Bank during the COVID-19 pandemic, as well as data from over a million other fixed-coupon bond trades and intraday quotes. We find that the programme was successful at shoring up market confidence and addressing dislocation in the government bond market. We show that bond spreads fell both on announcement and after purchases themselves. Bond pricing adjusted slowly, with effects typically strengthening over the course of the trading day. We find that announcement effects dominated the impact of purchases themselves. Lastly, our intraday dataset enables assessment of the spillovers of central bank announcements in major economies and we show that the Federal Reserve played an important role in stabilising South Africa's bond market, helping to support the actions of SARB.

JEL classification: C5,E43,E58,G12,G14

Keywords: bond purchase programme, liquidity, yield curve

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1. Introduction[1]

We construct a dataset of over a million bond trades that enables the impacts of a central bank purchase programme on the bond market to be assessed with unprecedented precision. Our dataset details the timing and order details of individual bond trades during the March 2020 market distress related to the unfolding COVID-19 pandemic. This includes intraday quotes and trading activity from the bond exchange. The trade-by-trade and quote data allow for a careful comparison of three separate categories of events and their effects: (i) the announcement of the decision of the South African Reserve Bank (SARB) to actively intervene in the bond market on 25 March 2020; (ii) the actual interventions by SARB; and (iii) the spillovers of the interventions of advanced economy central banks, particularly the Federal Reserve, on the South African bond market.

The announcement of the SARB bond-buying programme is a unique event. There was no prior indication that SARB would undertake any such programme. As a result, this is an example of a clearly identifiable policy surprise. The reason for the decision to begin purchasing bonds was given as persistent financial market dislocation, and our dataset allows us to document the nature of the fragmentation of the bond market that occurred during the COVID-19 pandemic. Since the programme was implemented for financial stability purposes, we assess whether the announcement effect is associated with a statistically significant decline in bid-ask spreads (indicative of an improvement in market liquidity). Even though SARB's programme was not targeting bond prices, we also describe movements in bond yields following the announcement and bond purchases to enable comparison to the market impacts of bond purchase programmes of other emerging market central banks during the COVID-19 pandemic, and we benchmark these to spillovers of the Federal Reserve Bank's announcement during the COVID-19 pandemic on the South African bond market. We use a model to construct a counterfactual against which to compare observed market pricing and to consider an expanding intraday event window providing results over several assessment windows.

Overall, our results suggest that the introduction of the programme was successful at shoring up market confidence and addressing dislocation in the government bond market, and it improved the Reserve Bank's liquidity management. While the immediate intraday impact of the announcement and initial bond purchase were insignificant, the estimated impacts were larger over a daily window, with bond spreads falling on the announcement and continuing to fall after the initial purchases. The estimated announcement effects were large compared to estimates of the effects of the original quantitative easing programmes in advanced economies and the purchase programmes by emerging markets during the COVID-19 pandemic. We also provide some evidence that market impacts were stronger when purchase sizes were large relative to bond-specific liquidity at the time of the purchases. We argue that our approach can help

[1] We thank the Johannesburg Stock Exchange and National Treasury for data provision, and Jennifer Elliot, Rohit Goel, David Fowkes, Nick Sander and seminar participants at the IMF-SARB conference of the impact of COVID-19, seminars at the South African Reserve Bank, and an anonymous referee for comments and suggestions.

with real-time assessment of market conditions, market impacts of operations and calibration of operations in future. Our intraday dataset enables assessment of the spillovers of central bank announcements in major economies. Lastly, we show that the Federal Reserve played an important role in stabilising South Africa's bond market, helping to support the actions of SARB.

This paper contributes to a number of strands of literature. The first is the rapidly expanding literature on the impact of the COVID-19 pandemic on financial markets and the impacts of non-conventional policies like bond purchase programmes (see Rebucci et al. 2020, Goel et al. 2020, or De Padua et al. 2021). Given the absence of a bond purchase programme before the COVID-19 pandemic, SARB's programme is an ideal example of an unanticipated change in central bank policy in an emerging market economy with a deep and liquid sovereign bond market. Secondly, we present an intraday bond-by-bond assessment of the implementation effects of the SARB's bond purchase programme and compare it to the spillovers from the Federal Reserve programme announcement during the crisis. Most studies into the effects of bond purchase programmes focus on a daily frequency and the impacts on bond yields or risk premia at specific points on the term structure of interest rates (see Krishnamurthy and Vissing-Jorgensen 2011, Gagnon et al. 2011, or Christensen and Rudebusch 2012). Our unique dataset enables us to identify the exact market timings of purchases to better isolate the market impacts of the programme announcement and the purchases themselves than has been possible in other studies. A bond-by-bond focus also provides specific lessons for central banks about the operations of such programmes at the level of individual trades. Ours is also one of a relatively limited number of studies that assesses the impacts on bond-specific market liquidity conditions *and* volatility (recent papers in an emerging market context include Goel et al. 2020 and De Padua et al. 2021). Finally, another distinct feature of our study is an investigation into whether purchase size or bond-specific liquidity might affect the market impacts.

For advanced economies, the impact of central bank bond-buying programmes has received substantial empirical scrutiny. The evidence for emerging markets is, however, fairly limited. This is in part because emerging market central banks have been reluctant to engage in 'unconventional' monetary policy. Reluctance is in many ways justified: the largest emerging markets have recently had relatively high inflation rates and positive policy rates.[2] Accordingly, this paper is one of a very limited number of papers that assess the impact of unanticipated sovereign bond buying in an emerging markets setting. Indeed, the literature has focussed more on the impact of advanced economy 'quantitative easing' (QE) programmes on emerging markets, including Bhattarai et al. (2015), and the impacts of the taper tantrum (Eichengreen and Gupta 2014).

The extensive literature on the impact of bond purchase programmes on advanced economies (see Martin and Milas 2012, Krishnamurthy and Vissing-Jorgensen 2012 and Gorodnichenko

[2] Among the G-20, the IMF forecast for the average unweighted inflation rate was 2.1% in 2020, and the average unweighted policy rate for emerging markets was 4.6%.

and Ray 2017) faces a number of estimation challenges. Pre-eminent among these is that monetary policy actions are particularly difficult to identify. Government bond-buying programmes are often telegraphed months in advance by central banks and are carefully communicated. Alternatively, the market may have a sense of the central bank's reaction function and as economic information comes to light, the market develops an informed view on the timing and intentions of policymakers. A related challenge is that the information effects of unintended policy actions may counteract their intended effects. For example, if a central bank announces an unanticipated QE programme, this may lead market participants to assume the central bank has better information about economic conditions and to downwardly revise their expectations of economic growth. This may lead to a fall in inflation expectations and growth, rather than the intended opposite effect.[3] Moreover, usually QE is a programme implemented over a period of time, making it complex to tease out how specific purchases affect specific yields.

COVID-19 induced bond purchase programmes have tended to be quite different from the earlier programmes in advanced economies. Many advanced economy programmes before the crisis involved large-scale purchases of corporate and government bonds in aid of liquidity for bond markets, credit support for firms, and aimed at achieving further monetary easing when an economy has reached the zero lower bound for interest rates. Programmes since the COVID-19 pandemic, particularly by emerging market central banks, have tended to be focused on rectifying market dislocations and restoring confidence in the bond market, and therefore more temporary in nature (see Arslan et al. 2020 or Vissing-Jorgensen 2021 for further discussion).

A commonly used approach to assessing the impacts of bond purchase programmes is an event study methodology, which identifies impacts on financial markets (usually over a 1- or 2-day horizon). Many papers comparing the size of the initial announcement effects and implementation of programmes find that the effects of programmes diminish after the initial announcement (examples include Gagnon et al. 2011, Krishnamurthy and Vissing-Jorgensen 2011 and Vissing-Jorgensen 2021). Identifying the longer-run effects of such programmes is very challenging given the low statistical power of tests over long event windows where there are many confounding factors that affect financial markets.[4] Given concerns over how well such effects are identified during short event windows (Thornton 2013), we use a model to construct a counterfactual against which to compare observed market pricing and to consider an expanding intraday event window providing results over several assessment windows. There has also been a recognition that short-term estimates of spillovers from advanced economies to emerging market asset prices may not fully capture the effects of advanced economy bond purchase programmes impounded into financial market pricing (see Mamaysky

[3] Campbell et al. (2012) and later Gorodnichenko and Ray (2017) call this the Delphic effect.

[4] Studies that use a vector autoregression (VAR) approach to estimating the impacts of bond purchase programmes sometimes find more persistent impacts than event study approaches (see Eser et al. 2019 by way of example). However, VAR studies can be sensitive to reverse causality and regressor endogeneity problems as central banks could react to macroeconomic shocks during the months or quarters typically used in such studies (i.e. they may be poorly identified).

2018 or Fratzscher et al. 2018). For this reason, our analysis covers both an intraday and daily frequency to ensure comparability with other studies in the literature. Lastly, the majority of event studies focus on the impact on bond yields, ignoring the impacts on market liquidity or market volatility, an important focus for bond purchase programmes during the COVID-19 pandemic.[5] Ours is also one of a relatively limited number of studies that assesses impacts on bond-specific market liquidity conditions, yields and volatility. We do not assess the impact of the SARB bond purchasing programme on output or on inflation as there were a limited number of purchases over a short period of time (corresponding to periods of extreme financial market volatility) and the programme was not intended to stimulate the macroeconomy, but merely to stabilise bond market conditions. Our focus is on measuring the intraday markets impacts of the SARB programme and we leave further assessment of the channels through which the purchases transmitted to markets to future research.

2. The 2020 COVID-19 contagion

Around 31 December 2019, the World Health Organisation reported of a type of viral pneumonia in Wuhan, China.[6] The Chinese media reported the first death from the disease on 11 January 2020. The new infection was identified as a novel coronavirus, and named 'COVID-19'. Coronaviruses are relatively common nose, sinus and upper respiratory viruses but the uniqueness of COVID-19 was both the ease of transmission and the high mortality rate. The virus rapidly spread. On 11 March 2020, the World Health Organisation made the assessment that 'COVID-19 could be characterised as a pandemic'. The market reaction to this was relatively immediate and a significant market sell-off occurred.

In common with previous sell-offs, there was a well-documented and significant fall in stock markets around the world (Ashraf 2020, Alfaro et al. 2020, Baker et al. 2020 and Ramelli and Wagner 2020). The usual crisis playbook is that this precipitates a 'risk-off' 'flight-to-quality' and 'flight-to-liquidity', leading to US Treasury bill prices rising (and yields falling). During these episodes, emerging markets typically experience an outflow of foreign capital, leading to both equity market and bond market sell-offs (Reinhart and Rogoff 2009, Forbes and Warnock 2012 and Eichengreen and Gupta 2016).

The COVID-19 contagion did not follow this exact pattern. The most striking difference was that there were net sales of US Treasuries by non-residents in March and April of USD475.6 billion,[7] and March was the largest net sale month since records began in 1978. In particular, between 9 March 9 and 23 March, the ten-year Treasury yield *rose* by up to 60 basis points (Fleming 2020). The result was an unusual correlation between stock and bond returns –

[5] An exception is Schlepper et al. (2017), who assess the intraday impacts of QE on individual German government bond liquidity, showing that price impacts are small (1 to 3 bps), but stronger when the market is less liquid.

[6] The epidemiological timeline for COVID-19 is summarised from https://www.who.int/news/item/29-06-2020-covidtimeline. Unless otherwise indicated, the timeline of central bank responses is from Arslan et al. (2020).

[7] See: https://ticdata.treasury.gov/Publish/tressect.txt.

concerning as it indicated severe dislocations in the traditional safe havens. Bid-ask spreads rose significantly and order book depth declined indicating market illiquidity (Fleming 2020, Duffie 2020 and He et al. 2020). Price volatility also rose, as market players struggled to assess the impact of frequent news arrivals on economic conditions (Capelle-Blancard and Desroziers 2020). A particular feature was a decline in depth for short-term securities. Five- and ten-year depth reached levels as low as 10% of post global financial crisis levels. This is particularly notable as the traditional flight-to-safety comes with its complement – a shortening of duration that arises from the 'flight-to-liquidity' effect. Much of this has been ascribed to the costs (both regulatory costs and balance sheet costs) to dealers of holding inventory and making markets (Duffie 2020 and He et al. 2020).

US corporate bond markets also experienced dislocations (Kargar et al. 2020). Similar to the experience in the US Treasury market, the costs to corporate dealers of accumulating inventory were prohibitive. This encouraged dealers to facilitate slower, more costly bilateral trades. Faced with significant uncertainty, the market froze until the Federal Reserve intervened to support liquidity in corporate bond markets on 15 March 2020.

2.1 South Africa

South Africa has a number of unique features that make it a compelling case study. It has a large domestic savings base, and is able to borrow from both domestic and international sources. In comparison with other emerging markets, South Africa has both a high percentage of bonds issued in domestic currency (over 85%) and percentage of these bonds held by non-residents (over 35%).

South Africa experienced substantial capital outflows in 2020, with larger outflows than any other emerging market (see IMF 2020). This was driven by a decline in participation by non-residents, and led to both an increase in yields and increased volatility in mid to late March 2020.[8]

While traded yields rose substantially, Figure 1 highlights the significant increase in dispersion of trades. In panel (b), the increase in standard deviation during the week of 23 March is notable, highlighting how volatile trading activity became.

In Figure 2, we code each individual trade according to the nature of the counterparties – 'ForeignBuy' if the trade involves the purchase of a bond by a offshore counterpart, 'ForeignSell' if the trade is the sale of a bond by an offshore counterpart, and 'domestic trade' if the trade is between two domestic counterparties. The results of this coding are then summarised as

[8] Notably, the largest sell-off took place on 12 March 2020, with the majority of the sell-off during the hour between 08:00 and 09:00 Eastern Standard Time, corresponding to the opening of the New York market. This market was inundated with news about COVID-19, and experienced one of the worst trading days on record. Market dynamics were consistent with a temporary reversal of capital flows, with an increase in bond yields and a depreciation across emerging markets. The opening of trading in New York led to significant effects on the domestic South African market. While yields rose 30 bps on 12 March, they rose by over 100 bps on 24 March.

box-and-whisker plots in Figure 3 to show the key statistics of trades involving different counterparties.

On 23 March, trades in the three categories take place within approximately the same range, although already there is some evidence that foreign buyers purchase at lower yields. As yields are inverse to prices, this indicates that foreign buyers purchase at higher prices.

On 24 March, this difference becomes substantially more noteworthy. Trades involving foreign buyers take place at statistically significant lower yields (i.e. higher prices). Moreover, foreign activity on the market reduced significantly, from between 25% and 30% of all activity to 10% of all activity, highlighting how much 'thinner' the foreign market became.

In Figure 4, we use the data to fit yield curves.[9] A yield curve constructed for a day prior to the COVID-19 contagion (11 March) is compared to a yield curve constructed for the day of market disruption (24 March). This shows that across the yield curve, trades involving foreigners occurred at noticeably lower yields (i.e. higher prices) than trades involving domestic parties. Most notably, however, trades involving domestic counterparties at the very short end of the curve take place at almost zero, suggesting an extraordinary demand for liquid instruments (the short-term policy rate at the time was 5.25%). The dislocation was most severe for bonds maturing between 2030 and 2040, i.e. 10- to 20-year bonds. This is consistent with foreign investors rushing to exit relatively long positions, concerned possibly about both a significant deterioration in credit quality and the outflow from emerging market bond funds. This is also in line with Carstens and Shin's (2019) 'original sin redux' phenomenon where reliance on foreign capital leaves emerging market economies vulnerable to capital outflows.[10] It is also possible that the relative liquidity of the South African market made this market particularly sensitive to heightened global uncertainty, as was observed during the large capital outflows in 2001 and 2009.

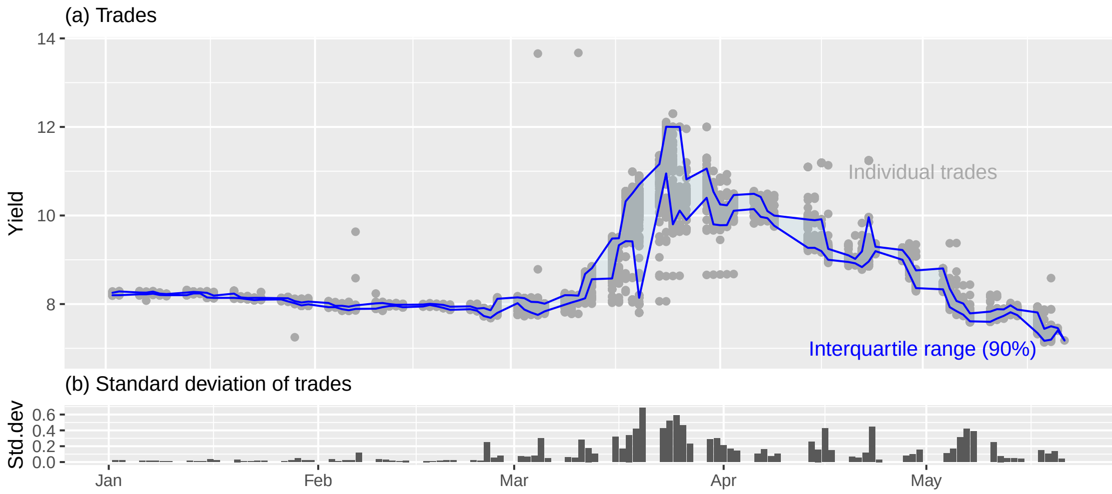
The market became increasingly characterised by low levels of liquidity and fragmentation.[11] The fragmentation observed was by counterparty: trades involving foreign counterparties took place at a different rate. Faced with a sudden capital flow reversal, particularly a fire-sale of bonds by foreign counterparties, there were times when prices differed depending on the counterparties (see Figure 3).

[9] The methodology for constructing the yield curves is discussed in Appendix A.

[10] Exchange-traded product obligations were also suspended at this time as primary dealers experienced difficulties in posting minimum required bid and offers, which de-anchored bid-ask spreads.

[11] There are a number of definitions of market fragmentation. Our definition of market fragmentation is one of a period when the 'law of one price' does not hold, i.e. an identical asset with the same cash flows and other characteristics should have the same price across all markets and between all counterparties. For a review of definitions, see Annexure 2 of Financial Stability Board (2019).

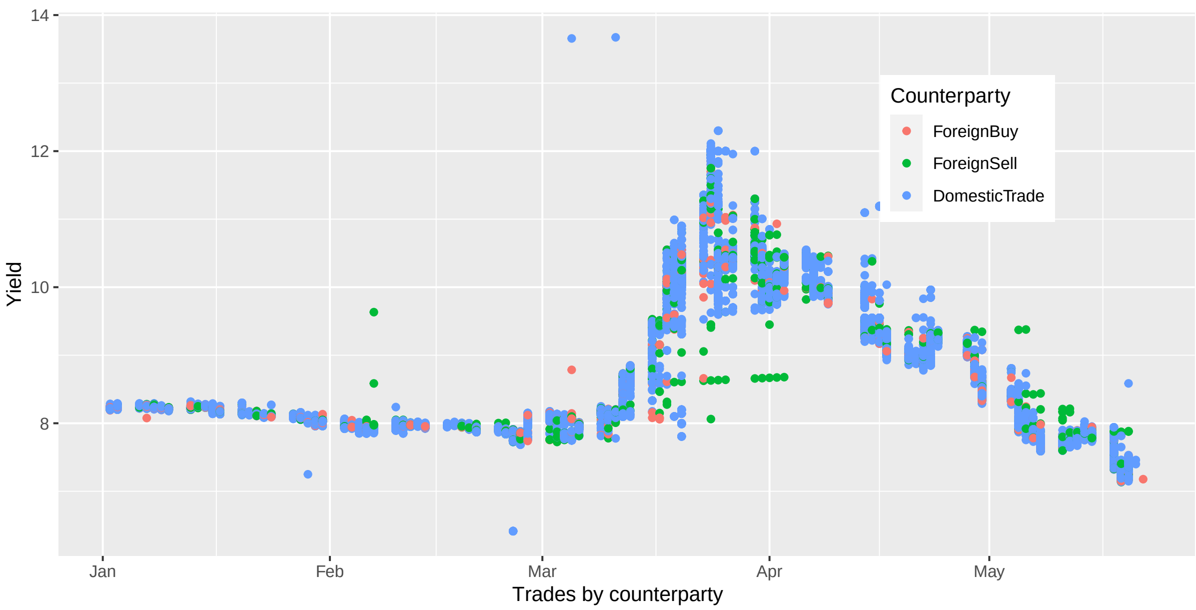
Figure 1: Market dispersion, benchmark bond (R186)



Source: JSE data, benchmark bond (R186)

Note: Each dot represents an individual bond trade, at the time that the trade was recorded and at the yield at which the trade took place. 90% of trades take place between the two blue lines.

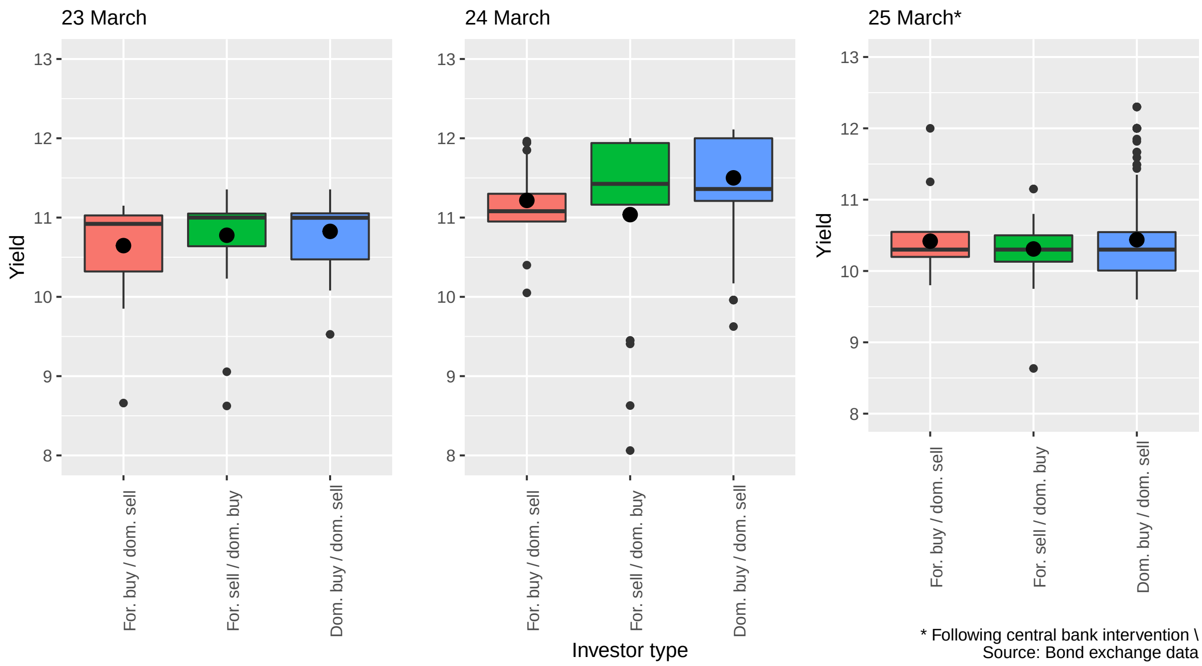
Figure 2: Trades in benchmark bond, by counterparty



Source: JSE data, benchmark bond (R186)

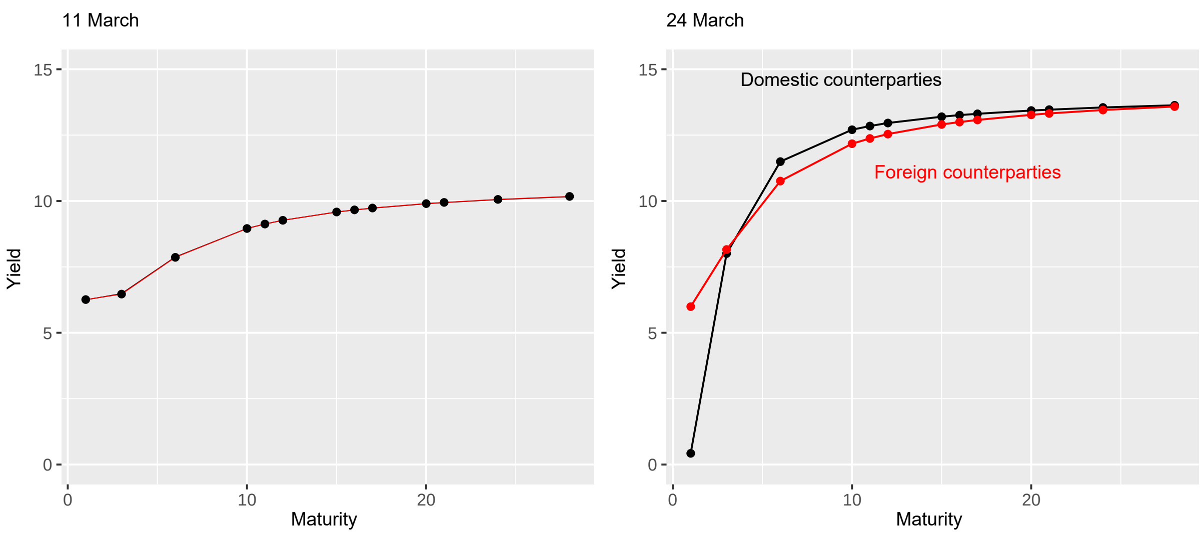
Note: Each dot represents an individual bond trade, coded by the two counterparties to the trade — 'ForeignBuy' are trades which involving purchases by offshore counterparties, 'ForeignSell' are trades involving sales by offshore counterparties, and 'DomesticTrade' are trades between two onshore counterparties. The data does not include trades between two offshore counterparties as these are typically done bilaterally or through global trading mechanisms. By law, all trades involving South African counterparties have to be recorded through the local central securities depository using the stock exchange system and are thus in our dataset.

Figure 3: Market fragmentation and dislocation



Note: In these three figures we present the data from Figure 2 as box-and-whisker plots. The solid line is the median and the solid dot is the average. On 23 March, the day prior to the COVID-19 freeze, trades between different counterparties took place within a reasonably narrow band. On 24 March, there is significant dislocation, with foreign sales taking place at higher yield. On 25 March, following the intervention, trades take place again within a reasonably narrow band.

Figure 4: Fitted yield curves



Note: Here we present evidence of market dislocation across the yield curve. Two yield curves are fitted – one on 11 March, prior to the COVID-19 market 'tantrum', and one on 24 March, during the tantrum.

2.2 South African Reserve Bank intervention in response to market dislocation

On 25 March 2020, at 8:06 am,[12] SARB announced an unprecedented bond buying programme. This calmed markets, and reduced yields across all counterparty types (see Figure 3).

[12] Bloomberg reported on the unscheduled announcement at 8:10 am.

As SARB had not had a bond purchases programme before, the announcement of the programme is an example of a clearly identifiable policy surprise. SARB announced it would purchase government bonds in the secondary market to provide liquidity, but did not specify the scale or maturity profile of such purchases. The goal of the programme was to address financial market dislocation; there was no intention to actively influence yields. Whereas other banks like the Federal Reserve publish details around the implementation of their programmes (such as the size and target frequency or maturities of purchases), the details of SARB bond purchases are confidential and so we do not discuss specific details of any specific interventions. Although SARB did not give an indication of the size or duration of the programme, the overall size of the programme, at less than 1% of GDP, was small compared to those in other economies. The programme in India, for example, amounted to about 1%, in Indonesia to 2%, in the Philippines and euro zone to about 6%, and the programmes in the UK and US to 12% (IMF 2020).

3. Data

We use a unique trade-by-trade dataset, comprising a universe of over a million fixed coupon bond trades between 1 January 2020 and 30 May 2021.[13] The trade dataset is provided to subscribers by the operator of the domestic bond exchange, the Johannesburg Stock Exchange (JSE). South African bonds are traded in a number of ways, depending on the counterparty. Onshore counterparties can trade with other onshore counterparties or with offshore counterparties via an electronic trading platform or via an over-the-counter market. In terms of the law, all domestic trades must be reported to the JSE prior to settlement. Both *de jure* and *de facto*, the exchange performs some clearing and settlement functions prior to the trades being passed onto the central securities depository, Strate. Thus, almost uniquely amongst emerging market bond markets, the JSE collects detailed trade data for what is effectively an over-the-counter market. Client information is anonymised. The dataset provides the following fields:

- A time stamp for both the trade[14] and the settlement;[15]
- The bond being traded – South Africa has a range of vanilla bonds across the yield curve. The R186 (maturing in 2026) is the current benchmark, and the R2030 (maturing in 2030) is the standard bullet 10-year bond;[16]
- The yield, quantity, price and total value of the trade;
- The two parties to the trade. For purposes of this paper, these are anonymised and coded according to whether the party is a ‘foreign client’, ‘local client’ or a ‘member’ of

[13] Inflation-linked bonds are excluded from the dataset.

[14] Using SARB’s records of order and trade timings.

[15] Using the JSE settlement timings.

[16] The data does not include treasury bills nor foreign-currency denominated bonds (which only make up approximately 10% of the stock outstanding).

the exchange. Members are nine large banks that act as primary dealers with market-making obligations.[17]

We complement this data with intraday quote data from Bloomberg data for a variety of indicators. We measure intraday liquidity using bid-ask spreads from Bloomberg to measure the tightness of the market for individual bonds,[18] and mid-yields for 12 specific sovereign bonds. To assess how the magnitude of purchases and market liquidity affect the measured impacts of the programme, we consider the ratio of individual bond purchase values to total individual bond trade volumes from the bond exchange. We construct a full list of the exact timings of SARB market tickets from the SARB's records.

4. Methodology

The paper is concerned with estimating the effects that the bond buying programme had on bond yields, the volatility of these yields, and market liquidity. We formally investigate whether the impact was largest when the announcement was made or when bond buying began. To estimate the effects, we rely on a methodology similar to that of Bessembinder et al. (2008) and Ederington et al. (2015). To assess the impacts of the bond purchases, we construct a counterfactual for bond pricing, i.e. what would have happened had this event not occurred. Our methodological contribution is to test a wide variety of different model specifications to most accurately predict a counterfactual for each specific bond and each specific event of interest.

Autoregressive Conditional Heteroscedasticity (ARCH) models (see (Engle 1982), and the Generalized ARCH (GARCH) extension in Bollerslev (1986) and Taylor (2007) provide a well-known and established econometric technique for modelling financial market volatility. They are particularly useful when time series show evidence of volatility clustering – periods of time when volatility rises. This is a common feature of financial markets, and indeed of significant relevance for the COVID-19 period, which was characterised by extreme volatility.

This class of models has also been extended to allow for asymmetric impacts, leverage effects and long-memory properties in volatility series. Asymmetry was introduced in the exponential GARCH (EGARCH) developed by Nelson (1991), and a related extension that can deal with leverage and asymmetric shocks effects in Glosten et al.'s (1993) Threshold GARCH model.

This particular application uses intraday data, and GARCH models are usually used for daily data. Intraday data present some challenges – most importantly there are theoretical and practical reasons why intraday volatility may not be stochastic. Diurnal volatility may rise, for example, when markets open, when futures close out, and just ahead of market close. Indeed, the data used above shows a clear increase in activity corresponding to when the New York

[17] Four foreign banks: Citi, HSBC, JPMorgan, Deutsche, and Rand Merchant Bank and five domestic banks: FirstRand, Standard, Absa, Nedbank and Investec.

[18] Bid-ask spreads are a commonly used measure of the costs of executing a trade.

market opens at 14:00 South Africa Time. Naively using intraday data might lead to coefficient bias.

For intraday data, Engle and Sokalska (2012) introduce the multiplicative component GARCH model (MCSGARCH), which has been practically implemented by Ghalanos (2014). Following the link in Ghalanos (2014), the model considers the continuously compounded return $r_{t,i}$, where t denotes the day, and i the regularly-spaced interval at which returns are calculated. In the case of the data used in this paper, the returns are standardised at 10-minute intervals. In this model, the conditional variance is now a combination of daily, diurnal, and stochastic components. This allows us to write the return process as:

$$r_{t,i} = \mu_{t,i} + \epsilon_{t,i} \tag{1}$$

In this implementation $\epsilon_{t,i} = (q_{t,i}\sigma_t s_i)$ and $z_{t,i}$ where $q_{t,i}$ is the stochastic intraday volatility, σ_t a daily exogenously determined forecast volatility, s_i the diurnal volatility in each regularly spaced interval i, $z_{t,i}$, the $i.i.d(0,1)$ standardised innovation which conditionally follows some appropriately chosen distribution.

Forecast volatility in Engle and Sokalska (2012) is derived from an exogenous model. In the Ghalanos (2014) implementation, forecast volatility is derived from a daily GARCH model, where daily volaility is defined by $s_i = \frac{1}{T}\sum_{t=1}^{T}(\epsilon_{t,i}^2/\sigma_t^2)$. In the implementation here, daily volatility is calculated as the average intraday standard deviation owing to data constraints.

The GARCH class of models have two properties that makes them ideal for this type of study. First, it allows simultaneous modelling of the mean and variance. This allows assessment of the impact that the purchase had on bond yields in level terms and the volatility introduced by the purchase. Second, the GARCH model controls for the heteroskedasticity that is present in bond yields (see Appendix B).

To study the effect of the purchases on bond yields we will first estimate the GARCH model using data prior to the purchases. We then obtain the parameters of equations, which are used to generate the counterfactual, i.e. to predict what the yield and volatility would have been absent the purchases. Hence, the abnormal yield is given as:

$$AY_t = y_t - \hat{y}_t \tag{2}$$

where y_t is the realised value after the purchases and $\hat{y}_t$ is the counterfactual.

To obtain the counterfactual spread, yield and volatility thereof, we test a variety of different GARCH specifications. Appendix C briefly describes each of the GARCH specifications in further technical detail. We select the type of GARCH model as well as its lag selection based on the average out-of-sample forecast performance over the pre-COVID-19 period (January 2020 to February 2020). Thus, we select the model which gives the most accurate counterfactual estimate based on its pre-COVID-19 performance. It is important to note that each counterfactual can have a different model specification given our model selection routine. That is, we have bond-specific model specifications for both spreads and yields.

The next step is to test whether the abnormal yield is statistically significant. This involves testing whether there is a statistically significant difference between the counterfactual yield and the realised yield. To test the significance a standardised t-test is used. Given that the counterfactual is essentially a forecasted value, the abnormal yield is standardised by the forecast error-corrected standard deviation:

$$SAY_t = \frac{AY_t}{\sigma_{AY_t}} \left(1 + \frac{1}{M} + \frac{(AY_t - \bar{AY_t})^2}{\sum_{t=T_0}^{T_1} (AY_t - \bar{AY_t})^2} \right) \tag{3}$$

The use of intraday data enables us to isolate the impacts of the programme announcement and purchases from other factors that could affect the market. We assess the intraday evolution of bond market prices at 10-minute increments. We present estimates for various window sizes to assess the speed at which information is impounded into prices and to compare our results to the rest of the literature. In the context of bond purchase impact assessment, our approach is most closely related to Ghysels et al. (2017), who assess the intraday (15-minute window) and daily yield impacts of the European Central Bank (ECB)'s purchases under the securities markets programme, but they use a standard GARCH model to produce a counterfactual scenario of no intervention. To reduce the possibility that other events that could impact the South African bond market contaminate our estimates of the impact of the bond purchase programme, we limit our study to a maximum window size of 1 day. We use a dynamic conditional correlation (DCC)-GARCH, which accounts for the 'purchase' effects that bonds at different maturities can have on each other.

Using the above methodology, there are three events that we will investigate. First, we will consider the effects that the announcement had on spreads, yields, and their respective volatility. We also assess the effects of bond purchases themselves. Lastly, we use the timing of the US Federal Reserve announcement of its COVID-19 related purchase programme to compare to the magnitude of SARB announcement effects. By standardising the effect of the event using equation 3, we can compare the magnitude of different interventions and whether there are significant differences between the effects caused by the announcement and by actual purchases.

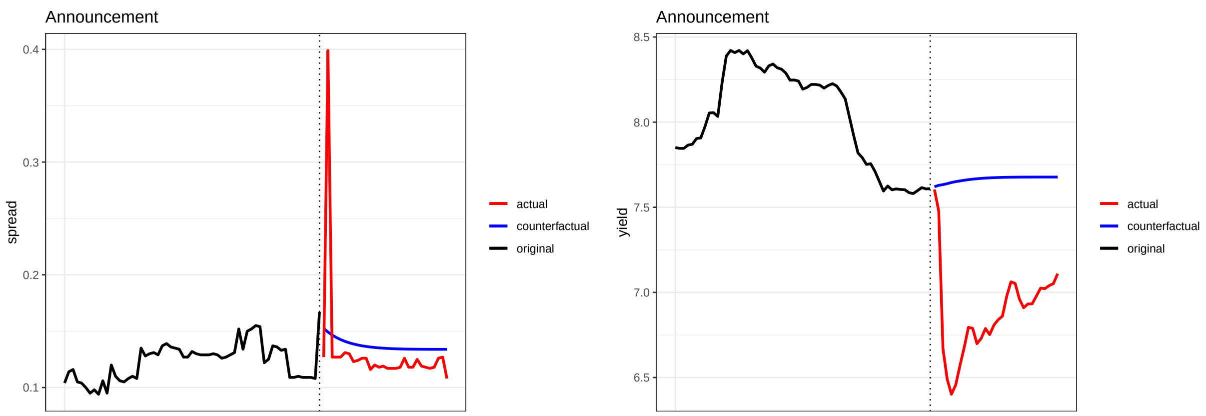
The advantage of our approach is that we do not base the model selection on goodness-of-fit. Instead, we select the model that provides us with the lowest out-of-sample forecast error. We therefore argue that this approach provides the best possible counterfactual estimate of each event for every bond.

5. Results

5.1 Counterfactual analysis

Figure 5 provides intraday plots of the evolution of the bid-ask spreads and yields of one of the short horizon benchmark bonds (denoted 'Bond A' so as not to reveal details of the purchases programme) by way of example. The red line in each chart plots the actual market pricing and the blue line represents the counterfactual scenario for each bond on an event day. The counterfactual estimates what the spread, volatility of the spread, yield or volatility of the yield would have been in the absence of each event. The dotted line represents the timing of the event (i.e. the announcement of the bond programme). We redact x-axis labels to protect the confidentiality of purchase timings. The length of the data being plotted is 60 observations prior to the event. Since the time frequency of our data is 10 minutes, this equates to 10 hours before the event. The counterfactual is plotted as 30 observations after the event, which equates to 5 hours.

Figure 5: Announcement effect: Bond A (spread and yield)



Tables 1 and 2 present a summary of the persistent impacts of the programme announcement and purchases. The value is the sum $\sum actual - counterfactual$ over the sample observations after the event. In the absence of interventions and if market conditions were normal, the estimated average effects should be close to 0 (i.e. the forecast model is unbiased). If the estimated average effects are different from zero, the analysis implies that the event induced some abnormal behavior in the behaviour of the specific bond. A negative value of an impact estimate implies that over the time span, the event caused the spread, volatility of the spread, yield or volatility of the yield to decline compared to what it would have been in the absence of the event. A positive value implies that the event caused the spread, volatility of the spread, yield or volatility of the yield to increase compared to what it would have been in the absence of the event.[19] We order the bonds by maturity from short to long maturity (ranging from approximately 2 years to over 25 years), but label them alphabetically for confidentiality reasons. We find that bond spreads and yields responded sluggishly to the announcement

[19] Our approach therefore does not assessed whether spreads or yields returned to their pre-crisis levels, but this was not an explicitly defined goal of the programme.

of the programme and the central bank bond purchases. While the immediate impact (at a 30-minute or even 5-hour window) of the announcement and initial bond purchase are very small and usually counter-productive (increasing spreads and yields), the estimated impacts are larger at a daily window (Figure 6). The sluggish impacts suggest that the market was slow to incorporate new information and that the initial announcement did not calm markets immediately. At a 1-day horizon, the announcement lowered spreads for all the bonds, with an average spread impact over that window exceeding 5 bps for bonds A, B, C, F, J and L over the full day window. Bond yields declined meaningfully for all bonds, with the largest impact on Bond F (100 bps). The initial purchases had smaller impacts than the announcement, although the immediate impacts on spreads were more constructive (Figure 7). In the case of average spread impacts, the impact was largest on the A and L bonds (over 4 bps at 1-day horizon), while the first purchase had the biggest impacts on the yield of the E and F bonds (over 30 bps). The average full programme impacts are much smaller (Figure 8). That said, we find that bond spreads narrowed (indicative of improved liquidity conditions) and yields fell for all bonds. Although our results suggest that the purchases lost some of their effectiveness over time, their average impacts remain meaningful across the maturity structure for bonds. Whereas much of the literature focuses on impacts on benchmark bonds (e.g. at 10-year maturity), there are noticeable differences in responses at different maturities, demonstrating the importance of assessing the impact across the term structure. We hypothesise that the different impacts reflect differences in purchase size relative to bond-specific liquidity, which we investigate in section 5.3. A common finding in the literature is that announcement effects tend to dominate the impact of the implementation of such programmes. For both liquidity and yields, we also show that announcement effects dominated the impact of purchases themselves.

Another distinguishing feature of our study is that we also explicitly assess the impacts on pricing volatility. Figures 9 to 11 show that there were some large impacts on specific bond spread and yield volatility from the announcements and purchases but that these vary greatly across the portfolio of bonds. The longer-term improvement in liquidity suggests that the purchases improved market confidence and helped to restore normal market functioning. That said, the small estimated impacts on yields could reflect a rise in credit risk premia embedded in long-term sovereign bonds (as suggested by Soobyah and Steenkamp 2020), or the possibility that the purchases themselves did not absorb a meaningful quantum of the supply in the bond market.

Table 1: Average effect on spreads bond-by-bond (bps, 1-day horizon)

	A	B	C	D	E	F	G	H	I	J	K	L
Announcement (level)	-0.0655**	-0.0902**	-0.0684***	-0.0289***	-0.0081***	-0.0680***	-0.0182***	-0.0264***	-0.0411***	-0.0658**	-0.0264***	-0.0581***
First buy (level)	-0.0470***	-0.0035**	-0.0202***	-0.0024**	-0.0025**	-0.0411***	-0.0206**	-0.0066***	-0.0100***	-0.0026***	-0.0158***	-0.0382***
Second buy (level)	-0.0293***	-0.0021**	-0.0350***	-0.0038***	-0.0047***	-0.0427**	-0.0465***	-0.0012**	-0.0100***	-0.0010**	-0.0015***	-0.0360***
Announcement (volatility)	-0.0169**	-0.0061***	-0.0175**	-0.0279***	-0.0043***	-0.0339***	-0.0026***	-0.0019**	-0.0646***	-0.0772**	-0.0013*	-0.0032**
First buy (volatility)	-0.0014***	-0.0012*	-0.0036***	-0.0028***	-0.0007**	-0.0010***	-0.0016***	-0.0069**	-0.0019***	-0.0019**	-0.0011***	-0.0002***
Second buy (volatility)	-0.0035**	-0.0010***	-0.0003***	-0.0042***	-0.0004**	-0.0000	-0.0015***	-0.0026***	-0.0019***	-0.0023***	-0.0003**	-0.0007**

Table 2: Average effect on yields bond-by-bond (bps, 1-day horizon)

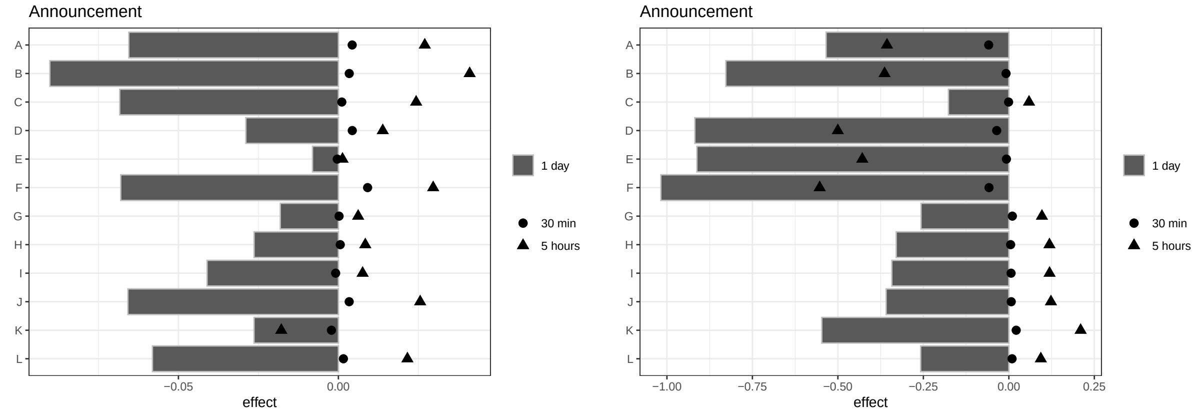
	A	B	C	D	E	F	G	H	I	J	K	L
Announcement (level)	-0.5344***	-0.8277***	0.1767**	-0.9183***	-0.9124***	-1.0178***	-0.2569***	-0.3294**	-0.3423**	-0.3589***	-0.5471***	-0.2580**
First buy (level)	-0.1692**	-0.2267***	-0.1601***	-0.0762*	-0.3565***	-0.3100***	-0.0238**	-0.1366***	-0.0690**	-0.1086***	-0.0874*	-0.0181**
Second buy (level)	-0.0751**	-0.2276***	-0.1959***	-0.1007***	-0.0417***	-0.3473***	-0.1851***	-0.3876***	-0.0692**	-0.2120***	-0.0091*	-0.0702**
Announcement (volatility)	-0.0608**	-0.0735***	-0.1917***	-0.0086**	-0.0350***	-0.0013**	-0.0496***	-0.1096**	-0.1417***	-0.1307**	-0.1826**	-0.1528***
First buy (volatility)	-0.0037**	-0.0005*	-0.0778**	-0.0035***	-0.0014***	-0.0524***	-0.0024***	-0.0186***	-0.0019***	-0.0167***	-0.0257***	-0.0062***
Second buy (volatility)	-0.0017***	-0.0021**	-0.1364***	-0.0007*	-0.0021***	-0.0470***	-0.0066**	-0.0094**	-0.0019**	-0.0050**	-0.0000	-0.0005

Table 3: Average effect on spreads and yields over entire programme bond-by-bond (bps, 1-day horizon)

	A	B	C	D	E	F	G	H	I	J	K	L
Spread (level)	-0.4718***	-0.3586***	-0.4507**	-0.4005***	-0.7173***	-0.4574*	-0.9277***	-0.5935***	-0.6706***	-0.1062**	-0.6095***	-0.2451**
Spread (volatility)	-0.2642**	-0.2338***	-0.2184***	-0.4262**	-0.2530***	-0.1532**	-0.1847*	-0.4364***	-0.0636*	-0.1749***	-0.0298*	-0.0018**
Yield (level)	-2.0460**	-13.2822**	-8.0826***	-10.4407***	-4.6684***	-1.3381***	-7.3529***	-5.1350***	-1.1910**	-0.6944*	-1.3455***	-1.6858***
Yield (volatility)	-1.2246***	-0.4652***	-1.4929***	-0.6462***	-0.2101**	-2.5189***	-0.8301**	-0.5720**	-0.5928***	-0.3552***	-0.4860***	-0.1254***

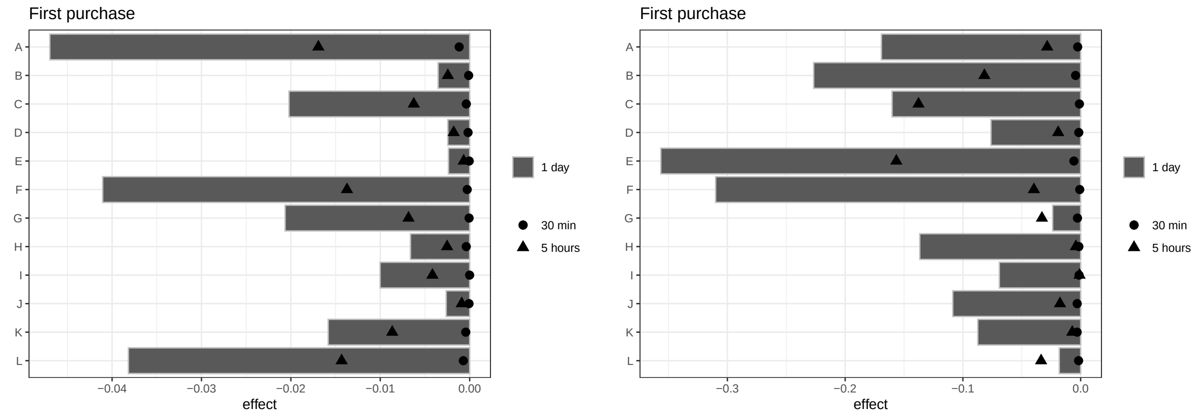
Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. If the estimated average effects are different from zero, the analysis implies that the event induced some abnormal behavior in the behaviour of the specific bond. A negative value of an impact estimate implies that over the time span the event caused the spread, volatility of the spread, yield or volatility of the yield to decline compared to what it would have been in the absence of the event. A positive value implies that the event caused the spread, volatility of the spread, yield or volatility of the yield to increase compared to what it would have been in the absence of the event. (*),(**),(***) denotes statistical significance at the 10%, 5% and 1% levels respectively. Bonds are labelled in order of maturity from short to long maturity as 'A' to 'L'.

Figure 6: Announcement effects on spreads (LHS) and yields (RHS) bond-by-bond



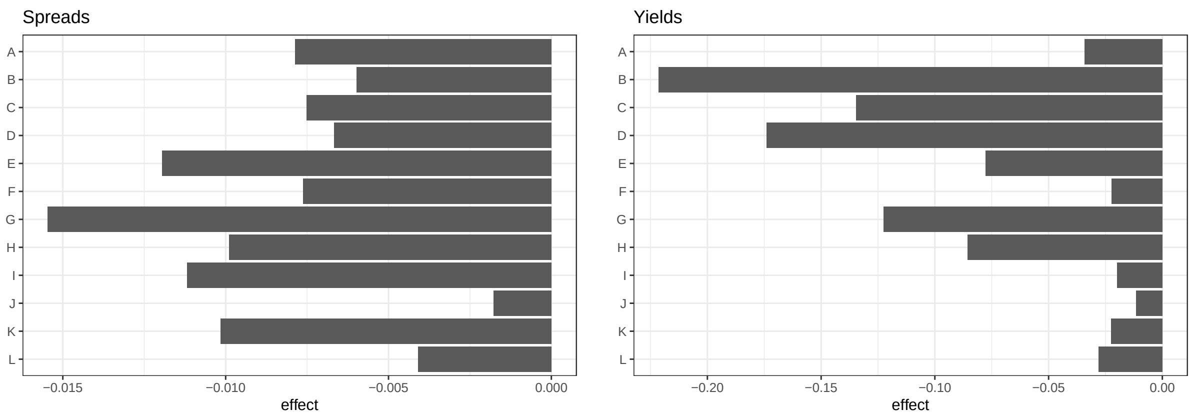
Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. Bonds are labelled from short to long maturity as 'A' to 'L'.

Figure 7: First purchase effects on spreads (LHS) and yields (RHS) bond-by-bond



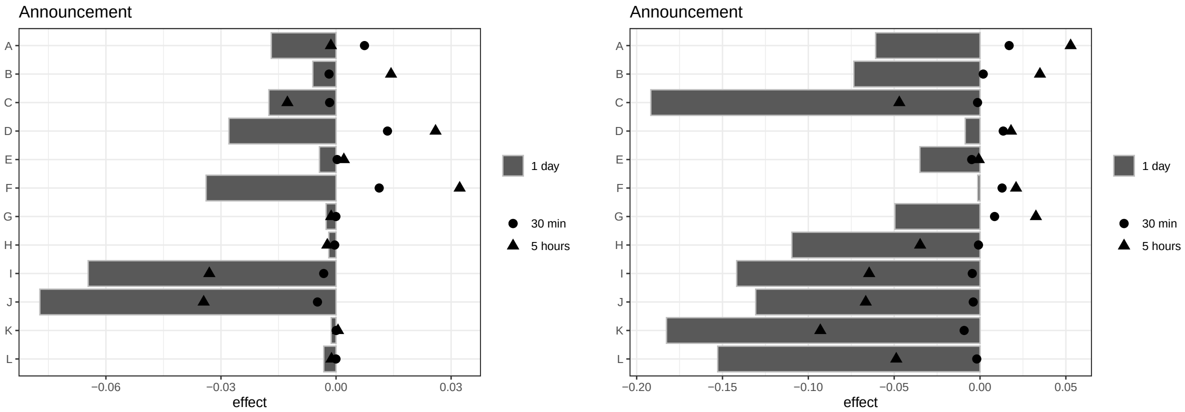
Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. Bonds are labelled from short to long maturity as 'A' to 'L'.

Figure 8: Average effect of entire programme on spreads (LHS) and yields (RHS) bond-by-bond (1-day horizon)



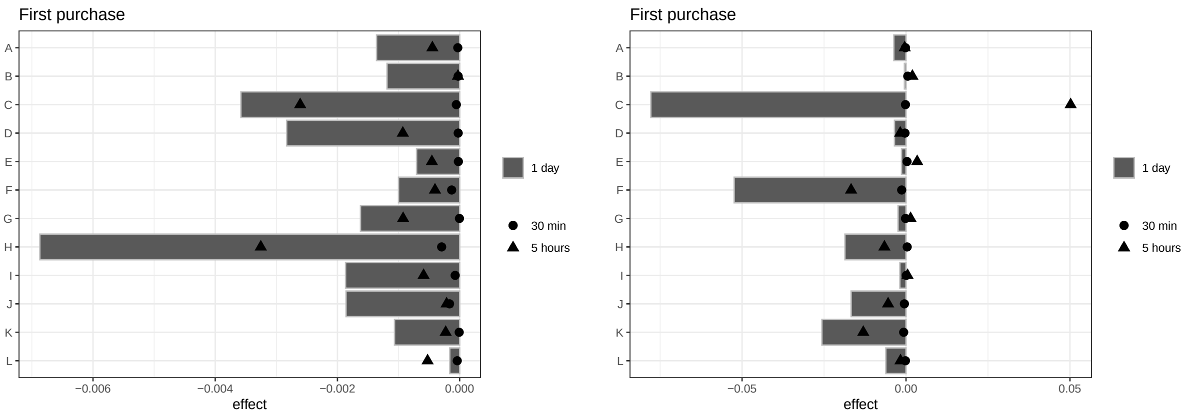
Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. Bonds are labelled from short to long maturity as 'A' to 'L'.

Figure 9: Announcement effects on spread volatility (LHS) and yield volatility (RHS) bond-by-bond



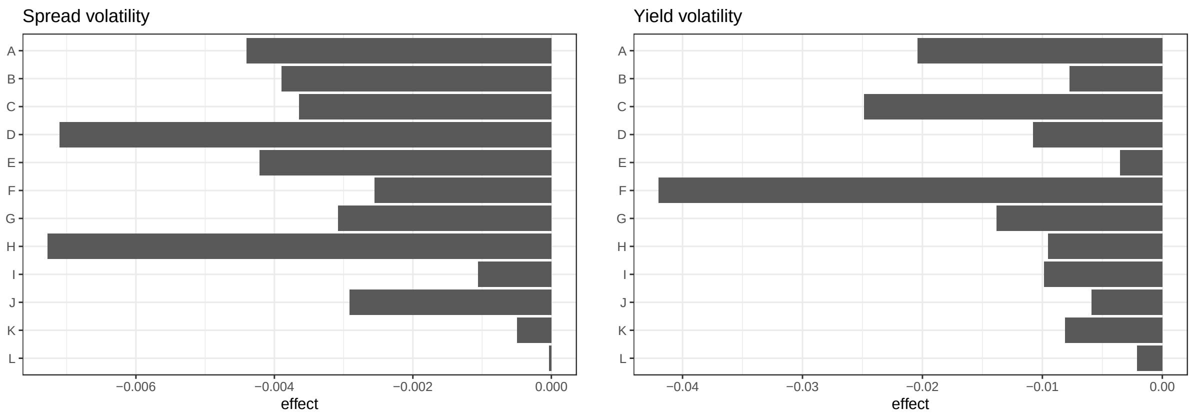
Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. Bonds labelled from short to long maturity as 'A' to 'L'.

Figure 10: First purchase effects on spread volatility (LHS) and yield volatility (RHS) bond-by-bond



Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. Bonds labelled from short to long maturity as 'A' to 'L'.

Figure 11: Average effect of entire programme on spread volatility (LHS) and yield volatility (RHS) bond-by-bond (1-day horizon)



Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. Bonds labelled from short to long maturity as 'A' to 'L'.

5.2 How does the impact of SARB's programme compare to other programmes and spillovers from the interventions of major central banks?

Even though SARB's programme was not targeting bond yields, we present estimates of the impacts of the programme announcement and bond purchases to enable comparison to the market impacts of bond purchase programmes of other emerging market central banks during the COVID-19 pandemic. These estimates also allow us to benchmark the estimates of SARB's programme to the spillovers of the Federal Reserve Bank's announcement during the COVID-19 pandemic on the South African bond market.

Our estimated announcement impacts are strong compared to the estimated impacts of the purchase programmes by emerging markets during the COVID-19 pandemic (Table 4). We find, for example, that the announcement of the programme lowered 10-year bond yields by about 87 bps. The only comparable study in an emerging market setting we are aware of is Goel et al. (2020), who estimate that yields were about 22 bps lower after bond purchase announcements in ten emerging markets. While other studies only allow a 1-day frequency assessment of the impacts, we also provide estimates of the immediate intraday impact and show that it was much smaller (first row, Table 4).[20]

Table 5 compares our estimates of the yield impact of the purchases themselves to estimates for advanced economies in earlier QE programmes. While SARB's programme was focused on stabilising the bond market, QE programmes were, at least in large part, implemented as a substitute for interest rate cuts that were not possible because of the zero lower bound. Yield reductions were therefore an important metric of success for advanced economy central banks implementing QE. We nevertheless compare movements in bond yields to quantify the relative size of spillovers of the Federal Reserve Bank's announcement during the COVID-19 pandemic on the South African bond market. We find that announcement effects dominated the impact of purchases themselves. In the case of the impacts of the Federal Reserve during the COVID-19 pandemic, Vissing-Jorgensen (2021) suggests that their purchases lowered treasury yields once implemented rather than when they were announced, starting on 19 March 2020. She argues that unlike earlier QE programmes, the Federal Reserve announcement in March 2020 did not stop selling pressure. Instead it was large purchases that stabilised the US treasuries market. Her interpretation is that the financial market effects of the COVID-19 pandemic were driven by a negative demand shock for treasuries from increased liquidity pressures, whereas earlier programme announcements signalled easy future policy or future Treasury scarcity.[21]

One advantage of our approach is we can compare the initial impacts to the more persistent

[20] Using intraday data, Arora et al. (2021) show that the Canadian programme announcement saw bond yields fall by around 10 bps across the curve on 27 March 2021. The disadvantage of absolute impact comparisons such as these is that they do not control for differences in levels of interest rates in different economies. For an assessment of the impact of policy rate cuts during the COVID-19 pandemic on the South African yield curve using daily data, see Nkuna et al. (2020).

[21] Estimates of the impacts of the Canadian Central Bank's Covid-19 programme suggest modest and transitory (at about 1.2 and 0.5 bps lower yield for 2-year and 10-year bonds for USD1 billion purchases, respectively, and are fully reversed after four days, see Arora et al. 2021).

impacts. We find that the impact on long bond yields was approximately -17 bps over a 1-day horizon, which is smaller than what most other studies find in a developed economy context where interest rates were at the zero lower bound. One possible explanation for this finding is an offsetting spike in South Africa's sovereign credit spread at the time of the COVID-19 pandemic. As demonstrated by Soobyah and Steenkamp (2020), the credit risk embedded in South Africa's sovereign bond yields rose dramatically during this time.

Our dataset also enables assessment of transmission of the announcement and the purchases of major economy central banks on emerging market bond markets. This is also an important consideration in South Africa, given the large role of foreign investors in the South African bond market (foreign holdings of government bonds exceeded 35% before the pandemic, for example). We compare the magnitude of SARB's announcement and the purchase effects to the spillovers from the Federal Reserve's programme announcement during the COVID-19 pandemic on 23 March 2020 onto the South African sovereign bond market. Whereas SARB's bond purchase programme was implemented for financial stability purposes, the Federal Reserve's measures announced on 23 March 2020 were meant to support both market functioning and effective monetary policy transmission of monetary policy to financial conditions and the economy.[22] We find that this announcement was meaningfully supportive of liquidity and helped to reduce South African yields (Figure 12). The Federal Reserve announcement's effects on spreads were larger than those of SARB's announcement, but smaller on yields. However, Figure 13 shows that the Federal Reserve announcement also had a bigger impact on the volatility of South African government bond spreads and yields than SARB's announcement. Overall, this suggests that the Federal Reserve played an important role in stabilising global bond markets, helping to support the actions of SARB. Our results are consistent with those of Rebucci et al. (2020) who highlight the Federal Reserve's role in the global transmission of interest rate shocks and that country-specific interventions nonetheless had meaningful local financial market impacts beyond those of the measured spillovers.

[22] The Federal Reserve announced purchases of at least USD500 billion of Treasuries and USD200 billion of mortgage backed securities at 5 pm on 15 March 2020, then unlimited purchases at 8 am on 23 March 2020 and expansion of corporate bond purchases to USD850 billion on 9 April. The Federal Reserve ramped up their purchases on 19 March, which lines up with the fall of US Treasury yields, while the Cboe Volatility Index (VIX) plummeted after the 23 March announcement (Vissing-Jorgensen 2021).

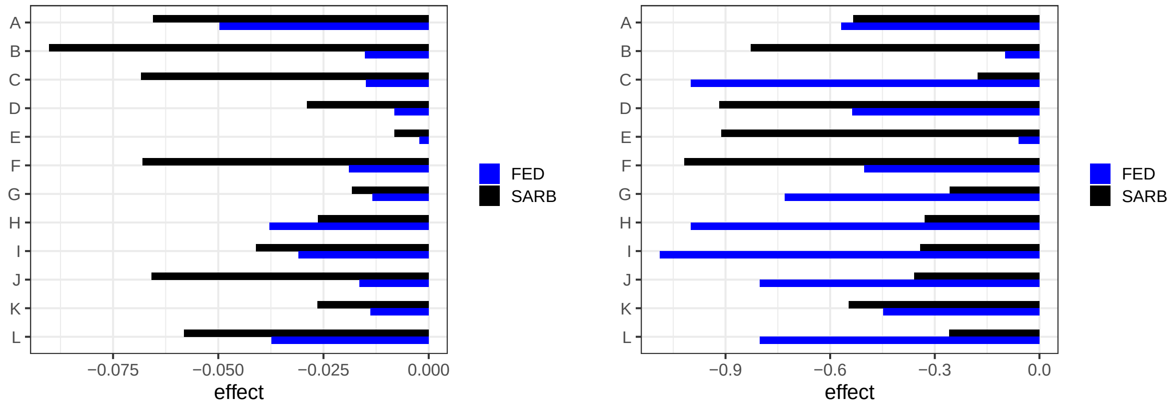
Table 4: Comparison of estimated announcement impact (bps)

Study	Window size	Event	Short term Treasury rate	10-Year Treasury rate
This paper	5 hours, 1 day	SARB Covid	2 Year: -35,-55	-50,-87
Krishnamurthy and Vissing-Jorgensen (2011)	2 day	US QE1	1 Year: -2	-36
Gagnon et al. (2011)	1 day	US QE1	2 Year: -2	-58
Christensen and Rudebusch (2012)	1 day	US QE1	2 Year: -14	-21
Christensen and Rudebusch (2012)	1 day	UK QE1	2 Year: -30	-20
Andrade et al. (2016)	2 day	ECB QE1		-45
Altavilla and Giannone (2017)	2 day	US QE1		-30
Rebucci et al. (2020)	1 day	EM Average, DM average		-23,-13
Goel et al. (2020)	1 day	Covid Emerging Markets		-22
De Padua et al. (2021)	1 day	Covid South Africa 25 March 2020		-66
De Padua et al. (2021)	1 day	Covid Columbia 23 March 2020		-50
De Padua et al. (2021)	1 day	Covid India 20 March 2020		-15
De Padua et al. (2021)	1 day	Covid Poland 17 March 2020		-45

Table 5: Comparison of cumulative effects of bond purchases (bps)

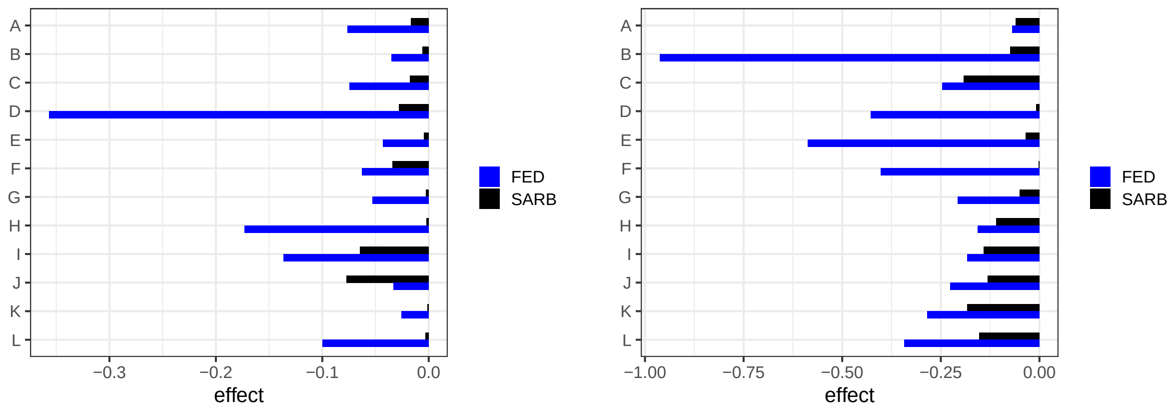
Study	Window size	Event	Short term Treasury rate	10-Year Treasury rate
This paper	1 day	SARB Covid	2 Year: -3	-17
Krishnamurthy and Vissing-Jorgensen (2011)	2 day	US QE1	1 Year: -23	-71
Gagnon et al. (2011)	1 day	US QE1	2 Year: -34	-91
Christensen and Rudebusch (2012)	1 day	US QE1	2 Year: -65	-89
Christensen and Rudebusch (2012)	1 day	UK QE1	2 Year: -31	-43
Altavilla and Giannone (2017)	1 day	US QE1		-97
Altavilla and Giannone (2017)	1 day	US QE2		-38
Altavilla and Giannone (2017)	1 day	US QE3		0.3

Figure 12: Average effect of SARB announcement vs Fed announcement (spreads (LHS) and yields (RHS) bond-by-bond, 1-day window)



Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. Bonds are labelled from short to long maturity as 'A' to 'L'.

Figure 13: Average effect of SARB announcement vs Fed announcement (spread volatility (LHS) and yield volatility (RHS) bond-by-bond, 1-day window)

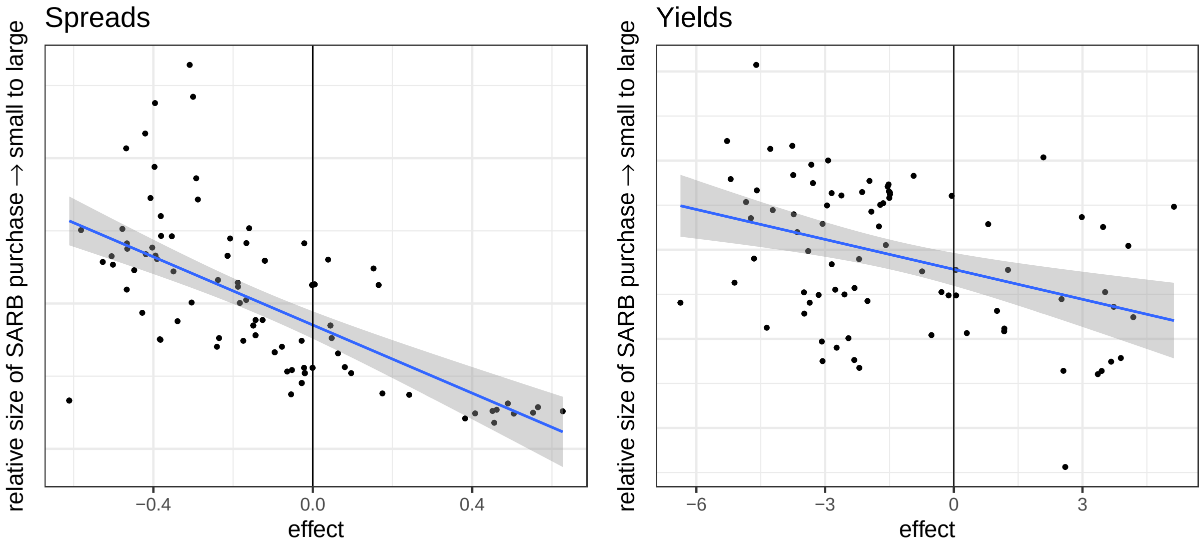


Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. Bonds are labelled from short to long maturity as 'A' to 'L'.

5.3 Did size of individual purchases relative to market liquidity affect the estimated impacts?

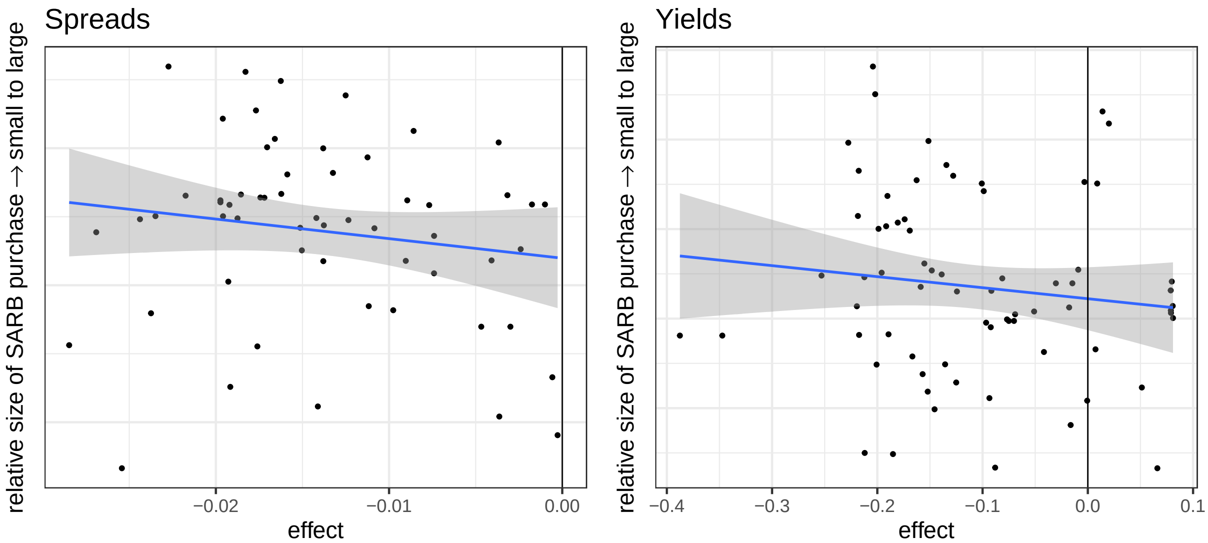
Next, we assess whether central bank asset purchases had larger impacts when the size of the purchase was relatively large compared to the liquidity in a specific bond on a specific day. Figure 14 compares the impact on bid-ask spreads and yields, controlling for the relative size of purchases for each bond compared to the volumes of trades in that bond on each day of a purchase. There is a weakly negative relationship in both cases, but stronger for spreads. The relationship is slightly weaker at a daily frequency (Figure 15). The results imply that purchases that were large relative to market liquidity tended to have larger impacts.

Figure 14: Purchase size and market impacts (5-hour window, basis points)



Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. Y-axis scale is redacted to preserve the confidentiality of the data.

Figure 15: Purchase size and market impacts (1-day window, basis points)



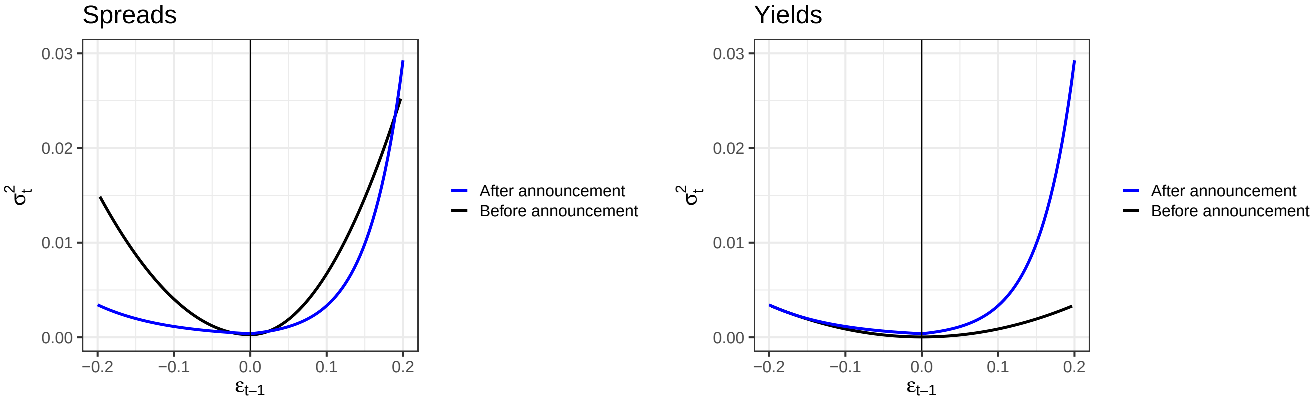
Note: The value is the sum $\sum actual - counterfactual$, where $actual$ is the observed value and $counterfactual$ is the estimated value from the 'best' GARCH model over the sample observations after the event. Y-axis scale is redacted to preserve the confidentiality of the data.

5.4 What was the impact of the programme announcement on intraday volatility?

We find that the announcement of the purchase programme and purchases had a dampening effect on volatility spikes. To investigate this more formally, we assess how the programme announcement impacted trading volatility. We use news information curves, popularised by the comprehensive survey and results set out in Engle and Ng (1993). We assess whether the transmission of news to the bond market changed with the announcement of the programme.

The results are presented in Figure 16.[23] The chart shows that shocks to bond spreads transmits differently to spread volatility after the crisis – that the same size shock (both for positive and negative shocks) has had a smaller volatility-raising impact since the announcement of the programme. This provides some further evidence that the programme (and actions by other central banks) have helped to dampen the volatility in the South African bond market. For yields, the impact of shocks for volatility is relatively unchanged for negative shocks, but slightly worse for positive shocks.

Figure 16: News information curves



6. Conclusion

This paper uses a unique trade-by-trade dataset and actual bond purchase timings to assess the high-frequency impact of SARB bond purchases on sovereign bond market liquidity, yields and their volatility. We compare the impacts of SARB's bond purchase programme's announcement and actual implementation on a bond-by-bond basis. Bond pricing adjusted slowly, with effects strengthening over the course of the trading day. Consistent with the literature, we find that announcement effects are generally much stronger than purchases themselves. Our estimated announcement impacts are larger than the estimated impacts of other emerging market purchase programmes during the COVID-19 pandemic. Lastly, we show that the Federal Reserve announcement on 23 March 2020 also stabilised the South African bond market, with larger effects on spreads but smaller effects on yields to those of SARB's announcement.

The paper also highlights the experience of significant bond market distress during a period of a sudden change in non-resident demand for sovereign bonds due to an exogenous event. We note a freeze of activity and a significant spike in yields. This highlights the financial stability risks of high levels of sovereign debt. Overall, our results suggest that the introduction of the programme was successful at shoring up market confidence and addressing dislocation

[23] We also find that news impact curves differ across types of investors, with domestic investors and foreign investors responding very differently to an unexpected shock. In the case of domestic South African investors, there is evidence of an *inflow* into domestic fixed-income funds with sovereign exposure – for domestic investors, sovereign bonds are 'safe', and the usual 'flight-to-safety' and 'flight-to-liquidity' effects take place. In the case of foreign investors, there was a 'flight-to-safety' and 'flight-to-liquidity', but naturally this was *out* of emerging market bonds and into safe assets, usually US Treasury bonds.

in the government bond market, and that it improved the Reserve Bank's liquidity management. While the programme helped to address the immediate liquidity stress in the bond market, bond yield impacts appear to have been partially offset by the increase in South Africa's sovereign credit risk at the time of the COVID-19 pandemic. Our approach could help real-time assessment of market conditions, market impacts of operations and calibration of operations. The South African experience shows, for example, that programme operations timed according to market conditions have larger market impacts. This type of intraday analysis could be used in real-time to assess market impacts and inform bond purchase decisions.

There are several interesting avenues for future research. Our dataset and approach could be extended to analyse the optimal design of a bond purchase programme (i.e. intervention criteria, purchase/programme limits and exit strategies). Future research should consider the impact of the programme on the South African term premium and perceptions of sovereign credit risk to enhance our understanding of the drivers of the observed market impacts. This would also allow for assessment of whether the programme improved the monetary transmission mechanism by reducing credit spreads and easing financial conditions. It would also be useful to better characterise the nature of the fragmentation that occurred during the COVID-19 pandemic to help design future policy interventions.

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Appendices

A Construction of term structure by counterparty

During the COVID-19 contagion, there were significant differences in trading activity involving domestic counterparties, and trades involving foreign counterparties. The dataset allows for a separation into two markets: (a) bond trading between foreign investors and local investors (which we designate as 'FOREIGN'); and (b) a market comprising trading between local investors ('DOMESTIC'). The market is the trade in identical underlying instruments (domestically-issued, domestic currency bonds). Arbitrage conditions should hold – and these two markets should behave as one. But the initial data analysis above suggests that for a period of time around 24 March 2020, the market for domestically-issued, domestic currency bonds split into domestic and foreign markets. This should not theoretically be possible, but in practice, given the extreme market stresses affecting foreign participants, it is perhaps not surprising that during the capital flow reversal, the two markets briefly biurficated.

To assess the impacts of the COVID-19 pandemic on market fragmentation, we construct a term structure of interest rates by counterparty. First, to analyze the data we construct and present average trading yields across the yield curve in Figure 4. There are a variety of ways to more formally estimate the term structure (for a review see Diebold et al. 2008). A widely-used method is the dynamic Nelson-Siegel approach proposed by Diebold et al. (2006), which builds on Nelson (1991). The Nelson-Siegel approach consists of three components – a constant (β_0), an exponential decay function (β_1) and a Laguerre function (β_2). The constant represents a long-term interest rate level. The exponential decay comes from the second factor, which has either a slope that is either downward ($\beta_1 > 0$) or upward ($\beta_1 < 0$). The Laguerre function is comes in the form $x.e^{-x}$, that is to say it is an polynomial multiplied by an exponential. With a first-degree polynomial, the Laguerre function in the model generates either a hump ($\beta_2 > 0$) or a trough ($\beta_2 < 0$). The higher the absolute value of β_2, the more pronounced the hump/trough is. Graphically, this creates what is known as what is an 'upward' or 'downward' sloping yield curve – the well-known concave or convex shape. The coefficient λ is the shape - and determines both the steepness of the yield curve, and where the maximum or minimum takes place. In the absence of such fragmentation, the yield curve should be the same for all investors.

B ARCH effects and volatility clustering

To motivate the use of GARCH models we provide the Lagrange multiplier test for conditional heteroscedasticity (ARCH) of Engle (1982), as well as a 5-hour rolling window of the variance for spreads and yields. The ARCH test results are reported in Table 6 while the rolling window of the variance is plotted in Figures 17 and 18. As can be seen in Table 6 all bonds display significant ARCH effects up to 12 lags in both spread and yield.

Table 6: Lagrange multiplier (LM) test for autoregressive conditional heteroscedasticity (ARCH)

	A	B	C	D	E	F	G	H	I	J	K	L
Spread	17040.759***	11774.975***	8439.289***	9732.933***	20427.638***	9574.162***	20563.636***	18519.774***	6576.287***	8093.581***	20696.954***	20492.192***
Yield	21466.892***	21465.185***	21379.422***	21426.186***	21394.148***	21414.91***	21330.524***	21360.428***	21431.619***	21356.878***	21389.587***	21411.993***

Note: (*),(**),(***) denotes statistical significance at the 10%, 5% and 1% levels respectively. Bonds labelled in order of maturity from short to long maturity as 'A' to 'L'.

Figure 17: 5-hour rolling variance of bond spreads

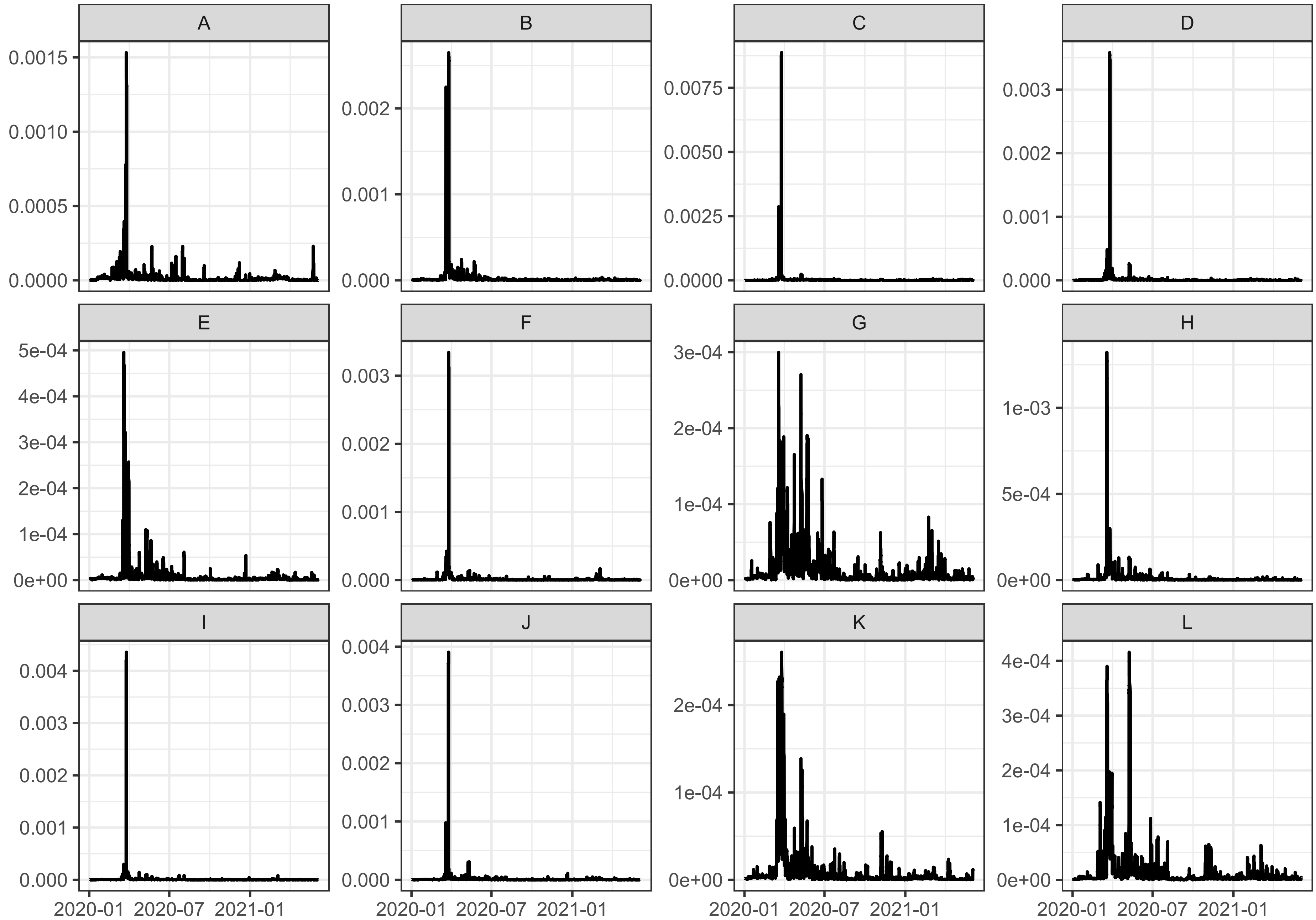
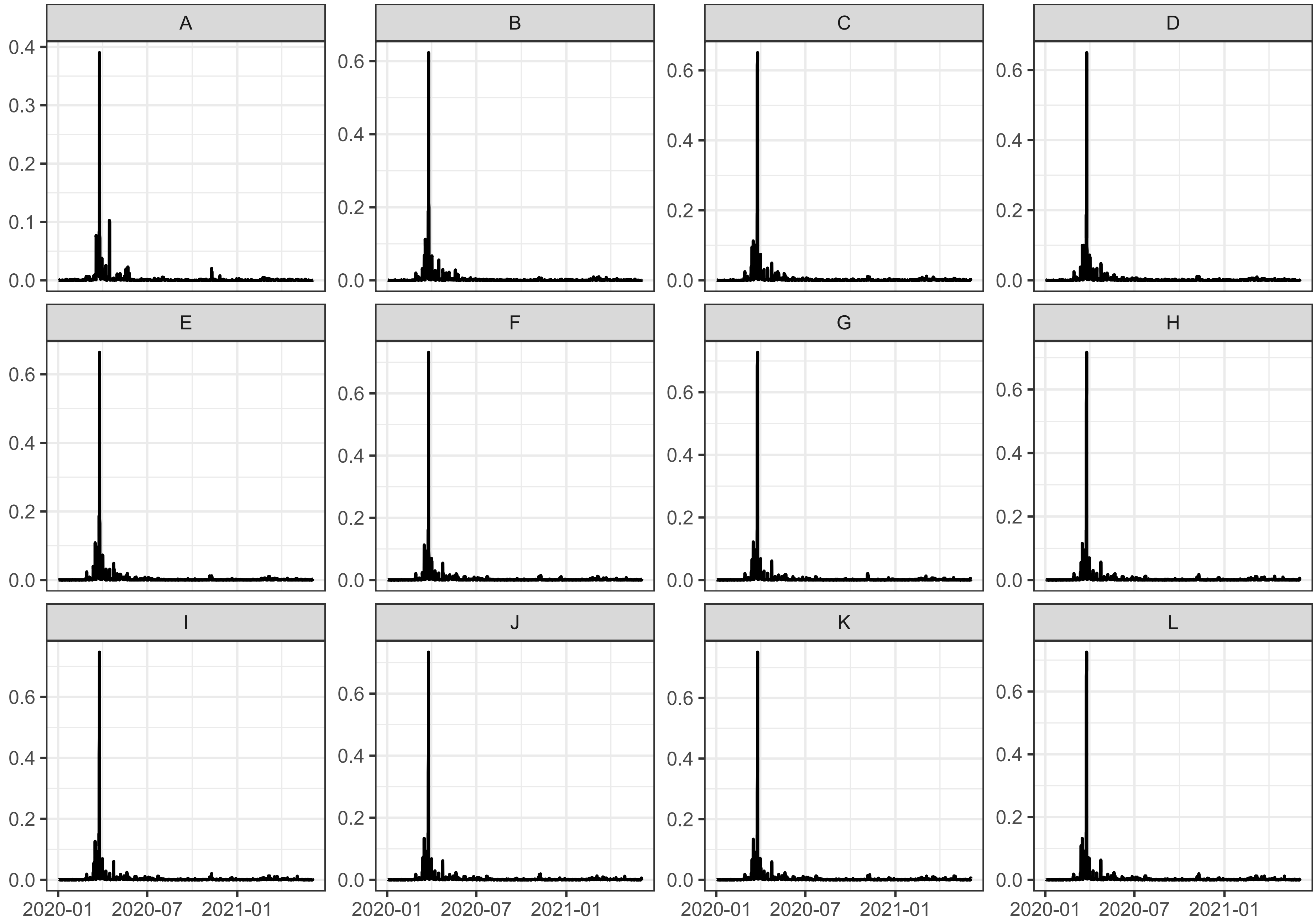


Figure 18: 5-hour rolling variance of bond yields



C GARCH models

We consider a variety of GARCH specifications for our counterfactual forecasts, and select specifications based on their out-of-sample forecasting performance. That is, we select the model and lag structure that provides us with the most accurate counterfactual result throughout the sample. For each GARCH model class, we consider up to 8 lags in both the mean and conditional variance equations. The following family of GARCH models are considered: sGARCH, iGARCH, eGARCH, GJR-GARCH and fGARCH. Each of these model types is discussed briefly in this section.

C1 Standard GARCH (sGARCH)

As proposed by Bollerslev (1986), the conditional variance of the model can be expressed as:

$$\sigma_t^2 = \left(\omega + \sum_{j=1}^{m} \zeta_j v_{jt}\right) + \sum_{j=1}^{q} \alpha_j \epsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{4}$$

where ω is the intercept and ϵ_t^2 is the residuals from the mean process.

C2 Integrated GARCH (iGARCH)

The integrated GARCH model put forward by Engle and Bollerslev (1986) assumes unit persistence in the sum of parameters of the squared residuals and variance. That is, in equation 4, it is assumed that:

$$\sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j = 1 \tag{5}$$

As a result of the assumption of unit persistence, the unconditional variance cannot be estimated. To circumvent this issue, the α and β parameters are subtracted from 1 to form an identity so that it is not required to be estimated.

C3 Exponential GARCH (eGARCH)

The exponential GARCH refers to the model set out in Nelson (1991). The eGARCH model is well suited for cases where the unconditional distribution of the parameters in the variance equation presents excess kurtosis. Furthermore, Nelson (1991) shows that the model performs well when the variables display volatility clustering. The model accounts for this feature by allowing persistence in volatility. That is, there is likely to be high volatility at time t when there was also high volatility at time $t-1$.

The variance of the eGARCH model can be expressed as:

$$log(\sigma_t) = \left(\omega + \sum_{j=1}^{m} \zeta_j v_{jt}\right) + \sum_{j=1}^{q} \left(\alpha_j z_{t-j} + \gamma_j(|z_{t-j}| - E|z_{t-j}|)\right) + \sum_{j=1}^{p} \beta_j log(\sigma_{t-j}^2) \quad (6)$$

where z_t is Gaussian. The model allows for asymmetry through the interaction of γ and α. Hence, a negative shock will be associated with $\gamma - \alpha$ where a positive shock will be $\gamma + \alpha$.

C4 GJR-GARCH

The GJR-GARCH was first put forward by Glosten et al. (1993). The uniqueness of the GJR-GARCH stems from the ability to handle asymmetry in the conditional variance. The asymmetry is modelled through an indicator function.

The conditional variance can be written as:

$$\sigma_t^2 = \left(\omega + \sum_{j=1}^{m} \zeta_j v_{jt}\right) + \sum_{j=1}^{q} \left(\alpha_j \epsilon_{t-j}^2 + \gamma_j I_{t-j} \epsilon_{t-j}^2\right) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (7)$$

where I is the indicator function defined as $I = \begin{cases} 1 & \text{if } \epsilon \leq 0 \\ 0 & \text{if } \epsilon > 0 \end{cases}$

C5 Family GARCH (fGARCH)

The fGARCH is a hybrid of some of the before mentioned GARCH models. The model was first set out in Hentschel (1995) and allows for shifts and rotations in the news impact curve. As a result the model can take various forms akin to many other GARCH specifications.

The conditional variance of the model can be written as:

$$\sigma_t^\lambda = \left(\omega + \sum_{j=1}^{m} \zeta_j v_{jt}\right) + \sum_{j=1}^{q} \alpha_j \sigma_{t-j}^\lambda \left(|z_{t-j} - \eta_{2j}| - \eta_{1j}\left(z_{t-j} - \eta_{2j}\right)\right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\lambda \quad (8)$$

Equation 8 is a Box-Cox transformation for the conditional standard deviation. The shape of the transformation is determined by the parameter λ. The parameter δ is responsible for transforming the absolute value function of equation 8, which is subject to rotations through η_{1j} and η_{2j}.