Policy-at-Risk: The Effects of Financial Conditions on the Conduct of Monetary Policy in Australia

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Supervised by Professor James Morley

Statement of Originality

I hereby declare that this submission is my own work and to the best of my knowledge it contains no material previously published or written by another person. Nor does it contain any material which has been accepted for the award of any other degree or diploma at the University of Sydney or at any other educational institution, except where due acknowledgment is made in this thesis.

Any contributions made to the research by others with whom I have had the benefit of working at the University of Sydney is explicitly acknowledged.

I also declare that the intellectual content of this study is the product of my own work and research, except to the extent that assistance from others in the project's conception and design is acknowledged.

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Abstract

The global financial crisis (GFC) of the late 2000s marked an important event in terms of changing attitudes towards prudential and financial regulation. However, it also demonstrated the close connectivity between financial conditions and macroeconomic performance. It is therefore important to understand the influence of changing financial conditions on the conduct of monetary policy by central banks, particularly how central banks respond to these changes. This thesis constructs a financial conditions index (FCI) for Australia to represent the state of financial conditions between 1976 and 2023. I use a two-stage regression model as part of a novel policy-at-risk (PaR) model to assess the effects of financial conditions on monetary policy first at the mean level, and secondly at different quantiles along the distribution of interest rate changes. I also assess the uncertainty associated with monetary policy over time by plotting the conditional distribution of the overnight cash rate (OCR) together with its fitted quantiles. The findings reveal that when the OCR is low relative to systematic policy, the Reserve Bank of Australia (RBA) is less responsive to changes in financial conditions, resulting in smaller interest rate cuts. Conversely, the RBA reacts more strongly to financial conditions when the OCR is relatively high.

Contents

1 Introduction

August 2007 marked one of the most significant events in modern economic and financial history: the global financial crisis (GFC). This crisis, which began in the US, was the largest source of financial disruption and one of the most severe economic downturns since the Great Depression in the 1930s (Hatzius et al., 2010). Although the GFC brought about a renewed focus on financial and prudential regulation together with some structural reforms to the global economy, it also drew attention to the inextricable relationship between financial conditions and the macroeconomy.

This thesis will examine the distributional effects of financial conditions on the conduct or stance of monetary policy in Australia by using a policy-at-risk (PaR) model, a modified version of the widely-used growth-at-risk (GaR) model, which will assess the response of the Reserve Bank of Australia's (RBA) monetary policy to financial conditions over the period from 1976 to 2023. Through this PaR setup, I will focus on how current monetary policy responds to financial conditions from the past and whether the RBA responds systematically to changes in financial conditions. As a result, this thesis focuses on systematic or endogenous monetary policy as opposed to exogenous policy.

This thesis follows the approach of Hartigan and Wright (2023) in constructing a financial conditions index (FCI) for Australia to include in a PaR setting but extends that study by incorporating more recent data (from Khreish, 2024) up to 2023 to capture the impacts of the COVID-19 pandemic on financial conditions and the RBA's monetary policy. This thesis will assess the different impacts of financial conditions over time by using a quantile regression (see Section 4.2.3 for more details) to characterise the distribution of potential monetary policy responses to financial conditions, allowing for the fact that these responses will not necessarily be symmetric (as often assumed in theory).

In constructing an FCI for use in a PaR model, I seek to make a number of contributions to the existing literature.

First, I will construct an FCI for Australia that incorporates a broad range of financial variables and statistics by using the extended FCI of Hartigan and Wright (2023) constructed in Khreish (2024) up to the end of 2023, to capture financial conditions in

Australia both during and shortly after the COVID-19 pandemic. Unlike the above studies, I will exclude the policy interest rate and short-term interest rates from the FCI to avoid potential endogeneity issues since I am focusing on the endogenous effects on monetary policy. This FCI can then be used in subsequent analysis concerning monetary policy since it does not contain the policy rate and other very short-term interest rates which may be too closely correlated with the policy rate.

Secondly, this thesis investigates how financial conditions influence the RBA's conduct of monetary policy using a PaR model that includes a quantile regression to empirically analyse when financial conditions might influence policy. Although a few studies have used quantile regressions to analyse the relationship between financial activity and macroeconomic outcomes, they are primarily for other settings such as in the Euro area (Chavleishvili et al., 2023). Moreover, no papers explicitly use quantile regressions to analyse the relationship between financial activity and monetary policy in Australia. In addition, papers such as Adrian et al. (2018) assess the importance of financial conditions to the conduct of monetary policy globally, but do not focus precisely on how central banks alter their policy rates in response to changing financial conditions over time. It is hoped that assessing the connection between financial conditions and the conditional distribution of monetary policy changes will more comprehensively capture how policymakers respond to changes in financial conditions in Australia.

Furthermore, by focusing on the risk that financial conditions pose to monetary policy through a novel PaR model instead of economic output in a GaR model, this thesis seeks to contribute to the existing literature on how central banks respond to risks posed by changing financial conditions through their conduct of monetary policy.

In Section 2, this thesis first examines the key literature on the relationship between financial conditions and monetary policy, as well as how previous studies used FCIs and quantile regressions. Section 3 then describes the primary data sources to be used, while Section 4 outlines the general methodology that this thesis uses, including specific details on the construction of the FCI, related statistical tests, quantile regressions and the PaR model. Finally, Section 5 contains the key results from my PaR analysis as well as important checks to ensure the robustness of these results.

2 Literature Review

2.1 Relationship between Financial Conditions and Monetary Policy

Our understanding of the connectivity between financial conditions and the macroeconomy can be attributed to the extensive empirical research conducted on the transmission mechanism of monetary policy. This research has primarily looked at the way monetary policy can influence economic variables by "altering the financial conditions that affect economic behaviour" (Hatzius et al., 2010). For instance, Curdia and Woodford (2010), Gertler and Karadi (2011), and Gambacorta and Signoretti (2014) assessed possible welfare gains arising from the response of monetary policy to credit spreads (a form of financial sector shock).

More recently, Adrian et al. (2019) assessed the significance of financial conditions as forecasting variables for the "conditional distribution of the output gap" by using a New Keynesian model that incorporates a Phillips curve characterised by staggered price setting by producers. After using a quantile regression method (see Section 2.3 for more details) within a growth-at-risk (GaR) setup to estimate the distribution of future real GDP growth as a function of economic and financial conditions, Adrian et al. (2019) found evidence of significant variability in lower quantiles of future GDP growth as a function of financial conditions, but relative stability for upper quantiles. Financial conditions were represented using the National Financial Conditions Index (NFCI) from the US, which includes weekly measures of money, equity and debt market conditions.

There is also an extensive literature on the theoretical response of monetary policy to both inflation and output gaps. Clarida, Gali and Gertler (1999) summarised the comprehensive research by other authors into a range of Taylor-type rules and used these to assess their effectiveness in portraying the actual responses of central banks to changes in these variables. They found that inflation targeting is inherently embedded in optimal policy and reaffirmed the theory that a central bank should adjust nominal interest rates "more than one-for-one with expected future inflation". Despite the various Taylor rules proposed by other authors and the notion that a commitment to a particular policy rule can improve the effectiveness of monetary policy, Clarida, Gali and Gertler (1999) noted that none of the world's main central banks make binding commitments with regard to the future path of policy.

As to the role of monetary policy in achieving financial stability, Svensson (2017) examined a policy of "leaning against the wind" (LAW) in which central banks maintain higher interest rates to deal with financial imbalances such as asset bubbles, despite this having adverse effects on output. Although this policy can help to avoid financial crises, in assessing its costs and benefits, Svensson (2017) argued that other macroprudential policies such as regulation are better suited than monetary policy to achieving financial stability. Saunders and Tulip (2019) concurred with the former, arguing that the costs of higher interest rates (especially higher unemployment) exceed their benefits because interest rate hikes tend to have very small impacts on the probability of a financial crisis occurring. However, the authors acknowledge the need for further research into LAW.

2.2 Financial Conditions Indices (FCIs)

An increasingly popular method of measuring the general financial conditions of an economy is through a financial conditions index (FCI). Hatzius et al. (2010) define an FCI's purpose as one that "summarizes the information about the future state of the economy contained in these current financial variables". By incorporating numerous financial variables, FCIs aim to transform large amounts of information into a single data series which can be used by both policymakers and economic agents in their decision-making (Murphy & Gadsby, 2024). Furthermore, an FCI should optimally measure "exogenous shifts in financial conditions" (Hatzius et al., 2010) which are predicted to influence future economic activity. FCIs are especially useful in summarising a broad array of financial and economic data relevant to financial conditions in a single index which can be incorporated into a wide variety of econometric models.

The first broad measure of financial conditions was introduced in the mid-1990s by the Bank of Canada (BOC) as a monetary conditions index (MCI) (Freedman, 1994). This MCI simply consisted of an exchange rate and a refinancing rate which were assigned weights based on macroeconomic model simulations. This measure played a key role in helping the BOC to determine the necessary refinancing rate to maintain its target stance of monetary conditions.

Subsequently, many versions of these indices began to be constructed using a principal components methodology, particularly as more variables were incorporated such as equity prices, long-term interest rate measures and asset prices. The broader scope of these indices led to them becoming known as FCIs and they are widely recognised as useful measures of financial conditions, particularly following the GFC. Today, many different versions of FCIs are used by private and public institutions, including the Bloomberg FCI, Citi FCI, Deutsche Bank FCI, Goldman Sachs FCI, Kansas City Federal Reserve Financial Stress Index, and the OECD FCI (Hatzius et al., 2010). Although these indices incorporate different variables and methodologies, they all aim to summarise the overall state of financial conditions in the economy.

Hatzius et al. (2010) proposed their own FCI containing 45 variables and sought to extend both the number of financial variables incorporated and the length of time covered by this FCI. In constructing their FCI, Hatzius et al. (2010) used the principal components methodology in which each of the variables was regressed on current and two lagged values of real GDP and inflation growth. The FCI was then evaluated by analysing its ability to predict economic activity growth relative to other measures and existing FCIs, and the authors found that this new FCI outperformed existing measures partly due to its wider coverage of financial conditions.

More recently, Koop and Korobilis (2014) proposed a variation of the factor model approach used to construct many FCIs. This uses time-varying factor loadings and volatilities in order to better account for the impact of structural changes over time on the underlying relationship between the financial sector and the real economy. This methodology has subsequently been used in the construction of many FCIs and elements of it will be adopted in this thesis.

Most of the FCIs discussed above reflect conditions either for the US or the global economy. More recently, however, a few FCIs have also been constructed for Australia. The prime example of an Australian FCI can be found in Hartigan and Wright (2023), who developed a GaR model to assess the explanatory power of current financial conditions on “future downside risk to key macroeconomic variables” (Hartigan &

Wright, 2023). That paper constructed a comprehensive FCI containing 75 variables from the categories: “Survey measures”, “Interest rates and spreads”, “Credit and money”, “Asset prices”, “Debt securities outstanding”, “Banking sector”, “Financial system complexity (ratio)”, “Leverage measures (ratio)”, and “Risk indicators”.

Hartigan and Wright (2023) then incorporated this FCI into a GaR model which included variables such as household consumption, business investment and the labour market to establish a link between present financial conditions and future economic conditions, and to “quantify the magnitude of expected losses in economic activity caused by financial conditions”. They found that their FCI provided information about both downside risks to GDP and employment growth as well as upside risks to changes in the unemployment rate.

2.3 Quantile Regressions

Quantile regressions offer a flexible way of analysing the relationship between variables across a distribution by estimating conditional quantiles through a regression. This method allows for a more detailed examination of any heterogeneous effects at different points in a distribution. Koenker and Hallock (2001) attribute the catalyst of the quantile regression method to be the work of Gary Chamberlain in 1991 in relation to wage premiums of different deciles of workers. Other works in the area of labour economics followed, such as Buchinsky (1994), and Arias, Hallock and Sosa-Escudero (2001) which both looked at issues within the US labour market. Quantile regressions have also been commonly used in demand analysis studies in areas such as Engel curves (Deaton, 1996, as cited in Wilde, 2000), demand for alcohol (Manning, Blumberg and Moulton, 1995) and earnings inequality (Conley & Galenson, 1998).

Moreover, the quantile regression method has been increasingly employed in studies related to empirical finance, most notably in Taylor (1999), Bassett and Chen (2001), and Engle and Manganelli (2004). This may be because inferences for quantile regressions tend to be more robust than many other econometric methods (Koenker & Hallock, 2001). Furthermore, Chernozhukov and Umantsev (2001) developed their value-at-risk (VaR) model using a quantile regression function to relate returns and asset prices.

Chernozhukov and Hansen (2005) used a quantile regression to study the distributional effects of monetary policy on asset prices. They found evidence of substantial heterogeneity in the response of different quantiles of the asset price distribution to changes in monetary policy shocks. These results led the authors to conclude that this methodology could provide a comprehensive understanding of the monetary policy transmission mechanism. Unlike that and several other papers which look at the effects of monetary policy on various macroeconomic and financial variables, I will use a quantile regression to assess the effects of financial conditions on the RBA's conduct of monetary policy at different quantiles to study the potential for heterogeneous effects.

3 Data

In order to construct the FCI for the PaR analysis in this thesis, I will be using the dataset from Khreish (2024) which is an extension of the data used in Hartigan and Wright (2023) up until 2023. This enables the PaR model to assess the effects of financial conditions on monetary policy in Australia during and especially after the COVID-19 pandemic when the policy rate was lifted from the zero lower bound (ZLB). However, to avoid endogeneity issues with the FCI later in the PaR model, I have excluded the overnight cash rate (OCR) and the 3-month bank bill rate from the above dataset. I have also excluded the "Momentum" factors included in Khreish (2024) which measure the speed and momentum of interest rate changes by the RBA, since these would be an additional source of endogeneity in the PaR model.

As a result, the FCI constructed in this thesis uses a total of 71 data series over the period from Q2:1966 to Q3:2023 which all reflect a broad range of variables crucial to the Australian financial system and the broader macroeconomy. A full description of the data series, that I will be incorporating into my new FCI, including source, relevant economy, and date range, is provided in Table A1 in the Appendix.

As emphasised by Hartigan and Wright (2023), it is important for an FCI to contain historically important variables such as value of housing or dwelling stock as well as variables which may indicate any future sources of risk such as ratios measuring financial system complexity. For this reason, I have attempted to include a wide variety of both types of variables to best reflect historical and future sources of financial risk in my own FCI. However, as noted by Khreish (2024), one limitation of this FCI is the lack of access to a few of the data series used by Hartigan and Wright (2023), but this is not necessarily an issue given that this FCI reflects a considerably large number of variables.

As part of the PaR model, data are needed for a few macroeconomic variables for Australia (see Section 4.2.2 for more details). This is to enable the model to control for such macroeconomic influences on monetary policy which may not be fully accounted for by the FCI component series. Real gross domestic product (GDP) data from June 1976 to December 2023 was obtained from Federal Reserve Economic Data (FRED) and data for quarterly inflation based on the domestic consumer price index (CPI) from June 1976 to December 2023 was obtained from the RBA. The interbank overnight cash rate (OCR) series from June 1976 to December 2023 was also obtained from the RBA.

I have followed Hartigan and Wright (2023) and Khreish (2024) in converting these macroeconomic data series into quarterly frequencies. The GDP and CPI series were already in quarterly frequencies and did not therefore require any statistical transformations. However, the OCR series obtained was in monthly intervals. The OCR series was converted by simply taking the arithmetic average of all the months in each quarter (i.e. average of January, February, and March data for the March quarter), as shown in the formula below:

$$i_t = \frac{1}{\bar{\tau}} \sum_{\tau}^{\bar{\tau}} i_{t\tau} \tag{1}$$

where $\bar{\tau}$ represents, in this case, the number of months of OCR data within the quarter, t.

Furthermore, the real GDP series needed to be converted into a measure of the output gap for it to be incorporated into the PaR model. This conversion was made using the Beveridge-Nelson (BN) Filter Trend-Cycle Decomposition tool from Kamber, Morley and Wong (2024). This filter implemented the conversion using a natural logarithm with no differencing (levels) and the website's default filter parameters.

4 Methodology

4.1 Constructing an FCI for Australia

This thesis closely follows the construction of the FCI for Australia used in Hartigan and Wright (2023), namely a dynamic factor model (DFM) methodology. This method seeks to extract a common factor which "captures the greatest common variation in the variables" from a group of several financial variables to form the FCI (Hatzius et al., 2010).

In constructing their FCI, Hartigan and Wright (2023) used a DFM of the following form originally used by Bai and Wang (2015):

$$y_t = \Lambda_0 f_t + \Lambda_1 f_{t-1} + \ldots + \Lambda_s f_{t-s} + \varepsilon_t, \quad \varepsilon_t \sim iid\ N(0, R)$$

$$f_t = \phi_1 f_{t-1} + \phi_2 f_{t-2} + \ldots + \phi_p f_{t-p} + \eta_t, \quad \eta_t \sim iid\ N(0, Q) \tag{2}$$

where y_t is a vector of observables, f_t is a vector of dynamic factors estimated using principal components analysis (PCA) and Λ_j is a matrix of dynamic factor loadings for f_{t-j}. Furthermore, these dynamic factors are assumed to follow a VAR(p) process where ϕ is a matrix of autoregressive coefficients.

Hartigan and Wright (2023) then provide the state-space representation of the DFM to be:

$$y_t = \Lambda F_t + \varepsilon_t$$

$$F_t = \phi F_{t-1} + G\eta_t \tag{3}$$

where Λ is a $qk \times qk$ matrix of factor loadings which determines how changes in latent factors influence observed variables, y_t. ϕ is a matrix of VAR coefficients, and G is a selector matrix with dimensions $qk \times q$. As noted in numerous papers including Hartigan and Wright (2023) and Hatzius et al. (2010), the DFM outlined above has the benefit of being able to incorporate dynamics into the estimation of the FCI and unbalanced datasets such as that employed in this thesis.

Then, using a quasi-maximum likelihood estimation of the DFM, this thesis slightly modifies the data log likelihood function of Hartigan and Wright (2023) to reflect the different variables used in this new FCI. This involves two important stages. The first is obtaining the state-space parameters by using PCA with a balanced subset of the 71 component series and secondly, applying the Kalman filter on the unbalanced original dataset to finally get the factor estimates. By following the approach of Hartigan and Wright (2023) in constructing an FCI, the FCI in this thesis has the same interpretation as the former as well as the EY Australian Financial Conditions Index (Murphy & Gadsby, 2024) that a positive index value suggests restrictive financial conditions and a negative index value suggests expansionary financial conditions. This is reflected in Figure 1 which plots the new estimated FCI from this thesis over the period 1976:Q4 to 2023:Q2.

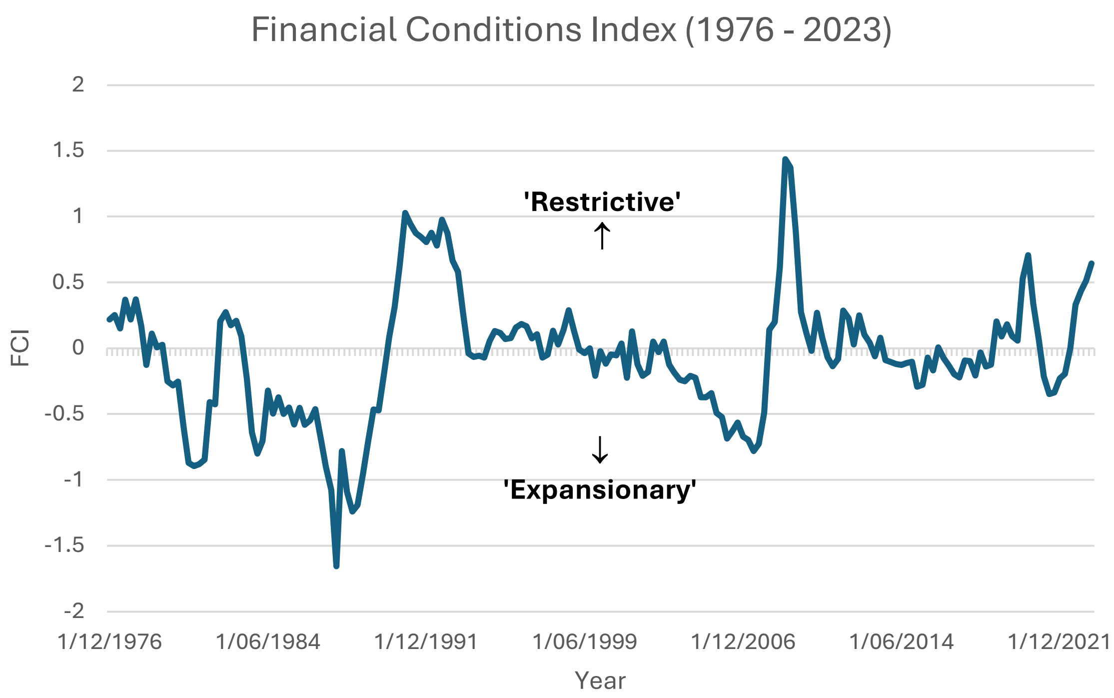

Figure 1: Financial conditions index for Australia from 1976:Q4 to 2023:Q2

From Figure 1, it is evident that the FCI does well in reflecting historical financial conditions in Australia and, by extension, the overall state of the macroeconomy. For instance, the most restrictive financial conditions are represented by the peaks at around 1990, 2009 and 2020 when Australia experienced significant economic downturns because of the early 1990s recession, the GFC and the COVID-19 pandemic respectively.

4.2 Policy-at-Risk (PaR) Model

4.2.1 Granger Causality Tests

A key statistical test of any model involving multiple time series is a Granger causality test. The Granger causality statistics obtained from this test can be used to assess whether the explanatory variable's lagged values (the FCI) offer additional explanatory power for the dependent variable (the OCR) above that of just the lags of the dependent variable. If this is the case, we can conclude that past financial conditions (the lagged FCI) "Granger cause" current monetary policy (through the OCR).

Since Granger causality tests are sensitive to the determined lag length, this thesis follows Hartigan and Wright (2023) in testing for the lag lengths from one to four periods. Moreover, using multiple lags can help to mitigate the issue of misspecification when the test may be unable to detect causality when the two variables' interactions exhibit lags over time.

The Granger causality test is the starting point for any analysis using the PaR model because it assesses whether changes in the FCI help to forecast changes in the OCR based on historical data. Although they do not provide an indication of direct causality, Granger causality tests assess whether there is a predictive relationship between these two variables and are useful in establishing the statistical foundation for exploring this relationship in more detail through the PaR model.

This test can be conducted using the following setup:

$$\Delta i_t = \alpha + \sum_{j=1}^{4} \phi_{1j}\pi_{t-j} + \sum_{j=1}^{4} \phi_{2j} y_{t-j} + \sum_{j=1}^{4} \phi_{3j} \hat{f}_{t-j} + \sum_{j=1}^{4} \phi_{4j}\Delta i_{t-j} + u_t \tag{4}$$

$$H_0: \phi_{31} = \phi_{32} = \phi_{33} = \phi_{34} = 0$$

where H_0 indicates the null hypothesis that the lags of two time series are equal and thus that one of the time series contains no predictive power in determining the other. In this case, the null hypothesis stipulates that the time series of the FCI in period t is equivalent to that of the FCI in each period from $t-1$ to $t-4$ and that adding in a lagged FCI into the model will not further reduce the forecasting error. It is important to note that the above setup for the Granger causality test is in essence a four-period version of the PaR model in Section 4.2.2 but assumes constant effects across quantiles to test for the usefulness of previous financial conditions series ($\hat{f}_{t-1}$) in predicting or "Granger causing" current monetary policy (i_t).

The results for the sequential Granger causality tests for lag lengths of one to four quarters are given in Table A2 in the appendix. Figure 2 plots a heatmap chart of the associated p-values for each of the Granger causality tests for each of the macroeconomic variables and the FCI.

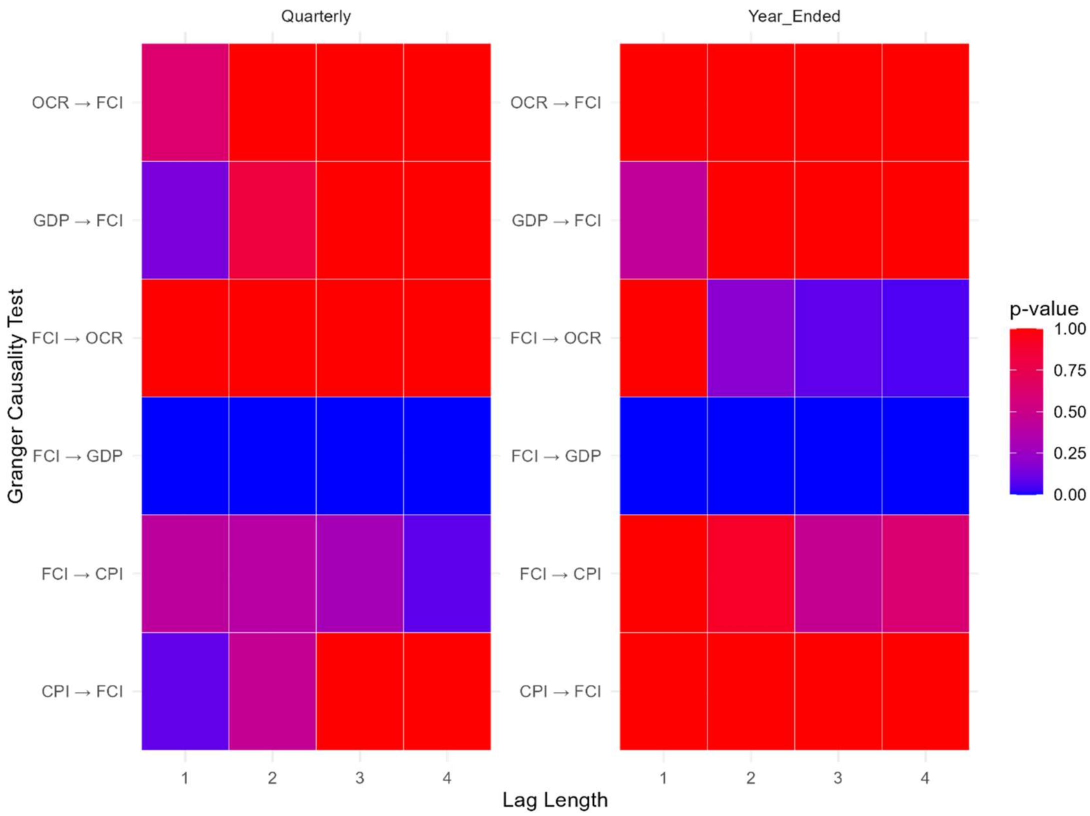

Figure 2: Heatmap chart of Granger causality test p-values

The results of these tests, and as shown in Figure 2, suggest that the FCI Granger-causes the output gap (GDP) at the 5% level of significance at both quarterly and yearly frequencies over all four lags. Most importantly, they suggest that the FCI Granger-causes the OCR at lag lengths 3 and 4 at a yearly frequency. This means that the OCR, on average, does not respond very much to changes in financial conditions as represented by the FCI, but the significant results at lag lengths 3 and 4 suggest that financial conditions have a delayed impact on changes made by the RBA to the OCR. In other words, the RBA may on average rely on longer term assessments of changes in financial conditions rather than reacting immediately to short-term fluctuations in the FCI (given by lags 1 and 2).

While these results may seem surprising, it reflects the fact that, historically, the RBA responds most strongly to changes in key macroeconomic variables such as the inflation rate or output as opposed to changes in financial conditions. It also supports the findings of Clarida, Gali & Gertler (1999) that central banks respond most strongly to macroeconomic variables, together with the LAW literature which suggests central banks do not use monetary policy to address fluctuations in financial conditions (see Svensson (2017) and Saunders and Tulip (2019)).

With these relationships established through the sequential Granger causality tests, I then formally assess the mean and quantile effects of financial conditions on monetary policy through a two-stage PaR regression model, as outlined below.

4.2.2 PaR Model

In order to effectively use the PaR model to assess distributional effects of financial conditions on monetary policy, it is necessary to only allow for quantile effects on the FCI. This can be done by constructing residuals from a standard reaction function which considers the macroeconomic variables mentioned in Section 3, namely the output gap, inflation and the FCI, and then setting their β coefficients to be fixed across the different quantile regressions.

The PaR model assesses the effect of financial conditions on monetary policy by regressing the OCR (the RBA's key monetary policy instrument) on a few important macroeconomic variables and the newly constructed FCI. This regression model is given by the following equation:

$$i_t = \alpha + \beta_1 \pi_t + \beta_2 \tilde{y}_t + \beta_{3\tau} \hat{f}_{t-1} + \ \beta_4 i_{t-1} + \varepsilon_t \tag{5}$$

where π_t represents domestic CPI inflation at time t and $\tilde{y}_t$ is the output gap at time t. $\hat{f}_{t-1}$ represents the FCI constructed in Section 4.1 at time $t-1$ and ε_t is an exogenous monetary policy shock. The lagged OCR, i_{t-1}, has been included to ensure that the residual from this regression becomes serially uncorrelated while also improving the robustness of the OLS regression[1] (Keele & Kelly, 2006).

The PaR model also includes the lagged OCR for two primary reasons. First, the lagged variables help to improve the forecast accuracy of the model by better capturing the dynamic effects associated with each of these variables to then analyse their impact on the OCR (the RBA's conduct of monetary policy). Moreover, the lagged variables help to model the relationship between the independent variables and the dependent variable (the OCR, represented by i_t) based on both current and past conditions. Secondly, the lagged variables also improve the overall model fit by including more information about each of the variables and potentially improving their explanatory power of the dependent variable. This can, as a result, improve the overall robustness of the PaR model, particularly when analysing the impacts on the OCR over an extended period of time.

The PaR model is implemented using a two-stage regression which I outline below.

The first stage involves regressing the following reaction function to obtain the estimated residual or policy shock, $\hat{z}_t$, accounting for the mean effect.

$$i_t = \alpha + \beta_1 \pi_t + \beta_2 \tilde{y}_t + \beta_3 \hat{f}_{t-1} + \beta_4 i_{t-1} + z_t \tag{6}$$

[1] Ordinary least squares.

This reaction function represents a type of Taylor rule which characterises how the RBA systematically responds on average to the FCI and key macroeconomic variables for Australia. It allows for the assessment of the relevance of the FCI in influencing the policy interest rate on average. This first stage regression obtains the coefficient estimates of the macroeconomic variables of CPI inflation, the output gap, as well as the lagged FCI (our variable of interest).

The second stage involves running a quantile regression (see Section 4.2.3 for technical details) for the estimated policy shock, $\hat{z}_t$, obtained from the first stage regression:

$$\hat{z}_t = \alpha_\tau + \beta'_{3\tau}\hat{f}_{t-1} + v_t \tag{7}$$

where v_t is the residual from each quantile regression. Using this regression, we can obtain the estimate of $\beta'_{3\tau}$, which represents the effect of the FCI at quantile τ on the OCR. This then allows for the analysis of whether there are any quantile or distributional effects of financial conditions on the OCR above and beyond the mean effects. This thesis follows the approach of Hartigan and Wright (2023) in assessing impacts at the quantiles, $\tau = \{0.05, 0.25, 0.50, 0.75, 0.95\}$.

With this two-stage regression framework, the total effect of financial conditions on the conduct of monetary policy, $\hat{\beta}_{3\tau}$, can be expressed as:

$$\hat{\beta}_{3\tau} = \hat{\beta}_3 + \beta'_{3\tau} \tag{8}$$

where $\hat{\beta}_3$ is the mean effect of the FCI on the OCR (the first stage) and $\beta'_{3\tau}$ is the quantile effect of the FCI on the OCR at quantile τ (the second stage).

This two-stage regression setup is being used for a few key reasons. First, including the lagged residual instead of the lagged version of each variable greatly simplifies the PaR model equation without neglecting past information contained within these variables. Secondly, the two-stage regression allows for a much easier distinction between the mean and quantile effects. The first stage regression identifies potential mean effects of both the FCI and macroeconomic variables on monetary policy, while the second stage regression identifies the quantile effects of the FCI on monetary policy, represented by the estimated policy shock obtained in the first stage. I believe that this will also enable a clearer interpretation of the distributional effects of financial conditions on monetary policy. Moreover, the two-stage regression setup separates the systematic part of monetary policy (i.e. the response of policy to key variables in the first stage) from the policy shock (contained in the second stage). This means that the second stage regression can examine effects beyond the mean effect.

4.2.3 Quantile Regression Technical Details

The quantile regression in this thesis seeks to choose the slope of the regression, β_τ, that minimises the quantile weighted absolute value of errors, based on the method used in Adrian et al. (2019):

$$\hat{\beta}_\tau = arg \min_{\beta_\tau \in R^k} \sum_{t=1}^{T} \{\tau \cdot I_{i_t^r \geq x_t\beta} |i_t^r - x_t\beta_\tau| + (1-\tau) \cdot I_{i_t^r < x_t\beta} |i_t^r - x_t\beta_\tau|\} \tag{9}$$

In this general quantile regression model, $I_{i_t^r}$ is the indicator function and τ represents the proportion of i_t terms greater than or equal to $x_t\beta$. For example, if we set $\tau = 0.1$, we would minimise $\hat{\beta}_\tau$ such that only 10% of i_t terms are greater than or equal to $x_t\beta$, where x_t represents a vector of conditioning variables. These weights on errors differ depending on whether the error term is above or below the quantile and allows for a closer examination of any heterogeneous effects in the model.

After obtaining $\hat{\beta}_\tau$ from the above model, this thesis obtains the predicted value of the regression as in Adrian et al. (2019), which can be expressed as a consistent linear estimator of the quantile function of i_t conditional on x_t:

$$\hat{Q}_{i_t|x_t}(\tau|x_t) = x_t\hat{\beta}_\tau \tag{10}$$

To obtain the estimates for each of the quantiles, I employ numerical optimisation to solve Equation (9). Numerical optimisation is implemented using the "ucminf"[2] function

[2] "General-Purpose Unconstrained Non-Linear Optimization" package.

in R. The initial values for the numerical optimisation were set to OLS estimates for the second stage regression. The standard errors are obtained using non-parametric bootstrapping with 1000 bootstrap samples estimated for each quantile. This is because non-parametric bootstrapping provides more robust standard error estimates, since it does not make any strong assumptions about the parameters in the regression model.

In the context of the PaR model, a positive β_j value for a quantile below the median quantile means that when interest rates are already low relative to what would be set under a "systematic policy response"[3], a worsening of financial conditions (represented by an increase in the FCI, or x_t) leads to less of an effect on the RBA lowering interest rates as compared to the systematic policy response. In other words, the RBA would be reducing interest rates by a relatively smaller amount.

On the other hand, a negative β_j value for a quantile above the central quantile means that when interest rates are already high relative to what would be implied by the RBA's systematic policy, a worsening of financial conditions (represented by an increase in the FCI, or x_t) leads to more of an effect on the RBA lowering interest rates relative to its systematic response. In other words, the RBA would be reducing interest rates by a relatively large amount.

I then assess the conditional distribution of the effects of the FCI on the RBA's conduct of monetary policy by fitting the above model using the discrete quantiles from both Hartigan and Wright (2023) and Adrian et al. (2019), $\tau = \{0.05, 0.25, 0.50, 0.75, 0.95\}$[4]. The estimation period is from Q2:1977 to Q4:2023 which is the maximum length of time available for both the FCI and macroeconomic data. By running this quantile regression model, we can obtain $\hat{Q}(x_t)$, the predicted value for each quantile of the distribution of the OCR.

[3] Systematic policy response is captured by the first stage regression equation which reflects how the RBA responds to variables such as the output gap, CPI inflation and the FCI using the OCR, at the mean level.

[4] The discrete quantiles of the distribution of the RBA's OCR. For instance, quantile 0.95 corresponds to the upper 95th percentile of the OCR, representing the upper end of possible rate changes by the RBA. In the PaR model, quantile 0.95 assesses how extreme upper-end cash rate changes are influenced by financial conditions.

5 Results

5.1 Policy-at-Risk: Do Financial Conditions Affect the Conduct of Monetary Policy?

In this section, I will assess the results of the PaR model outlined in Section 4.2.2, with a particular focus on whether there are any effects of financial conditions on the RBA's monetary policy at the mean level and along different points on the distribution of monetary policy changes through the quantile regression model. As noted above, the primary advantage of using a quantile regression model to analyse the relationship between financial conditions and monetary policy is that it provides an insight into how the RBA adjusts the OCR in response to changes in financial conditions not just at the average level, but also across the entire distribution, including more extreme changes.

Recall that the first stage regression of the PaR model outlined in Section 4.2.2 (Equation 6) represents a type of policy reaction function of the RBA and allows us to analyse the effects of both financial conditions and key macroeconomic variables on the RBA's conduct of monetary policy at the mean level.

Table 1 contains a summary of the regression output from this first stage of the PaR model. It is evident from the first stage regression that the key macroeconomic variables, CPI inflation and the output gap, both have a statistically significant positive effect on monetary policy (a relation firmly established in the literature, see Clarida, Gali and Gertler (1999)). In other words, when either inflation or economic growth increase, the RBA tends to increase the OCR, on average, by 21.18 and 13.58 basis points respectively. This is not a surprising result given that inflation targeting central banks in most advanced economies base their policy decisions heavily on both inflation and output data. It is also not surprising that these relationships are positive given that central banks tend to reduce interest rates when output and inflation are low but increase them when output and inflation are high (Sergi & Hsing, 2010).

Table 1: PaR First Stage Regression Results

Variable	Estimate	Standard Error	t-value	p-value	Significance
Intercept	0.1014	0.1229	0.83	0.410	
CPI inflation	0.2118	0.0933	2.27	0.024	*
Output gap	0.1358	0.0585	2.32	0.021	*
lag_FCI	-0.3953	0.1722	-2.30	0.023	*
lag_OCR	0.9471	0.0175	54.01	$<2e^{-16}$	***

Notes:
* indicates statistical significance at the 95% level.
** indicates statistical significance at the 98% level.
*** indicates statistical significance at the 99.998% level.

Furthermore, at the mean level, the lag of the FCI also has a statistically significant effect on monetary policy at the 95% level of significance. However, the lagged FCI has an inverse relationship with the OCR, meaning that when the FCI increases (i.e. financial conditions worsen), the RBA reduces interest rates, on average, by 39.53 basis points. An interesting point to note is that this coefficient is negative and statistically significant, meaning that the RBA does exhibit elements of the "leaning against the wind" behaviour documented by Svensson (2017) by setting the OCR to be countercyclical to financial conditions. This countercyclical relationship between the FCI and OCR is especially evident in Figure 3 below, which plots the FCI and OCR over the entire PaR adjusted sample period from 1977 to 2023.

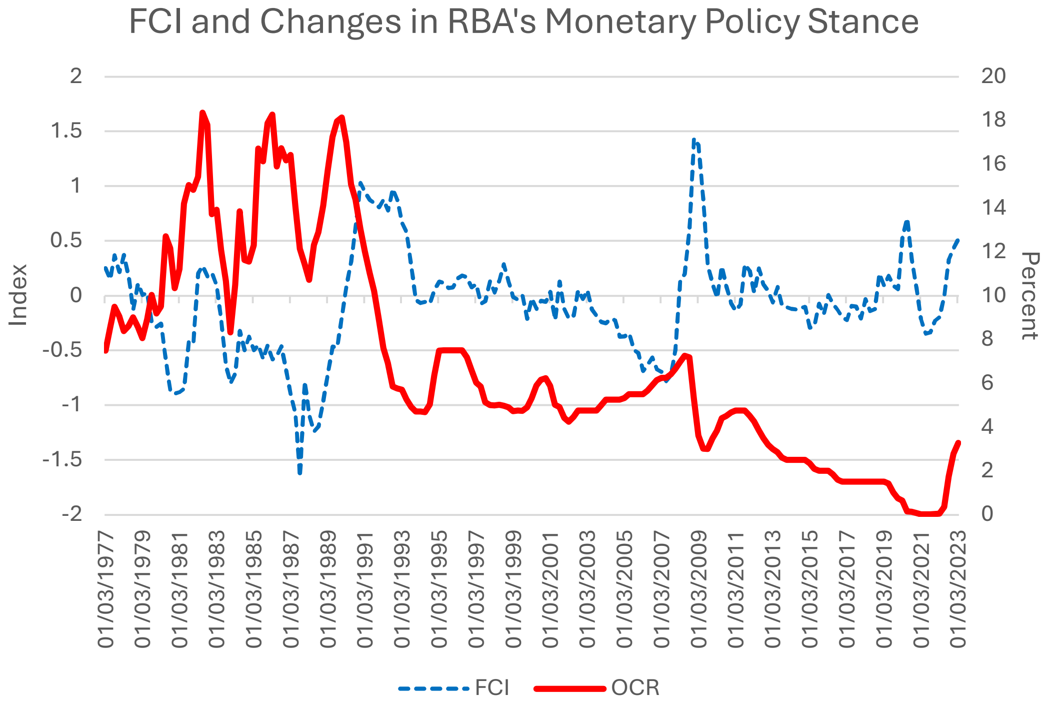

Figure 3: Time series plot of the FCI and OCR (1977-2023)

Particularly during times of very restrictive financial conditions, such as the early 1990s recession, the late-2000s GFC and the 2019-2020 COVID-19 pandemic, we see a very clear countercyclical relationship in which more restrictive financial conditions (higher FCI) are associated with a lower OCR. Similarly, more accommodative financial conditions (lower FCI) are associated with a considerably higher OCR. Figure 3 therefore confirms the negative mean effect of the FCI on the OCR found in the first stage regression above throughout this period.

Having established that the FCI has a statistically significant effect on the RBA's conduct of monetary policy at the mean level, I now turn my attention to analysing whether the FCI has any substantial effect on the OCR at different quantiles along the distribution of interest rate changes. These are the effects above and beyond those found in the first stage regression at the mean level.

Table 2 contains the estimates of the intercept and coefficient on the lagged FCI (lag_FCI) for each of the quantiles, $\tau = \{0.05, 0.25, 0.50, 0.75, 0.95\}$.

Table 2: Summary of quantile regression results

	Intercept	lag_FCI
Quantile: 0.05	-1.3567 (0.2690)	0.5937* (0.2904)
Quantile: 0.25	-0.2644 (0.0570)	0.2638 (0.2774)
Quantile: 0.50	-0.0521 (0.0317)	0.0925 (0.1446)
Quantile: 0.75	0.2621 (0.0740)	-0.0402 (0.1421)
Quantile: 0.95	1.2781 (0.2481)	-0.9407* (0.4080)

Notes:
Standard errors (in parentheses)
* indicates statistical significance at the 95% level.

It is clear from Table 2 that the coefficient on lag_FCI is only statistically significant at the lower 5th and upper 95th percentiles. The precise interpretation of these two statistically significant coefficients can be summarised as follows.

For the lower 5th percentile[5] (quantile 0.05), the positive coefficient suggests that when the current level of the OCR is already lower than the interest rate that would be set under the RBA's systematic policy (i.e. when the policy shock from the first stage regression is low), worsening financial conditions have less of an impact on the RBA lowering interest rates further compared to its systematic response (given by the first stage regression). In other words, when the OCR is already relatively low, a tightening of financial conditions has less of an effect on the RBA's monetary policy decisions. For instance, in early 2007, before the full effects of the GFC had been felt in Australia, the RBA still undertook a series of interest rate increases due to concerns about high domestic inflation (Edey, 2021), which took precedence over the gradually tightening financial conditions of that time.

For the upper 95th percentile (quantile 0.95), the negative coefficient suggests that when the current OCR level is higher than that implied by the RBA's policy reaction function, worsening financial conditions have more of an impact on the RBA lowering interest rates further compared to its mean response. This is unsurprising given that many central banks throughout the world, including the RBA, responded to the significant

[5] This represents the lowest 5th percentile of the changes made to the OCR by the RBA from 1977 to 2023, represented by the residuals from the first stage regression.

downturn during the GFC by aggressively reducing interest rates in order to provide additional stimulus to their economies. This also indicates that central banks believed that interest rates at the time of the GFC were too high and needed to be reduced to provide sufficient stimulus and support for both the financial sector and real economy. Moreover, periods of tighter financial conditions are likely to be characterised by increased financial and economic volatility, as well as lower levels of consumer spending and business investment, perhaps due to constrained credit, and so the RBA would likely want to reduce its policy rate to help improve economic conditions during large financial downturns such as the GFC.

Since the coefficient on lagged-FCI is not statistically significant at the lower 25th, upper 75th and median percentiles, we cannot conclude that the RBA systematically responds to financial conditions in any way different to that of its policy reaction function when the OCR is at more moderate initial levels.

When we look at the total response of the RBA to changes in financial conditions (the combined first stage and second stage responses[6]), we see similar effects. Table 3 provides the estimate of the total effects of the FCI on the RBA's OCR. These are obtained by adding the coefficients on lag_FCI from both the first stage and second stage regressions. Figure 4 plots these combined effects.

Table 3: Total effect of FCI on the OCR

	Sum of lag_FCI Coefficients
Quantile: 0.05	0.1984
Quantile: 0.25	-0.1315
Quantile: 0.50	-0.3028
Quantile: 0.75	-0.4355
Quantile: 0.95	-1.336

[6] Recall the total effect of financial conditions on monetary policy is given by Equation (8): $\hat{\beta}_{3\tau} = \hat{\beta}_3 + \beta'_{3\tau}$

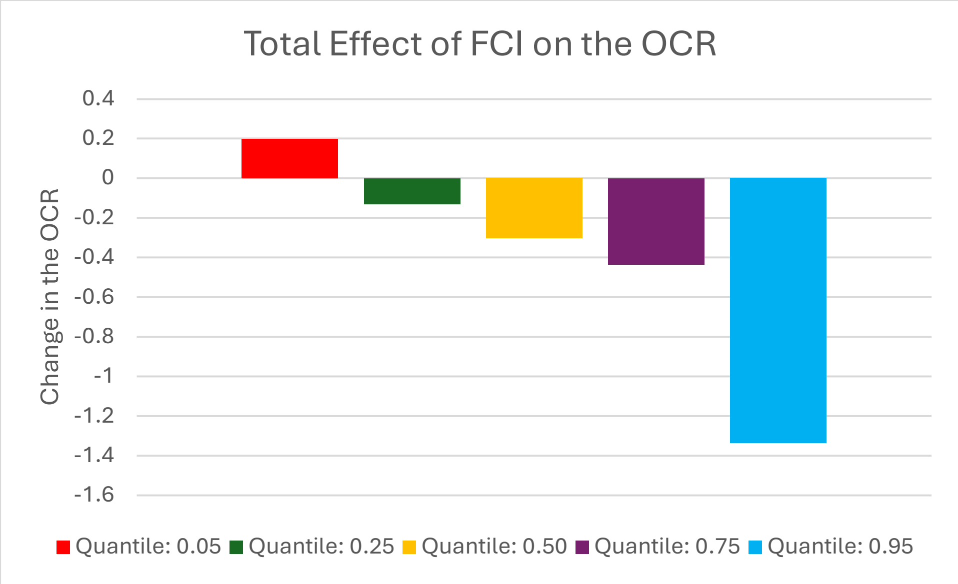

Figure 4: Combined first stage and second stage effects

Therefore, when monetary policy is accommodative relative to what would be implied under the RBA's normal policy reaction function, a tightening of financial conditions results in a minimal response by the RBA. However, when monetary policy is restrictive relative to its implied policy response under the reaction function, a tightening of financial conditions results in a stronger response by the RBA, through larger decreases in the OCR. It is also evident from Figure 4 that the RBA's response to financial conditions becomes stronger as the initial value of the OCR increases. In other words, when the OCR is increasingly above the interest rate that would be set under its policy reaction function, the RBA demonstrates a stronger propensity to cut interest rates more than would be implied under its systematic policy.

Overall, the results from these quantile regressions suggest that the RBA takes a relatively conservative stance on monetary policy when responding to changes in financial conditions. Across the distribution, the RBA responds more moderately to worsening financial conditions by not responding in any additional way when interest rates are close to levels prescribed by its systematic policy response. Moreover, worsening financial conditions do not significantly affect the RBA's decision to reduce interest rates when the OCR is already very low relative to the OCR under systematic policy. This could simply be because interest rates were already at the ZLB or that the RBA was cautious not to reduce interest rates too far, to balance low economic activity with risks of increased financial instability or speculative activity. However, the RBA demonstrates a propensity to implement large interest rate cuts when the OCR is considered too high in times of worsening financial conditions, perhaps to provide support to both the economy and financial sector. The RBA is also likely to be careful not to overreact to short-term changes in financial conditions in a way that may conflict with its longer-term inflation objectives. This was evident, for example, during the GFC, when the RBA only began cutting the OCR by 400 basis points shortly after the collapse of Lehman Brothers, a time of significant financial volatility (Edey, 2021), despite inflation remaining moderately high.

Despite being statistically insignificant, the coefficients at the 25th and 75th percentiles demonstrate that the RBA continues to be less responsive to tight financial conditions when interest rates are already relatively accommodative, while it is more affected by tight financial conditions when interest rates are considered to be more restrictive than would be set under its systematic policy response.

Figure 5 provides further insight into the way the OCR responds to changes in the FCI over the full period from 1977 to 2023. In particular, this plot highlights the idea of "policy-at-risk", reflecting the uncertainty surrounding the RBA's setting of the OCR at different points in time along the distribution of potential interest rate changes (much like growth-at-risk looks at the relationship between macroeconomic variables and future growth). Although this thesis does not employ the quantile spacings method used by Hartigan and Wright (2023), which aims to avoid the issue of quantiles crossing when lags of the dependent variable are included in the model, we can be confident that the problem of quantiles crossing does not occur in this case. This is evident in the fact that the lower quantiles (0.05, 0.25) remain below the upper quantiles (0.75, 0.95) throughout the entire conditional distribution.

Figure 5 displays the conditional distribution[7] of the OCR over time in quarterly intervals. The distance between the different quantiles reflects the changes in the conditional distribution of the OCR over time. A larger gap between these quantiles reflects increased variability of the OCR at the different quantiles, while a smaller gap

[7] The conditional distribution of the OCR measures the behaviour of the different quantiles of the OCR "conditional" on the FCI data. It plots the same quantiles used in the quantile regression from Section 4.2.3.

reflects less uncertainty surrounding the OCR's movement across the whole distribution. An interesting point to note is that during periods of high volatility in financial conditions (such as the early 1990s recession, the late 2000s GFC and, to a lesser extent, the 2019-20 COVID-19 pandemic), the distance between the quantiles becomes much smaller. The more compressed conditional distribution at these three points suggests that the RBA had implemented very clear changes to the OCR during these periods. In other words, the RBA kept its policy rate lower for an extended period to mitigate the negative economic effects during these three periods.

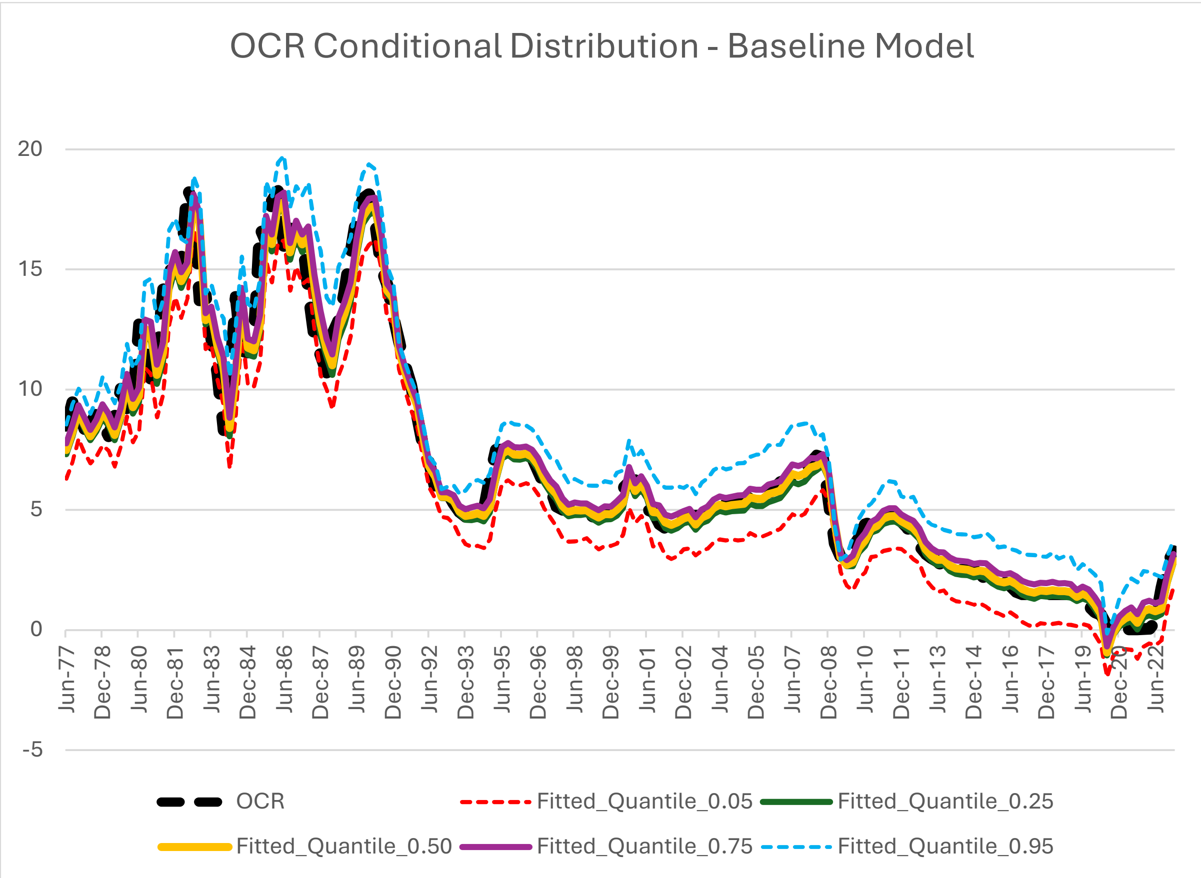

Figure 5: OCR conditional distribution (Quarterly) – PaR model

Another possibility is that since interest rates were lowered significantly during these three periods, the OCR may have approached the effective lower bound (or ZLB) leaving the RBA with very little room to make substantial changes to the OCR. This can reduce the variability of the OCR during these periods, and result in less variation in the conditional distribution of the quantiles. For example, around late 2019 to middle 2020, the peak of the COVID-19 pandemic, the OCR was very close to zero after a series of interest rate cuts by the RBA, and some of the fitted quantiles of the OCR (especially the 5th and 25th percentiles) go below zero. Although COVID-19 was not inherently a financial crisis, it was still a period characterised by significant volatility in financial markets (Kusumahadi & Permana, 2021) and is therefore still an important point in time to analyse the relationship between financial conditions and monetary policy.

5.1.1 Sub-Sample PaR Model

A potential caveat to the analysis above is the fact that the OCR only became the RBA's principal instrument of monetary policy in January 1990, when it began to announce the changes made to its monetary policy stance (Battellino et al., 1997). The sample period in this thesis starts from 1977, meaning that there is a period in which the OCR was not the primary instrument of monetary policy in Australia. However, this issue can be accounted for by comparing the results of our analysis by first using the full sample from Q2:1977 to Q3:2023 and then again from Q1:1990 to Q3:2023. The latter sample will allow us to analyse the effect of financial conditions on the RBA's conduct of policy only during the period in which the OCR was the central bank's primary instrument. However, the longer sample period remains important since it provides a much larger sample space for the PaR analysis and better reflects changes in financial conditions over time. The results from these two different sample periods can then be compared to assess whether there is any significant difference in effects.

In this section, I restrict the analysis to a sub-sample of the full dataset for both the FCI and macroeconomic variables to see the effects of financial conditions on monetary policy during the period in which the cash rate was the RBA's primary instrument for monetary policy.

Table 4 displays the results from the first stage regression of the PaR model using the sub-sample data for the FCI, OCR and macroeconomic variables.

Table 4: Sub-sample PaR First Stage Regression Results

Variable	Estimate	Standard Error	t-value	p-value	Significance
Intercept	0.1232	0.0643	1.92	0.0577	•
CPI inflation	0.1662	0.0534	3.11	0.0023	**
Output gap	0.0525	0.0303	1.73	0.0855	•
lag_FCI	-0.3976	0.0875	-4.54	$1.3e^{-05}$	***
lag_OCR	0.9335	0.0107	86.90	$<2e^{-16}$	***

Notes:
• indicates statistical significance at the 90% level.
* indicates statistical significance at the 95% level.
** indicates statistical significance at the 98% level.
*** indicates statistical significance at the 99.998% level.

As with the first stage regression from the full-sample PaR model, the macroeconomic variables CPI inflation and the output gap have a statistically significant positive effect on the OCR. When either inflation or economic growth increase, the RBA tends to increase the OCR, on average, by 16.62 and 5.25 basis points respectively.

In addition, the lagged FCI has a statistically significant negative effect on the OCR as in the full-sample PaR model in Section 5.1, indicating that the RBA still responded to changes in financial conditions, on average, during the period in which the cash rate was its principal instrument of monetary policy. This demonstrates the overall robustness of the first stage regression even during the shorter inflation targeting period.

Table 5 provides a summary of the quantile regression results for the PaR sub-sample analysis.

Table 5: Summary of sub-sample quantile regression results

	Intercept	**lag_FCI**
Quantile: 0.05	-0.4845	-0.2388
	(0.1070)	(0.2519)
Quantile: 0.25	-0.2184	-0.2355
	(0.0379)	(0.1809)
Quantile: 0.50	0.0069	0.1017
	(0.0292)	(0.0817)
Quantile: 0.75	0.1952	0.1150
	(0.0426)	(0.0666)
Quantile: 0.95	0.5129	0.3789
	(0.1624)	(0.3247)

Notes:
Standard errors (in parentheses)
* indicates statistical significance at the 95% level.

Restricting the sample from Q1:1990 to Q3:2023 in the sub-sample analysis yields very different results for the quantile regression. As seen in Table 5, none of the coefficients on lag_FCI are statistically significant at any of the quantiles. Furthermore, the previously statistically significant positive and negative coefficients for the 5th and 95th percentiles are now negative and positive respectively, demonstrating an opposite reaction by the RBA to tighter financial conditions to that in the baseline model. However, since these coefficients are statistically insignificant, we cannot conclude that the RBA responded more strongly when interest rates were low and less strongly when interest rates were higher than under its systematic policy.

The sub-sample quantile regression results confirm that the change in the RBA's monetary policy regime in the early 1990s[8] did have an impact on the RBA's response to financial conditions. It therefore suggests that the strong countercyclical responses of the RBA to financial conditions was largely driven by the pre-inflation targeting period before the 1990s. This may be because during the inflation targeting period, the RBA was less concerned about responding to short-term fluctuations in financial conditions, as it focused primarily on mitigating inflationary pressures in the economy, consistent with an inflation targeting mandate. Furthermore, the RBA may have taken a long-term view of financial stability, by enabling episodes of short-term tightening of financial conditions to achieve long-term financial stability. However, overall, we can conclude

[8] The RBA started using the OCR as its instrument for monetary policy in 1990 and then adopted an inflation targeting framework in around 1993 (McKibbin & Panton, 2018).

that due to none of the quantiles showing a statistically significant relationship, financial conditions had no overall effect on the distribution of monetary policy responses relative to the baseline model.

I run the same PaR model to assess the relationship between financial conditions and the OCR during the period from 1977 to 1990 in greater detail as part of a robustness check later in this thesis.

Figure 6 once again plots the conditional distribution of the OCR over time for each of the quantiles. Unlike the OCR's conditional distribution in the baseline model (Figure 5), the gaps between each of the quantiles are very small over the entire inflation targeting period from 1990 to 2023. This suggests that overall uncertainty about interest rates when responding to financial conditions during this period was very low, potentially because the RBA simply did not account for short-term changes in financial conditions when implementing monetary policy changes over the distribution.

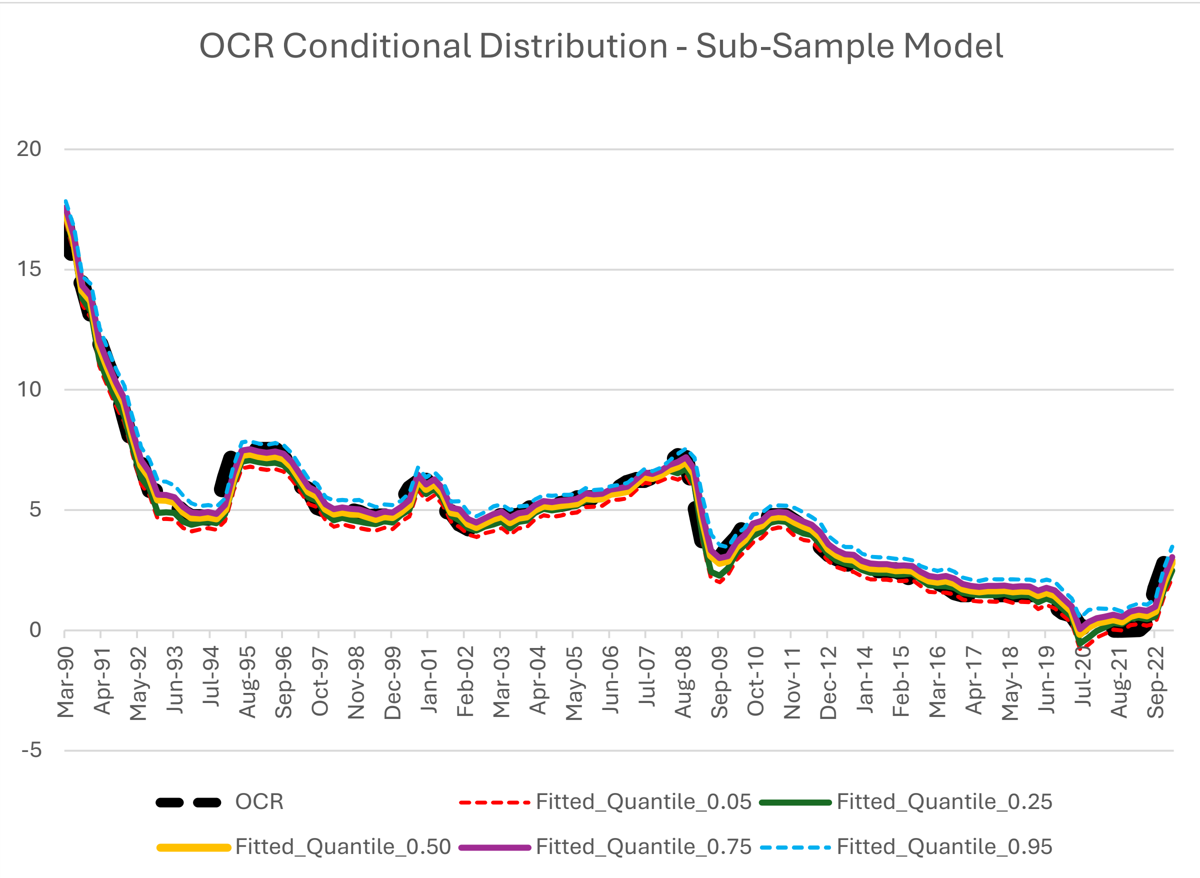

Figure 6: OCR conditional distribution (Quarterly) – Sub-sample PaR model

5.2 Robustness

This section includes some checks designed to assess the robustness of the primary results described in Section 5.1. I first run an additional modified version of the baseline PaR model. This involves restricting my analysis to the pre-1990s period (1977 -1989) to assess the influence of changing financial conditions on the RBA's monetary policy solely during the period when it was not explicitly targeting inflation. I then explore the differences in the uncertainty of the OCR over time by comparing the fitted quantile plots of this pre-1990s PaR model and the sub-sample model from Section 5.1.1. I do this by introducing a structural break between these two samples to clearly distinguish between the two periods.

I then conduct a check to confirm that the FCI used in the PaR model is exogenous of monetary policy effects. Through this test, I find that the original FCI constructed in this thesis is not influenced by monetary policy in an endogenous way, thus confirming its appropriateness in representing historical financial conditions in the PaR model.

5.2.1 Pre-Inflation Targeting Period

Recall the key results for both the baseline and sub-sample PaR models from Section 5.1. I found that, although the FCI has a statistically significant effect on the OCR at the two extreme quantiles (quantile 0.05 and quantile 0.95) in the baseline model, this relationship is not significant at any of the quantiles in the sub-sample model (from 1990 to 2023). However, to understand the potential reasons for the difference in results between these two samples, we need to analyse the relationship between financial conditions and monetary policy during the model's pre-inflation targeting period (from 1977 to 1989), and then compare these results with those of the sub-sample model. Allowing for a structural break in the quantile regression model between the pre-inflation targeting and inflation targeting periods permits us to more clearly identify what has changed in the FCI-OCR relationship at different points in time. We can then determine whether the difference in results between the baseline and sub-sample models is indeed due to the change in the RBA's monetary policy framework and approach in the early 1990s.

Table 6 contains the results from the first stage regression of this pre-1990 PaR model.

Table 6: Sub-sample PaR First Stage Regression Results

Variable	Estimate	Standard Error	t-value	p-value	Significance
Intercept	1.8012	1.0417	1.73	0.091	•
CPI inflation	0.0589	0.3527	0.17	0.868	
Output gap	0.3205	0.1929	1.66	0.103	
lag_FCI	0.2015	0.6775	0.30	0.768	
lag_OCR	0.8678	0.0753	11.52	$3.8e^{-15}$	***

Notes:
• indicates statistical significance at the 90% level.
* indicates statistical significance at the 95% level.
** indicates statistical significance at the 98% level.
*** indicates statistical significance at the 99.998% level.

The coefficients for both key macroeconomic variables (CPI inflation and the output gap) as well as for the lagged FCI (lag_FCI) are all statistically insignificant. This contrasts with the first stage results from both the baseline and sub-sample models, but this may simply be due to the very short sample period. However, the most interesting result is that, despite being insignificant, the coefficient on lag_FCI is positive, suggesting that the RBA set the OCR to be procyclical to changes in financial conditions from 1977 to 1989. In other words, when financial conditions tightened, the RBA tended to increase the OCR by 20.15 basis points, on average in this period.

Table 7 includes the results from the second stage quantile regression for this model.

Table 7: Summary of pre-1990 quantile regression results

	Intercept	Lag_FCI
Quantile: 0.05	-2.2573 (1.0274)	0.1286 (1.2590)
Quantile: 0.25	-0.5485 (0.3106)	1.0817* (0.5367)
Quantile: 0.50	0.5714 (0.2653)	0.3390 (0.6474)
Quantile: 0.75	0.9703 (0.3355)	0.1235 (0.5774)
Quantile: 0.95	3.1852 (0.8633)	0.5141 (1.3993)

Notes:
Standard errors (in parentheses)
* indicates statistical significance at the 95% level.

From Table 7, the lagged FCI (lag_FCI) only has a statistically significant effect on the OCR at the lower 25th percentile (quantile 0.25). The precise interpretation of this coefficient is that when the OCR is currently lower than implied by the RBA's policy reaction function, worsening financial conditions have less of an impact on the RBA lowering interest rates. This is consistent with the findings at the lower 5th percentile in the baseline model. The positive coefficients at the upper 75th and 95th percentiles suggest that the RBA is also less likely to decrease interest rates even when the OCR is higher than would be set under systematic policy. However, both coefficients are statistically insignificant.

Figure 7 plots the conditional distribution of the OCR over time for each of the quantiles in the period before the RBA adopted its inflation targeting framework.

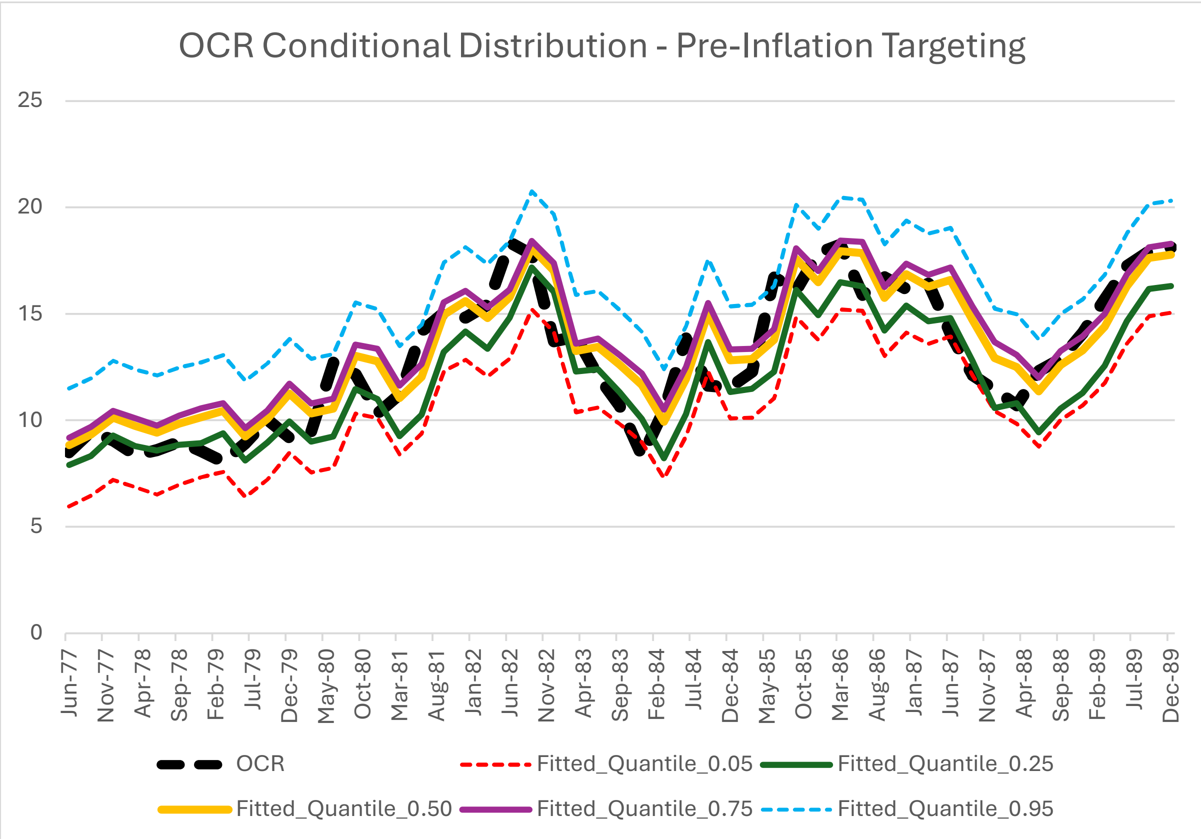

Figure 7: OCR conditional distribution (Quarterly) – Pre-1990 PaR model

In contrast to the OCR's conditional distribution from the sub-sample model (Figure 6), the gaps between each of the quantiles are now significantly larger. This suggests that there was higher uncertainty about interest rates responding to financial conditions during the period before inflation targeting was adopted in the early 1990s. One potential reason for this finding is that the RBA may have accounted for the state of financial considerations explicitly in its interest rate decisions, given that this was before the RBA based interest rate changes on the level of inflation (Bullock, 2023). Therefore, the RBA may have responded more frequently to short-term changes in financial conditions rather than focusing on longer-term financial stability, crucial to maintaining inflation within its 2-3% target range. This may explain the higher uncertainty regarding interest rate responses to financial conditions during this period.

Finally, it is useful to compare the uncertainty associated with the OCR over time by introducing a structural break between the pre-1990 and post-1990 sub-sample periods. In Figure 8, I plot the conditional distribution of the OCR and the fitted quantiles for both the pre-1990 and post-1990 periods, with a structural break at 1990, as opposed to the plot of the fitted quantiles for the baseline PaR model (Figure 5) which did not allow for a structural break between these two key periods of interest.

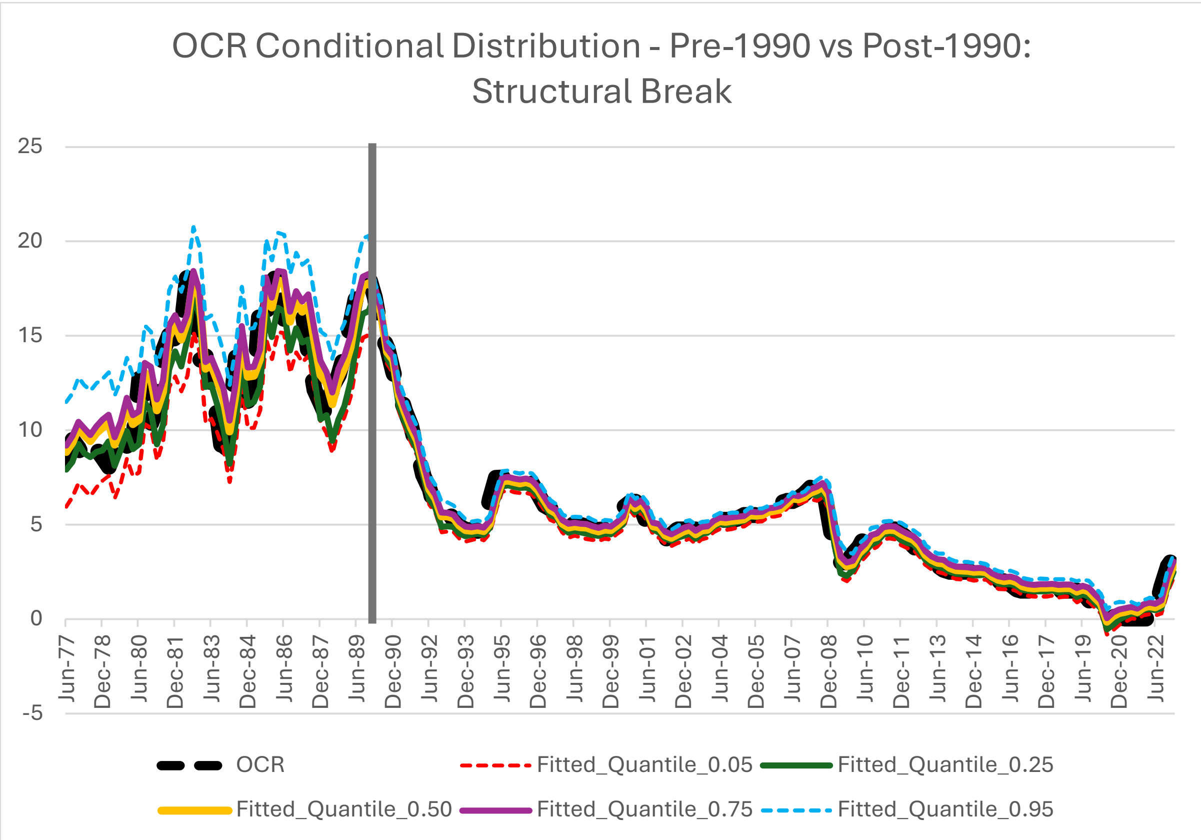

Figure 8: OCR conditional distribution (Quarterly) – Structural Break: Pre-1990 vs Post-1990

The structural break is represented by the grey vertical line, and it shows a clear distinction between the distributions of the OCR and fitted quantiles in both periods. As demonstrated earlier in Figure 7, the fitted quantiles show considerable dispersion during the pre-1990 period. These large gaps indicate that changing financial conditions had considerably uneven effects on monetary policy, being largely dependent on whether the OCR was initially high or low relative to systematic policy.

Moreover, the 95th percentile (blue dashed line) deviates significantly from the rest of the quantiles during the period from 1977 to 1989, suggesting the high sensitivity of the upper range of the OCR to changes in financial conditions. In other words, when the OCR was already at a very high level, the RBA was more likely to respond to changes in the FCI with a relatively large change in interest rates, compared to when the OCR was at lower initial levels.

However, in the post-1990 period, when the RBA adopted its inflation targeting regime and began officially using the OCR as its instrument of monetary policy, the gaps between the quantiles become significantly smaller. This suggests that the RBA's response to changes in financial conditions was fairly uniform across the distribution, primarily because monetary policy was more focused on maintaining price stability and full employment, as part of its inflation targeting framework.

5.2.2 Ensuring the FCI is Exogenous of Monetary Policy

A valid concern in the preceding PaR analysis is that there is potentially some endogeneity between the OCR and financial conditions represented by the FCI constructed in this thesis. For instance, asset prices, total credit and debt in the economy can be directly influenced by changes in interest rates by the RBA. Since this thesis focuses on the relationship between past financial conditions and current policy as opposed to the contemporaneous relationship between these two variables, the issue of endogeneity should not be a large concern. At the very least, the lagged FCI should be pre-determined and not correlated with the serially-uncorrelated residual in the first stage regression.

However, I conduct a robustness check to be fully confident that the issue of endogeneity is not serious. To ensure that any potential endogeneity between the OCR and FCI does not have an adverse impact on the PaR results, I check the relationship between these two variables by calculating the adjusted R-squared of each FCI component series with the exogenous monetary policy shock from Beckers (2020). If the R-squared figures between the individual FCI component series and the policy shock are all essentially zero, then this would indicate that there is no relationship between the FCI constructed in this thesis and monetary policy shocks.

The full set of R-squared calculations for each of the 71 FCI component series is provided in Table A3 in the appendix and some summary statistics are in Table 8 below:

Table 8: Adjusted R-Squared Summary Statistics

Statistic	Value
Mean Adjusted R^2	0.0013
Range	0.0553
Minimum Adjusted R^2	-0.0277
Maximum Adjusted R^2	0.0276
Standard Deviation	0.0102
25^{th} Percentile (Q1)	-0.0018
50^{th} Percentile (Median)	0.0009
75^{th} Percentile (Q3)	0.0054

Table 8 demonstrates that the adjusted R-squared figures for each of the FCI components are very close to 0, with an overall mean of 0.0013. The range of adjusted R-squared figures is also very low. Moreover, since the range of adjusted R-squared values fluctuates around 0 (highest ~ 0.03; lowest ~ -0.03), this indicates that there is no meaningful relationship between the overall FCI and monetary policy shocks. This is further supported by the very low adjusted R-squared figures for the 25^{th}, 75^{th} and median percentiles which suggest that all the original FCI component series essentially have no relationship with monetary policy shocks, thus demonstrating that this FCI is exogenous of any monetary policy effects.

The finding that monetary policy shocks explain almost no variation in the individual FCI component series is in line with the results of many empirical papers focusing on the effects of monetary policy shocks. For instance, Coibion (2012) finds that the real effects of monetary policy shocks in the US are quite small for a range of macroeconomic variables such as industrial production. Other papers such as Bernanke, Gertler and Watson (1997), and Faust, Swanson and Wright (2004) confirm the relatively small effects that monetary policy shocks have on GDP. It is therefore of little surprise that monetary policy shocks also have very minimal impacts on the financial variables included in this FCI.

6 Conclusion

As the literature regarding the conduct of monetary policy and how it is impacted by various macroeconomic outcomes and variables continues to grow, it is important to investigate the way in which variations in financial conditions impact the conduct of monetary policy. This is particularly important following the events of the GFC, which demonstrated that financial vulnerabilities and shocks can be very easily transmitted to the real economy. For this reason, this thesis investigated the distributional effects of financial conditions on the conduct of monetary policy in Australia by the RBA using a two-stage PaR regression model, where the first stage investigated the mean effect, and the second stage looked at the quantile effects.

I first determined the relationship between financial conditions and the RBA's conduct of monetary policy using the baseline PaR model for the entire period of data (1977-2023). In this model, I found that the lagged FCI has a statistically significant negative effect on the OCR in the first stage regression, while in the second stage regression, the coefficient on lagged FCI is only significant at the lower 5th (positive) and upper 95th (negative) percentiles. This indicated that when the OCR was already low compared to the rate that would be set under the RBA's policy reaction function (quantile 0.05), the RBA would be less responsive to worsening financial conditions, and it would have less of an effect on the RBA lowering interest rates. On the other hand, when the OCR was higher than the rate set by the RBA under systematic policy (quantile 0.95), worsening financial conditions would instead lead to a larger effect on the RBA lowering interest rates, meaning that it would be more responsive to worsening financial conditions.

I then assessed this same relationship by splitting the sample first into a sub-sample PaR model (from 1990-2023) and then a pre-inflation targeting model (from 1977-1989). While the lagged FCI again had a statistically significant negative mean effect in the sub-sample model, it did not have any statistically significant effects at any of the quantiles. On the other hand, in the pre-1990 PaR model, the lagged FCI had no statistically significant mean effect, but was significant at the 25th percentile.

Furthermore, I analysed the uncertainty associated with monetary policy under different financial conditions over time by looking at the OCR's conditional distribution incorporating the fitted quantiles for each of the three versions of the PaR models. This also included an extra plot incorporating a structural break between the two sub-samples which revealed that uncertainty associated with the OCR's response to changing financial conditions was significantly higher in the pre-1990 period, as represented by the more dispersed fitted quantiles, compared to the post-1990 period.

Another important part of this thesis was conducting a robustness check to ensure that the FCI used in the PaR models was not influenced by any endogenous monetary policy effects. This was done due to the concern that many measures of financial activity can be correlated with changes in interest rates. I did this by calculating the R-squared for each FCI component with the Beckers (2020) exogenous monetary policy shock series. Since the R-squared figures for all components were very low and essentially equal to zero, I confirmed that there were no such endogenous monetary policy effects.

There are several potential lines of future research that could extend the analysis presented in this thesis. First, since the novel PaR model developed in this thesis revealed some interesting characteristics of monetary policy's response to financial conditions (especially its dependence on the lagged level of the OCR) in Australia, it would be interesting to see whether these effects persist in other advanced economies with inflation-targeting central banks, such as the US or EU.

Secondly, it may be beneficial to assess the effects of monetary policy on financial conditions, reversing the relationship assessed in this thesis. This follows the work of Hambur and Haque (2023) who assessed the effects of monetary policy on a range of macroeconomic variables using high-frequency data around the points in time when announcements of monetary policy decisions were made. Using monetary policy shocks at times of interest rate decisions could provide clearer causal effects as opposed to simply looking at rate changes and this could provide interesting insights into how financial conditions are influenced by such monetary policy shocks.

Finally, since this thesis considered conventional monetary policy responses to financial conditions, another interesting area of research might be to analyse whether changes in financial conditions have spillover effects on the conduct of unconventional policies such as quantitative easing (QE). While papers such as Weale and Wieladek (2022) analyse the effects of QE on asset prices, credit and bond spreads, it would be beneficial to see how such conditions, in turn, influence the QE policies of central banks. This is especially of interest given that QE and other unconventional monetary policies were crucial components of the policy response to the GFC as well as to the COVID-19 economic downturn, and they remain effective methods of stimulating economic activity.

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Appendix

Table A1: FCI Components

Table containing the data series used to estimate the FCI, including source, economy, and date range.

No.	Variable Name	Source	Economy	Start Date	End Date
Survey Measures					
1	Business: Difficulty getting finance	ACCI-WBC	Aus	Q2:1966	Q3:2023
2	Consumer: Family finances now	WBC-MI	Aus	Q4:1974	Q2:2023
Interest Rates and Spreads					
3	3-year Australian Government Security (AGS) yield	RBA	Aus	Q3:1992	Q2:2023
4	5-year AGS yield	RBA	Aus	Q3:1976	Q2:2023
5	10-year AGS yield	RBA	Aus	Q3:1976	Q2:2023
6	Spread: 3-month bank bill to OCR	ASX; RBA	Aus	Q3:1976	Q2:2023
7	Spread: 3-year AGS to OCR	RBA	Aus	Q3:1992	Q2:2023
8	Spread: 5-year AGS to OCR	RBA	Aus	Q3:1976	Q2:2023
9	Spread: 10-year AGS to OCR	RBA	Aus	Q3:1976	Q2:2023
10	Federal funds rate (FFR)	FRED	US	Q3:1976	Q2:2023
11	3-month Treasury bill (Tbill) yield	FRED	US	Q3:1976	Q2:2023
12	3-year Treasury bond (TB) yield	FRED	US	Q3:1976	Q2:2023
13	10-year TB yield	FED	US	Q3:1976	Q2:2023
14	Spread: 3-month Tbill to FFR	FRED	US	Q3:1976	Q2:2023
15	Spread: 3-year TB to FFR	FRED	US	Q3:1976	Q2:2023
16	Spread: 10-year TB to FFR	FRED	US	Q3:1976	Q2:2023
17	Spread: 10-year AGS to 10-year USTB	RBA; FRED	Aus/US	Q3:1976	Q2:2023
Credit and Money					
18	Total credit	RBA	Aus	Q3:1976	Q2:2023
19	Housing credit	RBA	Aus	Q3:1976	Q2:2023
20	Personal credit	RBA	Aus	Q3:1976	Q2:2023
21	Business credit	RBA	Aus	Q3:1976	Q2:2023
22	Owner-occupier housing loan approvals (excluding refinancing)	ABS	Aus	Q1:1985	Q1:2023
23	Investor housing loan approvals (excluding refinancing)	ABS	Aus	Q1:1985	Q1:2023
24	Commercial fixed term loan approvals (excluding refinancing)	ABS	Aus	Q1:1985	Q2:2023

No.	Variable Name	Source	Economy	Start Date	End Date
25	Commercial revolving credit approvals (excluding refinancing)	ABS	Aus	Q1:1985	Q2:2023
26	Personal fixed term loan approvals (excluding refinancing)	ABS	Aus	Q1:1985	Q1:2023
27	Personal revolving credit approvals (excluding refinancing)	ABS	Aus	Q1:1985	Q1:2023
28	M1	RBA	Aus	Q3:1976	Q1:2023
29	M3	RBA	Aus	Q3:1976	Q1:2023
30	Broad money	RBA	Aus	Q3:1976	Q1:2023
31	Money base	RBA	Aus	Q3:1976	Q1:2023
Asset Prices					
32	Dwelling price index	CoreLogic	Aus	Q1:1980	Q2:2023
33	House price index	CoreLogic	Aus	Q1:1980	Q2:2023
34	Apartment price index	CoreLogic	Aus	Q1:1980	Q2:2023
35	Dwelling price index	FRED	US	Q1:1987	Q1:2023
36	All commercial property return index	MSCI	Aus	Q4:1984	Q1:2023
37	Retail property return index	MSCI	Aus	Q4:1984	Q2:2023
38	Office property return index	MSCI	Aus	Q4:1984	Q2:2023
39	Industrial property return index	MSCI	Aus	Q4:1984	Q2:2023
40	ASX 200 Index	Refinitiv; RBA	Aus	Q3:1976	Q2:2023
41	ASX 200 Financials Index	Refinitiv; RBA	Aus	Q3:1976	Q2:2023
42	ASX 200 Other Index	Refinitiv; RBA	Aus	Q3:1976	Q2:2023
43	ASX 200 Resources Index	Refinitiv; RBA	Aus	Q3:1976	Q2:2023
44	S&P 500 Index	FRED	US	Q3:1976	Q2:2023
45	RBA Index of Commodity Prices (AUD)	RBA	Aus	Q3:1976	Q2:2023
46	Gold (3pm London bullion market, USD)	FRED	US	Q3:1976	Q2:2023
47	Crude oil (West Texas intermediate, USD)	FRED	US	Q3:1976	Q2:2023
48	Australian dollar trade-weighted index (TWI)	RBA	Aus	Q3:1976	Q2:2023
Debt Securities Outstanding					
49	Short-term: Australia; banks	RBA	Aus	Q4:1992	Q2:2023
50	Short-term: Australia; non-financial corporations	RBA	Aus	Q4:1992	Q2:2023
51	Long-term: Australia; banks	RBA	Aus	Q4:1992	Q2:2023
52	Long-term: Australia; non-financial corporations	RBA	Aus	Q4:1992	Q2:2020
53	Short-term: Australia; government	RBA	Aus	Q4:1992	Q2:2023

No.	Variable Name	Source	Economy	Start Date	End Date
54	Long-term: Australia; government	RBA	Aus	Q4:1992	Q2:2023
55	Long-term: Overseas; non-government	RBA	Aus	Q4:1992	Q2:2023
56	Short-term: Australia; asset-backed securities	RBA	Aus	Q4:1992	Q1:2021
57	Long-term: Australia; asset-backed securities	RBA	Aus	Q4:1992	Q1:2023
58	Long-term: overseas; asset-backed securities	RBA	Aus	Q4:1992	Q1:2020
59	Residential mortgage-backed securities	RBA	Aus	Q4:1992	Q2:2023
Banking Sector					
60	Tier 1 capital ratio	APRA; RBA	Aus	Q2:1989	Q2:2023
61	Non-performing assets ratio	APRA; RBA	Aus	Q2:1990	Q2:2023
62	Distance to default	RBA	Aus	Q1:1983	Q2:2020
Financial System Complexity					
63	Total financial institutions' assets to nominal GDP	ABS; RBA	Aus	Q1:1990	Q1:2023
64	Total off-balance sheet to fixed income assets	ABS; RBA	Aus	Q1:1990	Q1:2023
Leverage Measures					
65	Household debt to assets	ABS; RBA	Aus	Q3:1988	Q1:2023
66	Household debt to income	ABS; RBA	Aus	Q2:1988	Q1:2023
67	Household interest payments to income	RBA	Aus	Q1:1977	Q1:2023
68	Current account balance to nominal GDP	ABS	Aus	Q3:1976	Q1:2023
69	Net total foreign liabilities to nominal GDP	ABS	Aus	Q3:1988	Q1:2023
Risk Indicators					
70	Chicago Board Options Exchange equity volatility (VIX Index)	FRED	US	Q4:1986	Q2:2023
71	Moody's corporate bond yield spread: BAA to AAA	FRED	US	Q3:1976	Q3:2023

Notes:
'ABS' is Australian Bureau of Statistics; **'ACCI-WBC'** is Australian Chamber of Commerce and Industry-Westpac; **'ASX'** is Australian Securities Exchange Ltd; **'FRED'** is Federal Reserve Economic Database, Federal Reserve Bank of St. Louis; **'MSCI'** is Morgan Stanley Capital International; **'WBC-MI'** is Westpac and Melbourne Institute

Table A2: Sequential Granger Causality Tests – *p* values

	Lag Length			
	1	2	3	4
Quarterly				
GDP does not Granger-cause FCI	0.1413	0.8198	1.00	1.00
FCI does not Granger-cause GDP	3.24E-07	7.83E-06	8.97E-06	2.25E-05
CPI does not Granger-cause FCI	0.0876	0.4512	1.00	1.00
FCI does not Granger-cause CPI	0.4138	0.3823	0.3018	0.081
OCR does not Granger-cause FCI	0.6295	1.00	1.00	1.00
FCI does not Granger-cause OCR	1.00	1.00	1.00	1.00
Year-Ended				
GDP does not Granger-cause FCI	0.4404	1.00	1.00	1.00
FCI does not Granger-cause GDP	6.18E-06	1.92E-05	4.59E-05	9.80E-06
CPI does not Granger-cause FCI	1.00	1.00	1.00	1.00
FCI does not Granger-cause CPI	1.00	0.8996	0.4641	0.6047
OCR does not Granger-cause FCI	1.00	1.00	1.00	1.00
FCI does not Granger-cause OCR	1.00	0.1907	0.0849	0.0526

Notes**:**
All *p*-values have been adjusted using the Bonferroni correction method (as used in Hartigan & Wright, 2023); **'GDP'** is the growth rate of nominal gross domestic product converted to a measure of the output gap using the BN Filter (Kamber, Morley & Wong, 2024); **'CPI'** is the growth rate of the domestic consumer price index; **'OCR'** is the growth rate of the domestic overnight cash rate

Table A3: R-squared - FCI and Exogenous Monetary Policy Shock

Series	R^2	Series	R^2
BUSINESS	0.0200	ASXOTHER	0.0070
CONSUMER	0.0141	ASXRES	0.0001
FCMYGBAG3	-0.0036	SP500	-0.0015
FCMYGBAG5	-0.0044	QNUCOMPI	0.0009
FCMYGBAG10	-0.0060	GOLD	2.17E-05
SCRIB90	0.0034	WTI	-0.0001
SCRIGBAG3	-0.0262	FXRTWI	0.0009
SCRIGBAG5	-0.0216	DSOSNAB	-0.0035
SCRIGBAG10	-0.0103	DSOSNANC	0.0097
FFYF	0.0054	DSOLNAB	0.0001
TB3MS	0.0033	DSOLNANC	0.0075
GS3	0.0005	DSOGSAS	0.0159
GS10	-0.0006	DSOGSAL	-0.0230
STB3MFFYF	0.0157	DSONSOT	0.0025
SGS3FFYF	0.0276	DSOSNAA	-0.0031
SGS10FFYF	0.0163	DSOLNAA	0.0055
SCRIGBAGGS10	0.0041	DSONSOA	0.0077
DLCACS	0.0014	DSOMIRMS	0.0076
DLCACH	0.0010	DLCAOHT	0.0041
DLCACOPS	0.0016	DLCAIHT	0.0187
DLCACBS	8.61E-06	DLCACF	0.0026
DMAM1S	-0.0019	DLCACR	-0.0004
DMAM3S	0.0004	DLCAPF	0.0095
DMABMS	0.0001	DLCAPR	-0.0070
DMAMMB	-0.0215	T1CAP	-0.0008
DWELP	0.0019	NPA	-0.0277
HOUSEP	0.0020	DTD	0.0201
APARTP	0.0016	TOTALFIA	-0.0004
CSUSHPISA	0.0101	BBCGOTOS	0.0028
COMMPROP	-0.0049	BHFDA	-0.0017
RETAILPROP	-0.0010	BHFDDIT	-0.0019
OFFICEPROP	-0.0072	BHFIPDT	0.0023
INDUSTPROP	-0.0085	HCAGSCPGDP	1.68E-05
ASX200	0.0027	HANFLST	0.0005
ASXFIN	0.0091	VXOCLS	0.0203
		CDRISK	-0.0074