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Financial and Business Cycles in Brazil

by Ivo Krznar and Troy Matheson

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Financial and Business Cycles in Brazil[1]

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Abstract

This paper explores the nexus between the financial cycle and business cycle in Brazil. Cycles are estimated using a variety of commonly-used statistical methods and with a small, semi-structural model of the Brazilian economy. An advantage of using the model-based approach is that financial and business cycles can be jointly estimated, allowing information from all key economic relationships to be used in a consistent way. The results show that Brazil is now in the downturn phase of the financial cycle. Moreover, the results underscore the importance of macro-financial linkages and highlight risks to the recovery going forward.

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[1] We would like to thanks the Brazilian authorities for useful discussions or comments. The authors are solely responsible for all errors and omissions.

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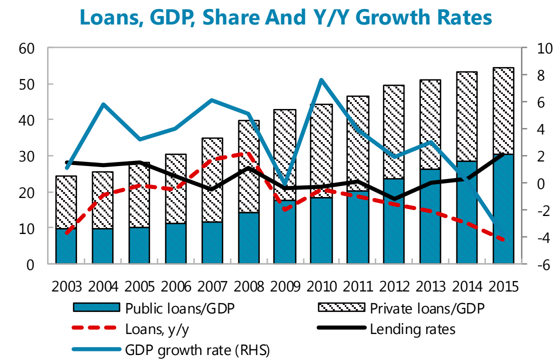
I. Introduction

In the decade prior to the recent recession, Brazil enjoyed a period of rapid economic expansion and relatively easy financial conditions (Chart). With the exception of a short and shallow recession in 2009, annual GDP growth averaged 4.5 percent in the period from 2004 to 2013; the unemployment rate halved, the policy rate trended down, and lending rates fell by almost 10 percentage points. The perception of foreign investors was also favorable until 2014 making the price of foreign borrowing low. Credit expanded very rapidly, more than doubling as a share of GDP since 2004 (from 25 percent of GDP in 2004 to 55 percent at the end of 2015), with a particularly sharp rise in public sector credit following the global financial crisis.



Source: Fund staff estimates.

While some of the rise in credit growth in Brazil can be attributed to financial deepening and rising income levels, it may have implications for economic activity going forward. Cross-country evidence suggests that periods of easy financial conditions can amplify economic fluctuations and possibly lead to adverse economic outcomes. For example, Jorda and others (2013) show that periods of strong credit growth are typically followed by periods of sluggish economic activity. Drehmann and others (2012) and Claessens and others (2011a) further show that the duration and amplitude of recessions and recoveries are influenced by the strength and intensity of financial cycles, with downturns being longer and deeper if accompanied by disruptions in financial and housing markets.

This paper assesses the importance of financial market developments for the business cycle in Brazil. To explore the nexus between the financial cycle and business cycle, cycles are estimated using a variety of commonly-used statistical methods and with a small, semi-structural model of the Brazilian economy. An advantage of using the model-based approach is that financial and business cycles can be jointly estimated, allowing information from all key economic relationships to be used in a consistent way. The model also allows a formal examination of linkages between financial and business cycles using impulse response functions and historical shock decompositions. The results underscore the importance of macro-financial linkages in Brazil and highlight the potential risks of a slow economic recovery going forward. We conclude with some policy implications.

II. Literature Review

While there is no consensus on the definition of the financial cycle, two main approaches to analyze short- and medium-term developments in financial markets have been used in the literature.

- **Financial/Credit cycles: medium-term concept.** One strand of the literature focuses on credit, credit-to-GDP and property prices either taken individually (see Aikman and others, 2013; Jorda and others, 2011, Dell'Arriccia and others, 2012 for studies focusing on credit only; and Claessens and others, 2011a, 2011b for studies focusing on credit and property prices) or combined (Drehmann and other, 2012).[2] Beyond credit and house prices, equity prices are found to behave differently from house prices and credit variables; they exhibit greater short-term volatility and are less clearly associated with financial crises (Claessens and others, 2011; Drehmann and other, 2012). The financial cycle is then defined either as an average of a cyclical component of the financial variables, most frequently real credit, credit-to-GDP or property prices, extracted using a univariate, statistical filter targeting a specific frequency. Alternatively, a financial cycle can be identified using turning-point analysis algorithms that that define downturn phases (from peak to trough) and upturn phases (from trough to the next peak). Most of the literature suggests that the financial cycles evolve at a relatively slow pace and capture medium-term developments in financial markets.[3]

- **Financial conditions index: short term concept.** Another strand of the literature combines a variety of financial variables into a financial conditions index (FCI) (see Ng, 2011; Hatzius and others 2010). These indexes can be thought of as capturing short-term developments in financial markets.

Financial sector developments are found to be an important source of macroeconomic fluctuations. Financial accelerator models highlight the role of credit and asset prices in shaping the business cycle (see, for example, Bernanke and Gertler, 1989, Bernanke, Gertler and Gilchrist, 1999, Kiyotaki and Moore, 1997). Models that highlight strategic complementarities between banks that generate a tendency for banks to collectively take on more risk suggest that small changes in fundamentals can generate large swings in credit. There is a growing empirical literature documenting the importance of financial factors for business cycle fluctuations (Claessens and others, 2011a) and systemic crises (Dell'Arricia and others, 2012). Moreover, the financial cycle is closely associated with banking crises (Aikman and others, 2013), which tend to occur close to cyclical peaks and lead to severe recessions (Borio, 2012).

Understanding the role of the financial cycle is key for policy design. The financial cycle can help to identify risks of a financial crisis in the future. For example, Borio and Drehmann (2009) suggest that deviations of credit-to-GDP and asset prices from their trends are the best leading indicators of financial crises. Furthermore, the literature has shown that financial conditions indices are good leading indicators of growth.[4] As such, policymakers can use measures of the

[2] Borio (2012) claims that combining credit and property prices is a useful way to characterize the financial cycle, because credit booms are often associated with housing bubbles, reinforcing risks to financial stability.

[3] For example, Drehmann and others (2012) find that the average length of financial cycle in advanced economies has been around 16 years and Claessens and others (2011a) find that financial cycles are longer, deeper and sharper than business cycles.

[4] See, for example, English and others (2005), Estrella and Trubin (2006), Hatzius and others (2010), Ng (2011).

financial cycle to better identify risks of financial crisis, allowing them to build buffers during the financial booms that can be released during the downturns, thereby stabilizing the system.

III. Characterizing Brazilian Financial Cycles

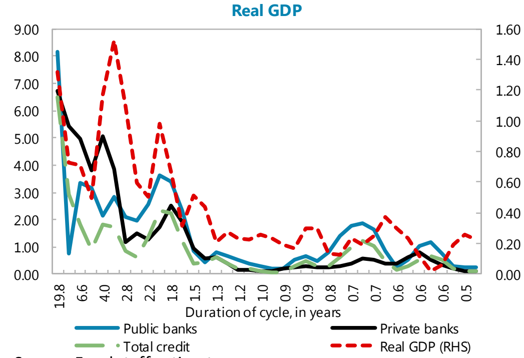
To characterize the financial cycle in Brazil, two complementary approaches are used. Since time series of house price indices are too short and equity prices exhibit significant short-term volatility, the focus is on medium-term credit cycles only.[5] A broader range of financial variables that help to characterize the financial cycle at a higher frequency are summarized in a financial conditions index (FCI).

In addition to statistical measures of financial cycles, a semi-structural model of the Brazilian economy is used to jointly estimate financial and business cycles. When extracting a cycle, univariate statistical filters take into account only the data of the time series being filtered. One advantage of using a multivariate, model-based approach is that it allows information from all key economic relationships to be used in a consistent way to estimate cycles. Moreover, the model can be used to quantitatively assess the linkages between business and credit cycles and to project all variables of interest, including credit and GDP.

Statistical methods

A band-pass filter is used to isolate credit cycles at a medium-term frequency. The methodology employed in Borio and others (2012) is used; this involves employing the band-pass filter developed by Christiano and Fitzgerald (2003) to isolate a cycle in real credit and credit to GDP, defined as a deviation of the two series from their trends. Cycles are extracted under the assumption that financial cycles have much lower frequency (8 and 20 years) than business cycles.[6] The estimated spectral densities of real credit growth justify setting a medium term frequency range to extract credit cycles (Chart).[7] The first peak in the density of real credit growth corresponds to a medium-term cycle with duration of around 20 years. The density also identifies a

Estimated Spectral Density For Real Credit Growth, Real GDP



Source: Fund staff estimates.

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[5] The OECD data on real house prices in Brazil start in 2008. Brazil's sale and lease price indices are also available since 2010 or 2012. While the central bank's residential real estate collateral value index is longer and available from 2001 only the HP trend component (calculated using a smoothing parameter of 3,600) is publicly available.

[6] The choice of 20 years as an upper bound is a function of data availability that start in 1995 following the implementation of the "Plano Real" stabilization program.

[7] A spectral density shows contributions to the series' variance from cycles at different frequencies. When a specific frequency accounts for the spectrum more than others, it features a peak at that frequency—defining the period of the underlying cycle.

number of peaks at higher frequency, corresponding to short-term cycles with duration of less than 4 years. The data were filtered for each series and combined into the aggregate credit cycle, the financial cycle, by averaging the two filtered series.[8,9]

Information in many financial variables was combined into a single indicator, an FCI, using principal component analysis (Table 1). The estimated spectral density also identified the importance of short-term developments for the overall variation in credit. To analyze the short-term financial market developments, an FCI is constructed. The following data are included to estimate the FCI: (i) risk measures (money market spread); (ii) collateral values (stock prices, house prices); (iii) quantities (total credit); and (iv) external financial conditions (EMBI, real exchange rate).[10] The FCI also includes interest rates.[11] The FCI is the first principal component of all the variables described above; it is essentially a weighted average the variables where the weights are derived so that the index explains the maximum amount of variation of all observed financial variables.[12] The weights (or "loadings") are displayed in Table 1.

Table 1. Variables Included in the Estimation of Financial Conditions Index 1/

Variable	Loadings
EMBI, y/y	0.44
Money market spread	0.14
Lending rate, y/y	0.52
Selic, y/y	0.51
Total loans, y/y	-0.05
Real exchange rate	-0.14
Stock prices, y/y	-0.48

Source: Fund staff estimates.
1/ The financial conditions index explains 42 percent of the covariance between the variables included in the estimation.

[8] Filtered series are additive as long as they are standardized.

[9] As a cross-check, HP filters were used as an alternative approach to isolating the trend component building on the BCBS's guidance for calculating credit gaps (one sided filter with the smoothing parameter lambda corresponding to cycles lasting 32 to 80 quarters). This led to broadly similar findings. Likewise, using the BIS broad definition of credit to non-financial sector, the filter identifies one more peak in the credit cycle in 2002 that can be explained by higher external borrowing by the corporate sector that ended following a sudden stop.

[10] CDS was not included as its dynamics are very similar to those of the EMBI but the data are only available from 2001.

[11] If the financial cycle is defined as fluctuations in perceptions and attitudes about financial risks (as in Ng, 2011), interest rates, which are predominantly driven by monetary policy, should not be included in the estimation of the FCI.

[12] To ensure stationarity, spreads were taken in levels, while collateral values, EMBI, interest rates, quantities are taken in y/y growth rates.

Quarterly projection model

A semi-structural model is used to estimate financial and business cycles and to model macro-financial linkages. The model is a variant of the models developed in Carabenciov and others (2008), and includes equations for output, inflation, interest rates, foreign demand, and the real exchange rate, among other key macroeconomic variables. Two versions of the model are developed: a version that includes total real credit and a version that includes real public and real private credit separately to account for differences in the behavior of private banks' and public banks' credit. The financial cycles in the model are defined as a credit cycle—the deviation of real credit from its trend estimated using the model—and the cycle in the FCI described above. Financial and business cycles are jointly estimated by specifying relationships between the cycles based on economic theory and empirical evidence, where the trend of each variable is endogenously determined. The models are estimated using Bayesian methods, with the sample beginning in 1999 and ending in 2015Q3. Appendices A and B provide more details on the model specifications and the parameter estimates.

The models incorporate key assumptions about financial and business cycles:

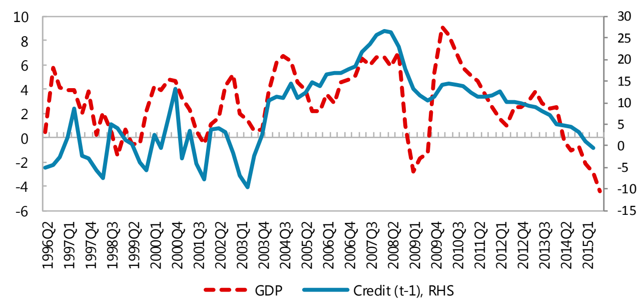
- The credit cycle is positively correlated with the business cycle and lags it by one quarter (Chart). The lagging relationship is motivated by the observation the banks cannot immediate adjust their credit levels in response to demand shocks (for example, due to an inability to recall credit that has already been extended).

- The FCI leads real GDP growth by two quarters and financial conditions ease with expectations of stronger growth (Chart).

- Autonomous shocks to credit (unrelated to demand developments) boost demand.

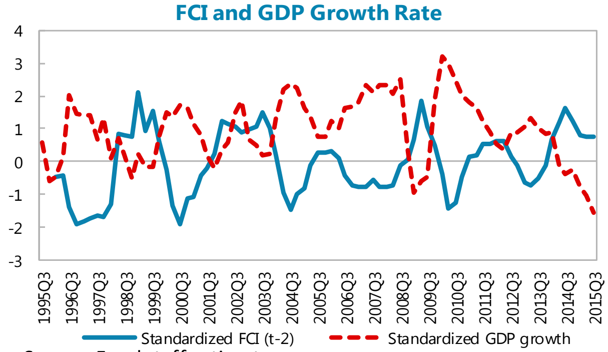
- An autonomous tightening of financial conditions (unrelated to demand developments) reduces demand.

Credit and GDP, Y/Y Growth Rates, in Percent



Source: Fund staff estimates.

FCI and GDP Growth Rate



Source: Fund staff estimates.

IV. Results

Brazil is currently in a downturn phase of the credit cycle. The statistical filter and the model identify one medium-term financial cycle in total credit with the trough in 2004–05 and the peak in 2010–11.[13] Dynamics of public and private cycles are somewhat different, reflecting the countercyclical use of public banks over 2008–13.

The FCI shows four episodes of rapid tightening in financial conditions since 1996. The first period is characterized by a loss of foreign investors' confidence associated with spillovers from the Asian Crisis in the period from mid-1997 to mid-1999 and the second period relates to the 2002 sudden-stop episode. Financial conditions were relatively easy following the 2002 episode up until the global financial crisis, which, in Brazil, was mostly marked by tighter external conditions. The last period of tighter financial conditions started in 2013 and was initially sparked by heightened uncertainty about the future course of monetary policy in the U.S. (the so-called "taper tantrum"), and subsequently followed by adverse domestic developments that resulted in lower credit growth, higher interest rates and spreads, and a depreciation of real.

Panel 1 highlights a tight correlation between financial market developments and the business cycle. *Both model-based and statistical-based estimates of financial and business cycles suggest that the financial cycle has both a longer duration and is of larger magnitude than the business cycle. The results also suggest that for every 1 percent increase in the output credit increases by around 3 to 5 percent, on average. Panel 1 also suggests that the business and the financial cycles move in tandem. Moreover, real GDP growth lags the financial conditions. Both facts suggest that financial sector developments are important for economic fluctuations in Brazil.*

Impulse responses underline the importance of demand shocks for credit and financial conditions shocks for output. The estimated financial linkages between real credit for the aggregate and disaggregate models are displayed in Panel 2 and Panel 3. For comparison, simple bivariate VARs are also estimated over the same sample.[14] The impulse responses following 1 percent shocks to output, credit and financial conditions suggest the following:

- ***Credit responds more to output than output responds to credit.*** In the aggregate model, a 1 percent shock to output leads to an increase in credit of around 0.7 percent, while a 1 percent shock to credit leads around a 0.3 percent increase in output. Likewise, in the disaggregate model, the public and private credit responses to demand shocks are less than half the size of the demand responses to credit.

- ***The peak impact of output and credit shocks occurs around one year after the shock.*** While the peak impacts on output and credit following shocks occurs relatively quickly, the

[13] It also appears that the medium term financial cycle in Brazil lags behind the financial cycles in the advanced economies (see Drehmann and other 2012 for financial cycles of other economies).

[14] The bivariate VARs include real credit or the financial conditions index and the output gap; where possible, the shocks are identified in a recursive manner based on the same timing assumptions used in the structural models. In each specification, real credit and real GDP are de-trended using a standard HP filter (i.e., λ=1600). Median impulse responses are displayed along with the 10th and 90th percentiles obtained from bootstrapped distributions.

effects of the shocks are persistent; a 1 percent shock to output boosts credit for between 2 and 3 years, likewise for the impacts of credit shocks on output.

- ***Private credit is more responsive to output shocks than public credit.*** Private credit increases by 1 percent following a positive output shock, while public credit only increases by around 0.7 percent. This result is not surprising. Intuitively, the extension of credit by private banks is likely more driven by macroeconomic developments than that extended by public banks, who have adopted countercyclical policy measures in the past.

- ***Output responds strongly to shocks to financial conditions.*** While financial conditions loosen following a positive demand shock, the response is relatively small and short-lived. On the other hand, there is a significant reaction of output to shocks to financial conditions.

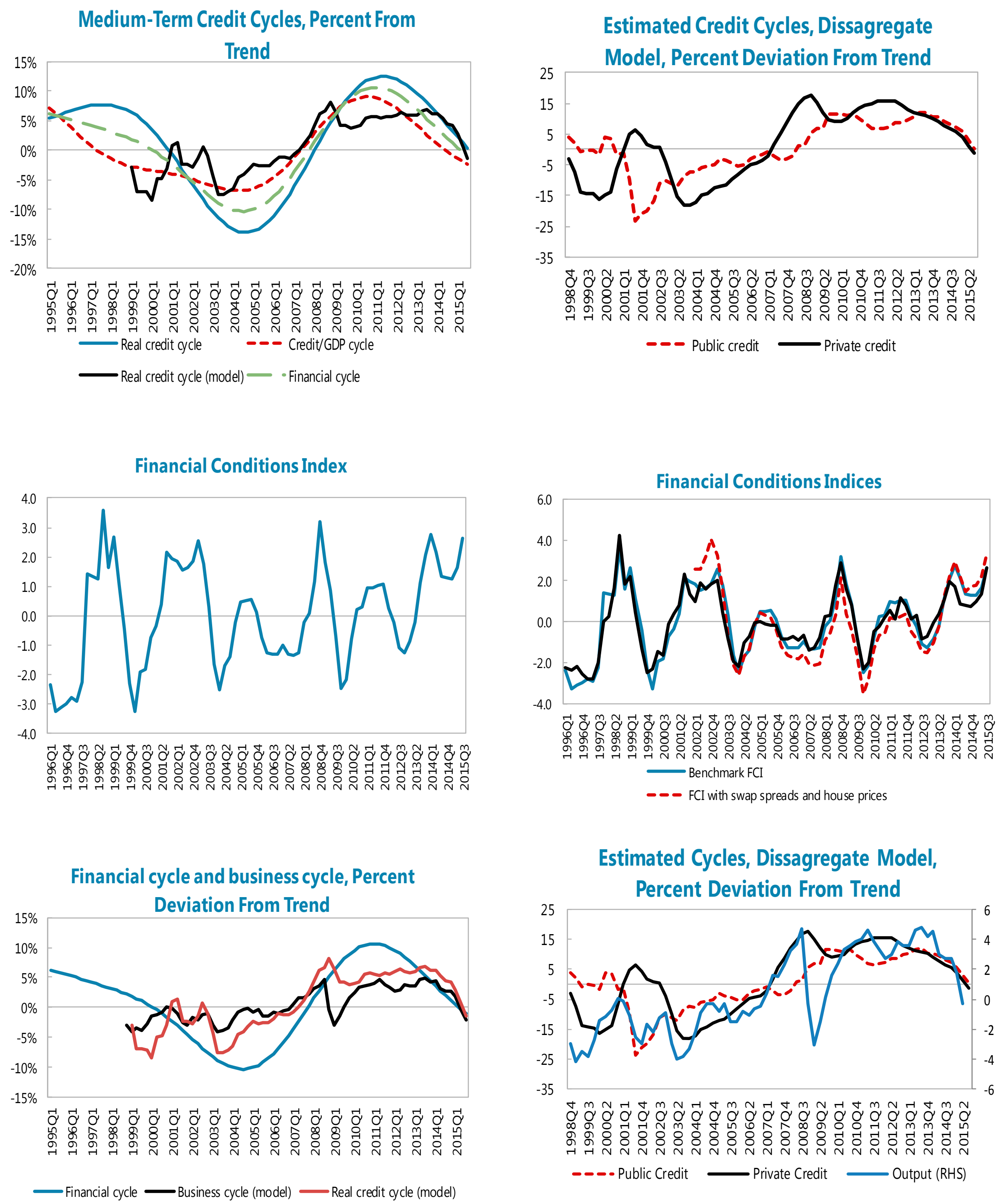
Historical decomposition of the output gap suggests that both short-term financial conditions shocks and medium-term credit shocks are important in explaining fluctuations in economic activity. The impacts of financial shocks on output since 1999 are displayed in Figures 4 and 5:

- **Private credit boosted output in the lead up to the global financial crisis and public credit boosted output following the crisis.** Strong growth in private credit in over 2005 to 2008 acted to support output. When the crisis hit in late 2008, private credit growth began to slow as private banks acted to bolster their balance sheets. At the same time, public credit was expanded in an effort to support demand after the crisis, providing a boost to output over 2009–10. The impact of the slowdown in private credit growth can be seen in the drop in importance of private credit shocks towards the end of 2008. Likewise, public credit went from being broadly neutral for growth in the lead up the crisis to being strongly expansionary.

- **Financial conditions played an important role both during the 2008/2009 and during the recovery period.** Looser financial conditions were a key driver in the 2009 recovery of output. The positive impact of financial conditions lasted until 2013 when financial conditions tightened drastically following the taper tantrum and a rise in foreign funding costs.

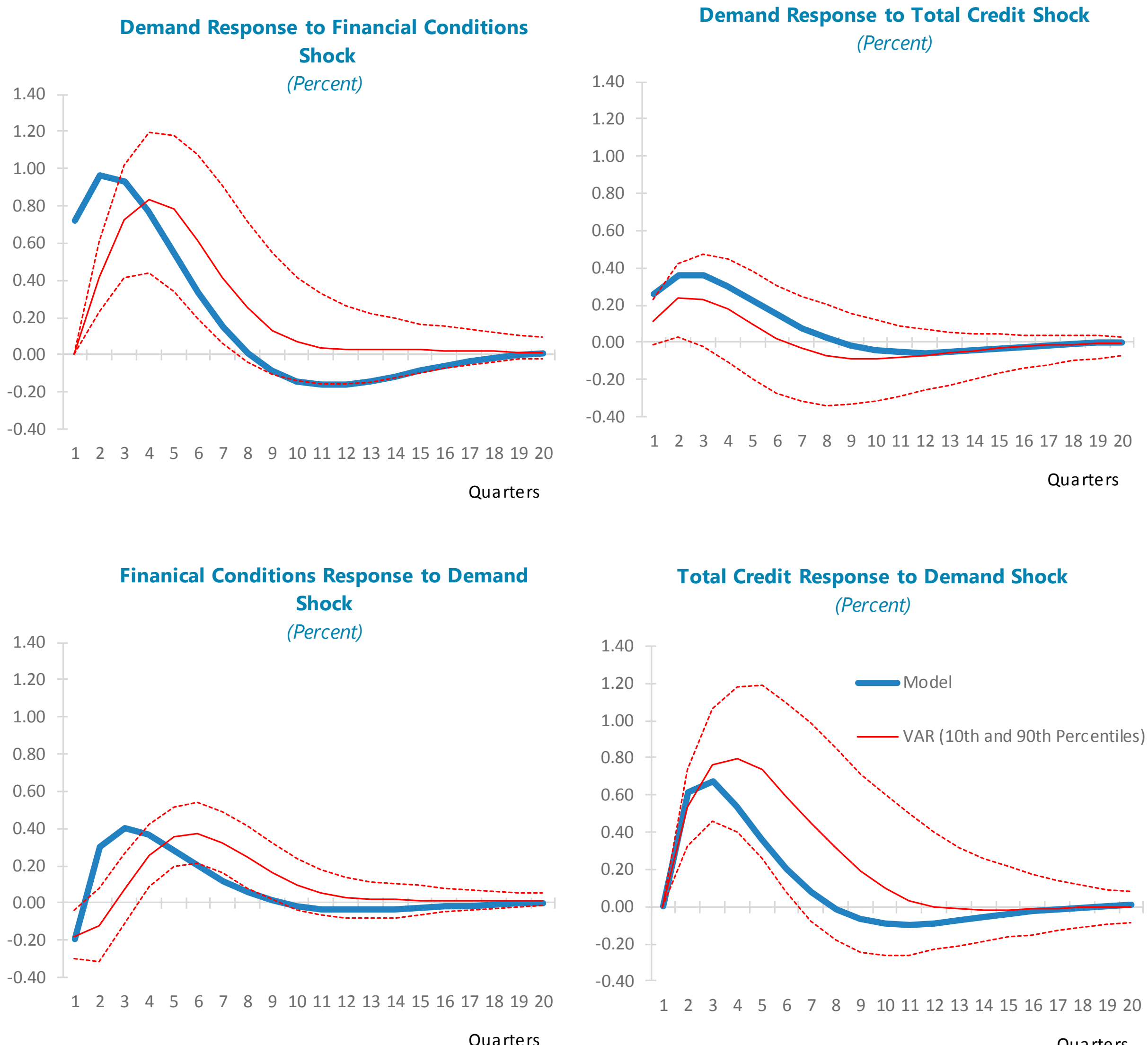
- **More recently, public and private credit and financial conditions have begun to be a drag on output.** In response to slowing demand, private credit began slowing before public credit. Estimates suggest both public and private credit have been a drag on output since early 2015 when a policy was adopted to limit the expansion of credit by public banks, largely due to fiscal efficiency considerations. Financial conditions also tightened in 2015, largely due to a rise in uncertainty related to the outlook for growth, inflation, and the public finances. A relatively large contribution of financial markets developments for economic fluctuations, at least in the recent period, reflect numerous macro-financial linkages as summarized in Table 2.

Figure 1. Financial Cycles, Business Cycle in Brazil



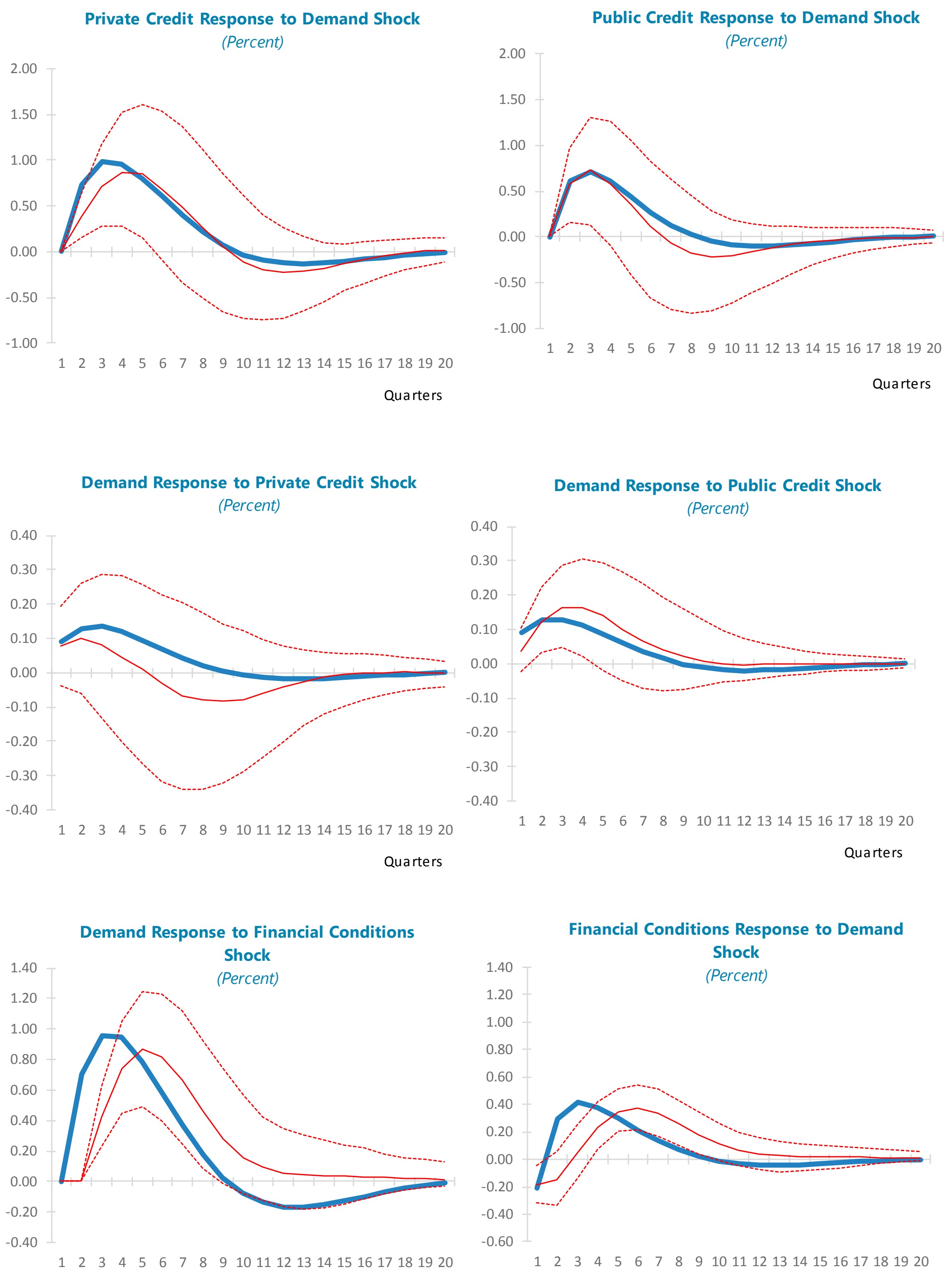
Source: Fund staff estimates.

Figure 2. Aggregate Model: Impulse Response Functions



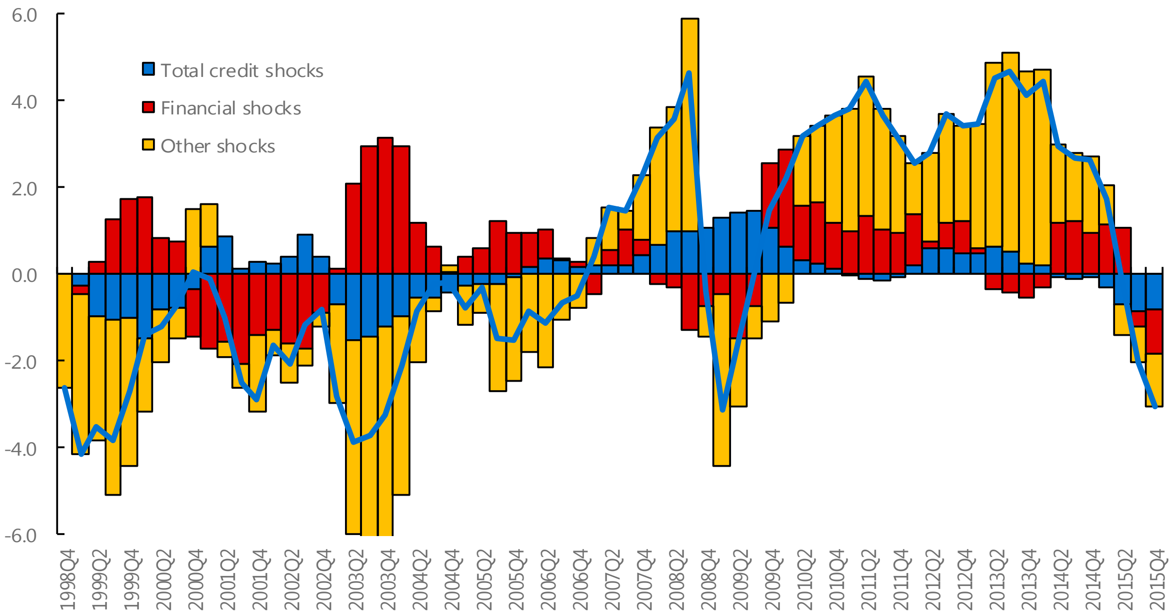
Source: Fund staff estimates.

Figure 3. Disaggregate Model: Impulse Response Functions



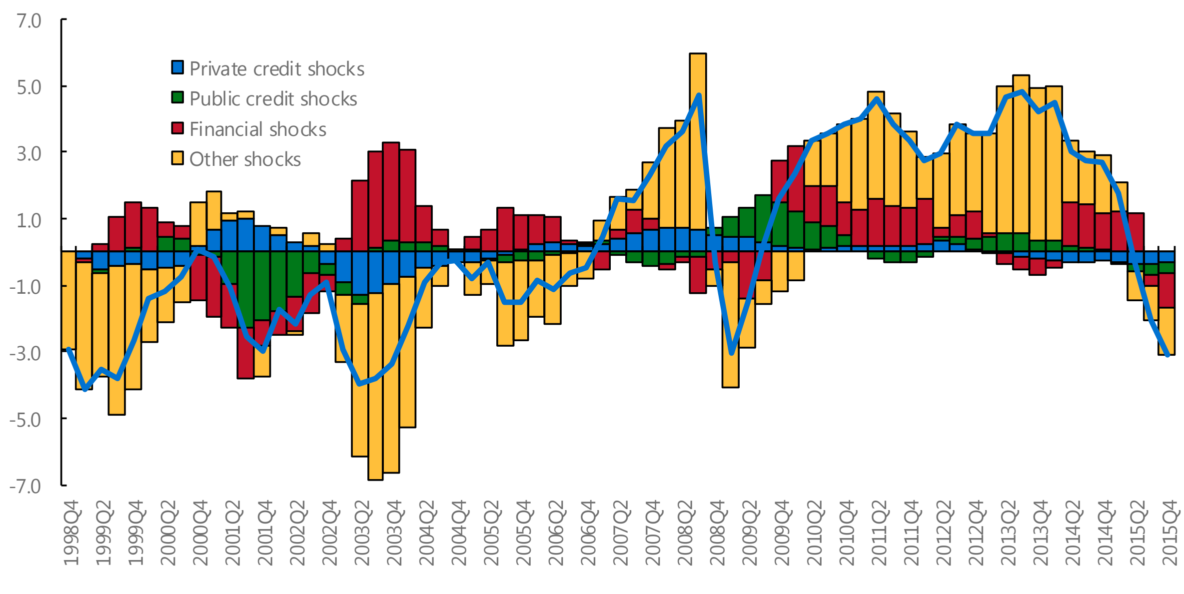
Source: Fund staff estimates.

Figure 4. Historical Shock Decomposition of Output Gap, Aggregate Model
(Percent deviation from trend)



Source: Fund staff estimates.

Figure 5. Historical Shock Decomposition of Output Gap, Disaggregate Model
(Percent deviation from trend)



Source: Fund staff estimates.

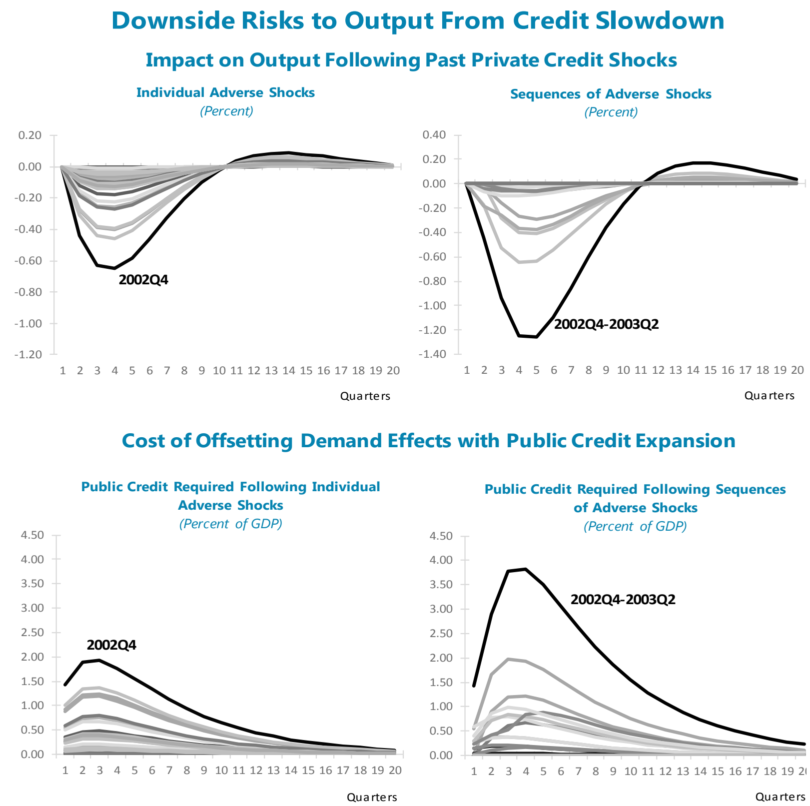
Table 2. Key Macro-Financial Linkages in Brazil

Macro Development	Direction of Link	Financial Sector/Balance Sheets	Short Description of the Link (With Direction of Link)
Uncertainties surrounding fiscal policy; higher government bond yields; sovereign downgrade	→	Overall banking sector	Higher funding costs; unrealized lossed on government bonds' holdings
	↔	Public banks	→ Lower funding opportunities from the government; slower expansion of balance sheet ← Lower dividends to Fazenda due to lower profits
	↔	Central bank	← Losses on reserves due to deprecitation of real ← Higher sovereing yields → Risk of fiscal dominance
Monetary policy tightening	→	Households	Higher debt/interest burden
	→	Corporate sector	Higher debt/interest burden
	→	Overall banking sector	Higher funding costs; Higher lending rates; higher demand for LFs, LCIs, LCAs; lower demand for deposits (due to a cap)
	→	Mutual fund industry	Expansion of the industry: Substitution between lower yielding deposits for mutual fund shares
	↔	Public banks	→ Higher TJLP ← Directed credit diminish effectiveness of monetary policy
Recession; higher unemployment; weak investment and consumption; uncertain outlook	↔	Households	Lower real wealth; lower consumption; lower confidence; higher interest rates
	↔	Corporate sector	Lower profits, Lower investment, lower confidence; higher funding costs
	↔	Overall banking sector	→ Higher NPLs; losses on equity exposures Higher funding costs (lower liquidity); higher interest rates; → Lower credit demand (due to higher unemployment; slower wage increases; higher interest rates; lower investment) ← Lower credit supply (tighter financial conditions)
Depreciation of BRL	→	Corporate sector	Higher debt/interest burden but mostly offset with hedging
	→	Overall banking sector	Higher funding costs but mostly offet with FX assets
Corruption probe	→	Corporate sector	Higher funding costs; lower profits; spilovers to suppliers
	→	Overall banking sector	Via deteriorating performance of Petrobras, contruction companies and their associated suppliers
Increase in taxes (over from 40 to 45; CSLL from 15 to 20)	↔	Overall banking sector	→ Lower profits; higher interest rate; lower credit ← Higher DTAs, lower fiscal revenues
Precatorios	→	Public banks	Lower funding; higher funding costs
Judicial deposits by subnationals	→	Public banks	Lower funding; higher funding costs
Extension of tax exemption of LCI and LCA	→	Banks, mutual funds	Banks' funding more attractive, mutual funds' shares less attractive

Source: Fund staff estimates.

V. What are the Risks from a Credit Slowdown?

The disaggregate model is used to analyze potential downside risks from an autonomous slowdown in private credit. Banks could become more cautious and act to limit credit beyond what historical relationships between the credit cycle and the business cycle suggest. This may be of particularly concern during a downturn, when profitability and liquidity are under pressure, corporate vulnerabilities are rising, and buffers reach more critical levels. These effects may be further exacerbated in the current context as banks restructure their balance sheets during the transition towards meeting Basel III requirements over coming years.



Source: Fund staff estimates.

History suggests that credit slowdowns have had significant effects on demand. The top two panels of the text chart show the estimated effects of adverse shocks to private credit since 1999; the top left panel shows the impact on output of all past adverse private credit shocks and the top right panel shows the impact of past sequences of adverse shocks (i.e. all negative shocks that occurred, where negative shocks were followed by further negative shocks in subsequent quarters). The largest adverse shocks occurred during the slowdown in 2002−03, where large negative private credit shocks occurred in 3 consecutive quarters beginning in 2002Q4. Our estimates suggest that this adverse sequence of shocks acted to reduce output by around 1 percent after a year.

Offsetting the negative effects of a slowdown in private credit with an expansion in public credit can be costly. The effects of fully offsetting the output effects of adverse shocks to private credit with an expansion in public credit are displayed in the bottom 2 panels of the text chart. The estimates suggest that offsetting private credit slowdowns can be costly; for example, the output effects of the slowdown in private credit that began in 2002Q4 would have required a 4 percent of GDP expansion in public credit to offset.

VI. Conclusions and Policy Implications

Rapid credit growth in the past points to vulnerabilities going forward. Statistical and semi-structural models show that the expansion of credit in the most recent cycle was both long in duration and large in magnitude. Moreover, Brazil is now in the downturn phase of the financial cycle. With cross-country evidence suggesting that periods of strong credit growth are typically followed by periods of sluggish growth, this may point to potential vulnerabilities for Brazil going forward.

A slowdown in credit could hurt growth. While our empirical results show that output has a stronger impact on credit than credit has on output, a sharp slowdown in credit could nevertheless be harmful to growth. Such a situation could be facilitated, for example, by a greater need to strengthen balance sheets as buffers reach more critical levels.

Offsetting a slowdown in private credit with an expansion in public-sector credit can be costly and lead to inefficiencies that are difficult to unwind. The active countercyclical role of public banks during the global financial crisis mitigated systemic risk, but also raised questions about the longer-term impact of public banks on the financial system as they are difficult to unwind; the evidence presented here suggests that reducing the size of public banks would entail a negative impact on output over time. Moreover, the rapid expansion of public banks since 2008 contributed to a deteriorating fiscal position and raising doubts about the credibility of the policy framework. Focusing public banks' activities on missing markets, such as providing guarantees for concessions, would improve the allocation of limited financing (see Coleman, Feler, 2015) and the effectiveness of monetary policy (see Bonomo, Martins, 2016). Similarly, reducing budget earmarking would release fiscal space and improve the allocation of limited fiscal resources.

APPENDIX. MODELS AND PARAMETERS

A. Models

Aggregate Model

The model assumes that credit fluctuations are driven by the business cycle. In other words, a strong/weak economy leads to strong/weak credit:

$$c_t = \nu_1 c_{t-1} + \nu_2 y_{t-1} + \epsilon_t^c \tag{1}$$

where c_t is the real credit gap, y_t is the output gap, and ϵ_t^c is a shock to real credit. Thus, banks are assumed to set their desired levels of credit based on past levels of economic activity (demand). Because banks cannot immediately adjust credit levels (for example, due to an inability to recall credit that has already been extended), it is also assumed that credit levels are slow to adjust to output fluctuations, reflected in the term $\nu_1 c_{t-1}$.

Financial conditions, on the other hand, are set based on expectations of economic activity. If annual growth is expected to the strong in the near future, there will be a tendency for financial conditions to ease:

$$f_t = \chi_1 f_{t-1} - \chi_2 (y_{t+2} - y_{t-1}) + \epsilon_t^f \tag{2}$$

where f_t is the financial conditions index and ϵ_t^f is a shock to financial conditions.

We next establish a link between the credit cycle and demand. It is assumed that shocks to credit and financial conditions, ϵ_t^c and ϵ_t^f in equations 1 and 2 respectively, that are unrelated to past levels of output and inertia, reflect changes in the lending practices of banks and/or financing conditions that can directly affect output. In this simple model, the output gap is assumed to be related to a lead and lag of itself, the real interest rate gap, r_t, a foreign activity gap, y_t^* , and the effective exchange rate gap, z_t ,in addition to 'autonomous' financial shocks, i.e:

$$y_t = \rho_1 y_{t-1} + \rho_2 y_{t+1} - \rho_3 r_t + \rho_4 z_t + \rho_5 y_t^* + \rho_6 \epsilon_t^c - \rho_7 \epsilon_t^f + \varepsilon_t^y \tag{3}$$

where ε_t^y is an idiosyncratic demand shock. The first five terms in equation (3) are elements of a fairly standard new Keynesian IS cure, with output being positively related to lags and leads of itself, negatively related to the real interest rate, and positively related to a depreciated real exchange rate and the level of foreign demand. An autonomous expansion in credit is assumed to increase demand, while an autonomous tightening of the FCI is assumed to reduce output.

Disaggregate Model

The disaggregate model allows for differences in the behavior of public and private credit. The behavior of credit extended by public banks has differed from that private banks, thanks, in part, to public credit being used as a counter-cyclical policy instrument, particularly over the past several years. While equations (1) and (2) allow for macro-financial linkages between total real credit, financial conditions and real output, it is relatively straightforward to incorporate more disaggregate credit data. The following equations allow for differences in both the cyclical responses for public and private credit and differences in the way non-cyclical, autonomous credit shocks impact aggregate demand:

$$c_t^{pb} = \nu_1 c_{t-1}^{pb} + \nu_2 y_{t-1} + \epsilon_t^{c^{pb}} \tag{4}$$

$$c_t^{pr} = \tau_1 c_{t-1}^{pr} + \tau_2 y_{t-1} + \epsilon_t^{c^{pr}} \tag{5}$$

$$y_t = \rho_1 y_{t-1} + \rho_2 y_{t+1} - \rho_3 r_t + \rho_4 z_t + \rho_5 y_t^* + \rho_6 \epsilon_t^{c^{pr}} + \rho_6 \epsilon_t^{c^{pb}} - \rho_7 \epsilon_t^{f} + \varepsilon_t^{y} \tag{6}$$

where real total credit c_t in the aggregate model is replaced with separate equations for private and public credit, c_t^{pr} and c_t^{pb}, respectively, and aggregate demand is impacted by both private and public credit shocks.[1]

Aggregate Model Details[2]

Stochastic Processes and Definitions

- ***Output gap***

$$y_t = Y_t - \overline{Y_t}$$

where Y_t is the (log) level of real GDP and $\overline{Y_t}$ is potential output.

[1] Note, for simplicity, the coefficient attached to public and private credit is the same.

[2] All shocks (denoted ε_t^x for variable x_t) are assumed to be independently and identically distributed white noise processes.

- ***Potential output***

$$\bar{Y}_t = \bar{Y}_{t-1} + \frac{1}{4} G_t + \varepsilon_t^{\bar{Y}}$$

Potential output growth

$$G_t = \delta\, g + (1 - \delta) G_{t-1} + \varepsilon_t^{G}$$

where g is steady state annual real GDP growth.

- ***Real credit gap***

$$c_t = C_t - \bar{C}_t$$

where C_t is the (log) level of real credit and $\bar{C}_t$ is trend real credit.

- ***Real credit trend***

$$\bar{C}_t = \bar{C}_{t-1} + \frac{1}{4} G_t^{C} + \varepsilon_t^{\bar{C}}$$

- ***Real credit trend growth***

$$G_t^{C} = \psi\, g^{C} + (1 - \psi) G_{t-1}^{C} + \varepsilon_t^{G^{C}}$$

where g^{C} is steady state annual real credit growth.

- ***Inflation target***

$$\pi_t^* = \pi_{t-1}^* + \varepsilon_t^{\pi^*}$$

- ***Headline Inflation***

$$\pi_t = \alpha \pi_t^{N} + (1 - \alpha) \pi_t^{R}$$

where π_t^{N} is non-regulated-price inflation and π_t^{R} is regulated-price inflation.

- ***Annual headline inflation***

$$\pi_t^4 = \frac{1}{4}(\pi_t + \pi_{t-1} + \pi_{t-2} + \pi_{t-3})$$

- ***Real interest rate gap***

$$r_t = rr_t - \overline{rr}_t$$

where rr_t is the real interest rate and $\overline{rr}_t$ is the trend real interest rate.

- ***Trend real interest rate***

$$\overline{rr}_t = \overline{rr}_{t-1} + \varepsilon_t^{\overline{rr}}$$

- ***Unemployment gap***

$$u_t = \overline{U}_t - U_t$$

where U_t is the unemployment rate and $\overline{U}_t$ is the NAIRU.

- ***NAIRU***

$$\overline{U}_t = \overline{U}_{t-1} + \varepsilon_t^{\overline{U}}$$

- ***Capacity utilization gap***

$$k_t = K_t - \overline{K}_t$$

where K_t is (log) capacity utilization and $\overline{K}_t$ is its trend.

- ***Trend capacity utilization***

$$\overline{K}_t = \overline{K}_{t-1} + \varepsilon^{\bar{k}}$$

- ***Real exchange rate gap***

$$z_t = Z_t - \bar{Z}_t$$

where Z_t is the (log) real effective exchange rate and $\bar{Z}_t$ is the trend real exchange rate.

- ***Trend real exchange rate***

$$\bar{Z}_t = \bar{Z}_{t-1} + \varepsilon^{\bar{Z}}$$

- ***Foreign output gap***

$$y_t^* = Y_t^* - \overline{Y}_t^*$$

where Y_t^* is the (log) level of U.S real GDP and $\overline{Y}_t^*$ is foreign potential output.

- ***Foreign potential output***

$$\overline{Y}_t^* - \overline{Y}_{t-1}^* = \overline{Y}_{t-1}^* - \overline{Y}_{t-2}^* + \varepsilon_t^{\overline{Y}^*}$$

Behavioral Equations

- ***IS Curve***

$$y_t = \rho_1 y_{t-1} + \rho_2 y_{t+1} - \rho_3 r_t + \rho_4 z_t + \rho_5 y_t^* + \rho_6 \epsilon_t^c - \rho_7 \epsilon_t^f + \varepsilon_t^y$$

- ***Phillips Curve (Non-Regulated-Price inflation)***

$$\pi_t^N = \gamma_1 \pi_{t-1}^4 + (1-\gamma_1)\pi_{t+1}^N + \gamma_2 Y_t + \gamma_3 \Delta z_t + \varepsilon_t^{\pi^N}$$

- ***Regulated-Price Inflation***

$$\pi_t^R = \omega \pi_t^* + (1-\omega)\pi_t^R + \varepsilon_t^R$$

- ***Policy Rule***

$$R_t = \xi_1 R_{t-1} + (1-\xi_1)(\overline{r_t} + \pi_{t+3}^4 + \xi_2(\pi_{t+3}^4 - \pi_{t+3}^*) + \xi_3 Y_t) + \varepsilon_t^R$$

- ***Real Interest Rate (Fisher Equation)***

$$rr_t = R_t - \pi_{t+1}$$

- ***Real Credit Gap***

$$c_t = \nu_1 c_{t-1} + \nu_2 y_{t-1} + \epsilon_t^c$$

where: $\epsilon_t^c = \nu_3 \epsilon_{t-1}^c + \varepsilon_t^c$

- ***Financial Conditions***

$$f_t = \chi_1 f_{t-1} - \chi_2 (y_{t+2} - y_{t-1}) + \epsilon_t^f$$

where: $\epsilon_t^f = \chi_3 \epsilon_{t-1}^f + \varepsilon_t^f$

- ***Okun's Law***

$$u_t = \kappa_1 u_{t-1} + \kappa_2 y_t + \varepsilon_t^u$$

- ***Capacity Utilization Gap***

$$k_t = \phi_1 k_{t-1} + \phi_2 y_t + \varepsilon_t^k$$

- ***Foreign Output Gap***

$$y_t^* = \lambda y_{t-1}^* + \varepsilon_t^{Y^*}$$

- ***Real Exchange Rate Gap***

$$z_t = \mu z_{t-1} + \varepsilon_t^z$$

Disaggregate Model Details

The disaggregate model described above is same as the aggregate model except the real credit and output gaps are replaced with the expressions below. We denote x as representing either private credit or public credit, e.g. $\mathrm{C}_\mathrm{t}^\mathrm{x}$ for $\mathrm{x} = [\mathrm{pr}, \mathrm{pb}]$, where pr denotes private credit and pb denotes public credit.

- ***Real credit gap***

$$c_t^x = C_t^x - \overline{C_t}^x$$

where C_t^x is the (log) level of real credit and $\overline{C_t}^x$ is trend real credit.

- ***Real credit trend***

$$\overline{C_t}^x = \bar{C}_{t-1}^x + \frac{1}{4} G_t^{C^x} + \varepsilon_t^{\bar{C}^x}$$

- ***Real credit trend growth***

$$G_t^{C^x} = \psi\, g^{C^x} + (1-\psi) G_{t-1}^{C^x} + \varepsilon_t^{G^{C^x}}$$

where g^C is steady state annual real credit growth of both public and private credit.

- ***Real credit and output gaps***

$$c_t^{pb} = \nu_1 c_{t-1}^{pb} + \nu_2 y_{t-1} + \epsilon_t^{c^{pb}}$$

$$c_t^{pr} = \tau_1 c_{t-1}^{pr} + \tau_2 y_{t-1} + \epsilon_t^{c^{pr}}$$

where: $\epsilon_t^{c^{pb}} = \nu_3 \epsilon_{t-1}^{c^{pb}} + \varepsilon_t^{c^{pb}}$ and $\epsilon_t^{c^{pr}} = \tau_3 \epsilon_{t-1}^{c^{pr}} + \varepsilon_t^{c^{pr}}$

$$y_t = \rho_1 y_{t-1} + \rho_2 y_{t+1} - \rho_3 r_t + \rho_4 z_t + \rho_5 y_t^* + \rho_6 \epsilon_t^{c^{pr}} + \rho_6 \epsilon_t^{c^{pb}} - \rho_7 \epsilon_t^f + \varepsilon_t^y$$

where real total credit c_t in the aggregate model above is replaced with separate equations for private and public credit, c_t^{pr} and c_t^{pb} and ϵ_t^c is replaced with separate equations for $\epsilon_t^{c^{pr}}$ and $\epsilon_t^{c^{pb}}$.

B. Estimated Parameters

The models outlined in Appendix A are estimated using Bayesian estimation. The tables below display the calibrated parameters and the estimated parameters, along with the prior distributions used in posterior maximization. For more details on Bayesian estimation see Herbst and Schorfheide (2015).[3]

[3] Herbst, Edward, and Frank Schorfheide (2015), "Bayesian Estimation of DSGE Models," Unpublished Manuscript. http://sites.sas.upenn.edu/schorf/files/herbst_and_schorfheide_v5.pdf

Table A1. Calibrated Parameters

Calibrated Parameters*	
g	2.00
g^c	5.00
δ	0.05
ψ	0.05
$\sigma_{\varepsilon^{\bar{Y}}}$	0.11
$\sigma_{\varepsilon^{G}}$	0.24
$\sigma_{\varepsilon^{\pi^*}}$	1.42
$\sigma_{\varepsilon^{\overline{rr}}}$	0.48
$\sigma_{\varepsilon^{\bar{Z}}}$	3.99
$\sigma_{\varepsilon^{\overline{Cpr}}}$	0.61
$\sigma_{\varepsilon^{G\ Cpr}}$	1.26
$\sigma_{\varepsilon^{\overline{Cpb}}}$	0.92
$\sigma_{\varepsilon^{G\ Cpb}}$	1.74
$\sigma_{\varepsilon^{\bar{U}}}$	0.22
$\sigma_{\varepsilon^{\bar{K}}}$	0.25

*The shock standard deviations are calibrated based on trends extracted using a standard HP filter (i.e. with $\lambda = 1600$)

Source: Fund staff estimates.

Table A2. Estimated Parameters

Estimated Parameters	Prior Distributions F(mean,std)	Aggregate Posterior	Aggregate Std.	Disaggregate Posterior	Disaggregate Std.
γ_1	$\beta(0.2{,}0.5)$	0.40	0.04	0.41	0.03
γ_2	$\gamma(0.35{,}0.05)$	0.24	0.04	0.23	0.02
γ_3	$\gamma(0.1{,}0.025)$	0.08	0.02	0.08	0.02
ρ_1	$\beta(0.8{,}0.05)$	0.66	0.04	0.67	0.03
ρ_2	$\beta(0.1{,}0.025)$	0.07	0.02	0.07	0.01
ρ_3	$\gamma(0.35{,}0.05)$	0.29	0.04	0.29	0.02
ρ_4	$\gamma(0.05{,}0025)$	0.02	0.01	0.03	0.01
ρ_5	$\gamma(0.5{,}0.2)$	0.29	0.08	0.29	0.04
ρ_6	$\gamma(0.5{,}0.2)$	0.21	0.05	0.07	0.02
ρ_7	$\gamma(1{,}0.2)$	1.08	0.09	1.10	0.04
ξ_1	$\beta(0.8{,}0.025)$	0.76	0.02	0.77	0.02
ξ_2	$\gamma(1.5{,}0.05)$	1.51	0.05	1.51	0.04
ξ_3	$\gamma(0.2{,}0.025)$	0.20	0.03	0.20	0.02
ν_1	$\beta(0.5{,}0.1)$	0.43	0.07	0.67	0.04
ν_2	$\gamma(0.8{,}0.2)$	0.62	0.11	0.73	0.04
ν_3	$\beta(0.8{,}0.05)$	0.78	0.05	0.83	0.03
τ_1	$\beta(0.5{,}0.1)$	0.49	0.11	0.49	0.03
τ_2	$\gamma(0.8{,}0.2)$	0.00	0.00	0.61	0.05
τ_3	$\beta(0.8{,}0.05)$	0.83	0.06	0.80	0.03
ϕ_1	$\beta(0.5{,}0.1)$	0.26	0.05	0.26	0.03
ϕ_2	$\gamma(0.5{,}0.2)$	0.47	0.05	0.47	0.02
κ_1	$\beta(0.5{,}0.1)$	0.67	0.09	0.67	0.04
κ_2	$\gamma(0.5{,}0.2)$	0.18	0.03	0.18	0.02
χ_1	$\beta(0.5{,}0.1)$	0.40	0.06	0.41	0.04
χ_2	$\gamma(0.8{,}0.2)$	0.48	0.05	0.49	0.03
χ_3	$\beta(0.8{,}0.05)$	0.74	0.05	0.75	0.03
ω	$\beta(0.5{,}0.1)$	0.33	0.06	0.33	0.03
μ	$\beta(0.5{,}0.1)$	0.61	0.09	0.62	0.04
λ	$\beta(0.5{,}0.1)$	0.75	0.05	0.75	0.02
Shock Standard Deviations					
$\sigma_{\varepsilon^{y}}$	$\gamma^{-1}(1,\infty)$	1.09	0.04	1.13	0.02
$\sigma_{\varepsilon^{C^{pr}}}$	$\gamma^{-1}(1,\infty)$	1.27	0.06	1.57	0.04
$\sigma_{\varepsilon^{C^{pb}}}$	$\gamma^{-1}(1,\infty)$	0.00	0.00	2.73	0.04
$\sigma_{\varepsilon^{\pi^{r}}}$	$\gamma^{-1}(1,\infty)$	5.12	0.13	5.12	0.06
$\sigma_{\varepsilon^{\pi^{n}}}$	$\gamma^{-1}(1,\infty)$	2.72	0.09	2.74	0.05
$\sigma_{\varepsilon^{R}}$	$\gamma^{-1}(1,\infty)$	1.09	0.04	1.09	0.04
$\sigma_{\varepsilon^{z}}$	$\gamma^{-1}(1,\infty)$	4.34	0.11	4.46	0.04
$\sigma_{\varepsilon^{u}}$	$\gamma^{-1}(1,\infty)$	0.24	0.01	0.24	0.01
$\sigma_{\varepsilon^{k}}$	$\gamma^{-1}(1,\infty)$	0.36	0.02	0.36	0.02
$\sigma_{\varepsilon^{y^*}}$	$\gamma^{-1}(1,\infty)$	0.59	0.02	0.59	0.02
$\sigma_{\varepsilon^{f}}$	$\gamma^{-1}(1,\infty)$	0.53	0.02	0.51	0.02

Source: Fund staff estimates.

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