Incorporating Financial Stability into Monetary Policy Framework: The Bank of Thailand's Experience*

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Abstract

Since the aftermath of the Global Financial Crisis during 2007-2008, financial stability (FS) has become top priority for central banks around the world. The conduct of monetary policy (MP) sees no exception. By leveraging on the existing literature, we propose a systematic approach to incorporate FS considerations into MP framework. This starts with calculating financial cycle (FC) which is a measure of financial imbalances and a predictor of financial crises. The interaction between FC and business cycle variables such as output gap provides important information for policy making, for it could stipulate an inter-temporal trade-off between financial and price stability. We then look at an FS dashboard which consolidates pockets of risks facing the financial sector, and show how it may be used in conjunction with FC in FS surveillance. Finally, we consider the calibration of monetary and macroprudential policies in order to design the optimal policy mix. As a demonstration of our approach, we discuss, in each section, an on-going attempt at the Bank of Thailand to systematically incorporate FS into flexible inflation targeting.

JEL classification: E52, G01, C54.

Keywords: Financial Stability, Monetary Policy Framework, Policy Trade-off.

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1. Introduction

Since the aftermath of the Global Financial Crisis during 2007-2008, financial stability (FS) has become top priority for central banks around the world. The conduct of monetary policy (MP) sees no exception. While the conventional monetary policy framework concentrated on maintaining price stability (PS) – commonly known as the 'Jackson Hole consensus' – it is now widely recognized that financial instability, when it break outs, is likely to be severely detrimental to PS. Indeed, as Minsky (1992) hypothesizes, financial sector imbalances could build up even under low and stable inflation, and closed output gaps. For many central banks, including the Bank of Thailand (BOT), FS has become one of the [explicit] MP objectives.

The emerging MP framework that ensures both price and financial stability takes into account several 'interactions' that were not acknowledged in the conventional framework such as the interaction between monetary policy mandates mentioned above. In addition, the implications of financial market movements on economic fluctuations, also known as the macro-financial linkage (e.g. Schularick and Taylor, 2012; Juselius et al., 2017), should also be taken into consideration as well. Figure 1 illustrates the conceptual framework of this endeavor. However, unlike PS which is usually gauged by movements of inflation, FS – or 'FS risks' to be more precisely – is likely to be measured with less precision, a complication to policy making.

By leveraging on the existing literature, we propose a systematic approach to incorporate FS considerations into MP framework. This starts with calculating financial cycle (FC) which is a measure of financial imbalances and a predictor of financial crises (Claessens et al., 2011; Drehmann et al., 2012; Borio, 2014). The interaction between FC and business cycle variables such as output gap provides important information for policy making, for it could stipulate an inter-temporal trade-off between financial and price stability, especially when those variables are moving in the opposite directions.

Despite its potential usefulness in detecting systemic risks, FC does not capture all FS risks, and might miss certain pockets that are not direct input to the FC calculation. We thus turn to sectoral indicators, and compile an FS dashboard which consolidates risks across key sectors of the economy. The dashboard not only aids in FS surveillance, but also suggests a suitable policy tool according to the prevailing risk types. Finally, we consider the calibration of monetary and macroprudential policies in order to design the optimal policy mix. This topic is a paper in its own right, and hence, for tractability, we only present key concepts that should be considered in decision making.

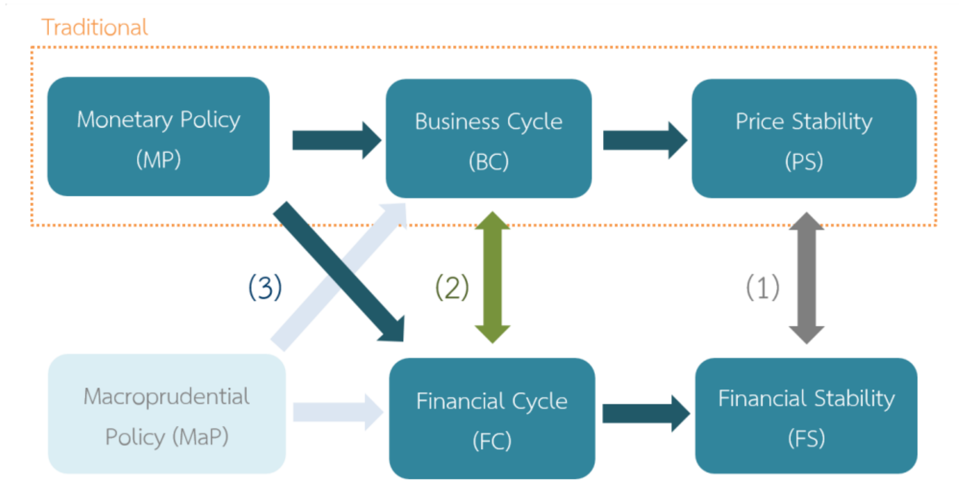

Figure 1. The Emerging MP Framework

Figure 1 provides an illustration of the emerging monetary policy framework which accounts for financial stability considerations, in comparison with the traditional approach in the dotted box. The new framework acknowledges a number of 'interactions' as follows. Link (1): PS and FS are mutually beneficial and re-enforcing; Link (2): FC and BC are related; and Link (3): There is an interaction between MP and MaP which affects their objectives.

As a demonstration of our approach, we discuss, in each section, an on-going attempt at the Bank of Thailand (BOT) to systematically incorporate FS into its monetary policy framework. The BOT conducts monetary policy under flexible inflation targeting, which allows for a balancing act of multiple objectives. Interestingly, the central bank explicitly acknowledges FS as one of the monetary policy objectives. Moreover, FS risks have been regularly cited by the Monetary Policy Committee (MPC), the rate setting panel, as one of the main reasons that justify their decisions.

FS surveillance at BOT has been constant, depending on issues of worry. Even though the approach serves the MPC well, it does not fully facilitates policy debate as the link between FS risks and the real economy is yet to be established. Without a quantitative measure of FS risks, moreover, policy communication is complicated to the extent that FS might be perceived by the public as a superior objective to PS. In the longer term, such perception may be harmful to the inflation targeting framework – which advocates the primacy of price stability – and to the conduct of monetary policy in general.

Our contribution to the literature is thus two-folded. First, we propose a set of procedure that enables a more FS-oriented monetary policy framework. This allows FS-related matters to be considered and communicated in a systematic manner. Second, we document a country's experience, including challenges facing the central bank staff, of implementing such a procedure. Hopefully, the experience would aid in the implementation of a similar framework elsewhere. The rest of the paper is organized in the similar structure to the ordering of topics outlined above.

2. Financial Cycle: A Measure of Financial Imbalances

The soundness of financial sector is one of the key factors to sustain economic growth. Nevertheless, FS risks are diverse in nature, ranging from volatility in financial markets to insolvency of financial institutions. For example, Thailand's financial stability issues currently concern underpricing of risks that stemmed from the search-for-yield behavior in the prolonged low interest rate environment. Without an appropriate measure of FS risks, proper policy formulation will be extremely difficult, if not impossible. How does one measure the overall health of the financial system then? The literature suggests a candidate indicator called 'financial cycle' (FC) which mainly reflects the cycle of expansions and contractions of financial variables.

Despite the lack of a commonly agreed definition, FC may be defined as 'self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms and followed by busts' (Drehmann et al., 2012). As discussed in Claessens et al. (2011, 2012) and Drehmann et al. (2012), the determinants of FC are primarily cycles of credit and of asset prices, both of which reflect the accumulation of vulnerabilities in the financial system. These cycles are potentially self-re-enforcing. During economic expansion, for instance, accelerating demand for housing credit will push up house price; the rise in collateral value will in turn fuel credit. More importantly, FC is recognized as a predictor of financial crises. The above authors also found strong association between previous peaks and subsequent systemic financial crises. This property makes FC a desirable core indicator for our framework, and the main subject of this section.

2.1. Characterizing FC

The seminal work of Drehmann et al. (2012) suggests applying Christiano-Fitzgerald filter (CFfilter) to financial variables of interest in order to extract their cyclical components, which are deviations from the long-run trend. The length of FC is prescribed at 8 to 30 years, a significantly longer time than that usually assumed for business cycle (BC) of around 1.5 to 8 years. The amplitude, on the other hand, is empirically estimated and associated with the size of financial imbalance. In contrast to the well-known Hodrick-Prescott filter (HP-filter), CF-filter is a linear band-pass filter making use of a two-sided weighted moving average of the data. Applying this filter with a lower frequency band – as the above construction of FC – provides a much smoother cycle, therefore less susceptible to short-term fluctuations.[1]

For our purpose, we construct 'financial cycle composite index' (simply abbreviated as FC) by applying CF-filter to four financial variables, namely credit aggregates, credit-to-GDP ratio, single-detached house (including land) price index, and land price index.[2] The first two components reflect 'credit cycle', and the others 'asset price cycle'.[3] The data series are quarterly collected over the period from 1994 Q1 to 2017 Q4. The configuration of the smoothing parameter follows Drehmann et al. (2012), where FC completes in 8 to 30 years. The composite index is finally obtained from a simple average of the four sub-indices. Figure 2 illustrates the result.

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1 To analyze cyclical movements of financial variables, alternatively, one may employ 'turning point analysis' to date the cyclical peaks and troughs in financial variables; see Claessens et al. (2011), Drehmann et al. (2012). However, this method can only specify the periods of expansions or recessions but cannot deliver the magnitude or the severity of the cycle at different stages, all of which are especially desirable for policymakers in order to gauge financial risks. Besides, the estimated dates are less reliable when the data span a relatively short horizon.

2 The credit aggregate is the total credit (loan and debt securities) to private non-financial sector including non-financial corporations, households and non-profit institutions, collected by Bank of Thailand. It also covers loans and debt securities from both financial institutions: banks and non-banks. The single-detached house (including land) price index and land price index are combined from several sources; the series of 1994-2008 are from Government Housing Bank while the series of 2008-2017 are from the Bank of Thailand. Condominium price is not included in the FC as the series are not long enough. Nevertheless, they may be proxied by land prices, which are major costs of launching condominium. All variables are in real terms (deflating by CPI), except for credit-to-GDP ratio. Moreover, before applying the filter, they are first normalized by their initial values in 1994 Q1. The resulting gaps obtained by the CF-filter are finally scaled by their trends for comparability of the results.

3 We do not include equity price cycle here as it has shown relatively large volatility compared to that of other financial variables, particularly credit-to-GDP cycle, which is consensually the main indicator in financial cycle literature. Incorporating equity price cycle could therefore distort FC. This result complies with the study of Drehmann et al. (2012) that equity price cycles of many advanced economy seem to be more fluctuated.

The generated cycles appear to move slowly, extending several years' time. We note in addition that our FC peaked in the eve of the 1997 Asian financial crisis, providing some evidence in support of the use of FC as a measure of financial imbalance. The filtered cycles also pass our qualitative and quantitative evaluation criteria. More precisely, (1) the series are long enough and have predictive power for Thailand's financial crisis in the past; (2) all of them have consistent cyclical patterns making the aggregation sensible and (3) the standard deviation (volatility) of medium-term component is much higher than that of the short-term component – which is interpreted in the similar way to signal-to-noise ratios – i.e. the influence of medium-term factors in the variables differs from their short-term counterpart; refer to Drehmann et al. (2012) for detail of this final criterion.

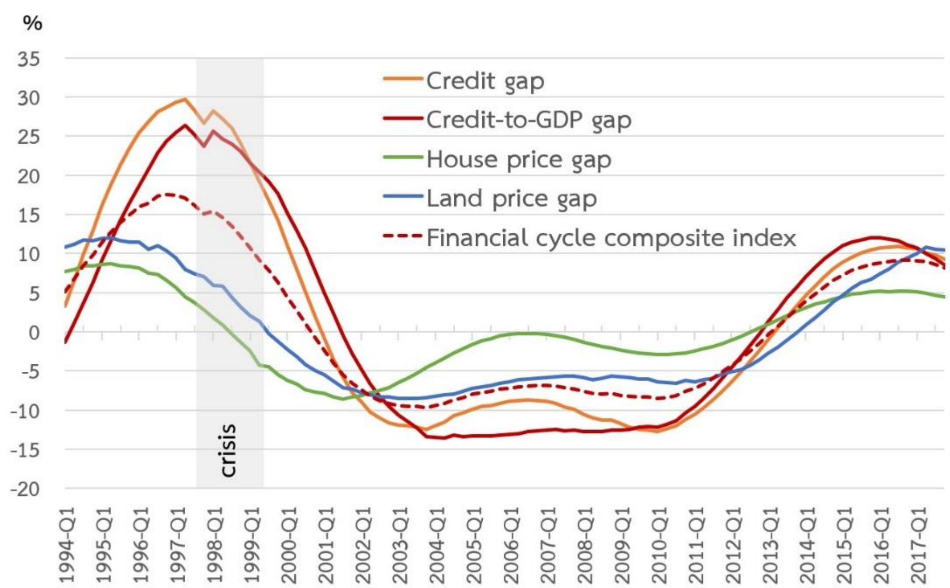

Figure 2. Financial Cycle Composite Index and Its Components

FC is an aggregate measure comprising of four cycles: credit cycle, credit-to-GDP cycle, land price index cycle and house price index cycle. Its peak is used as a predictor for financial crises. As shown here, Thailand's FC peaked in the eve of the 1997 crisis period in the shaded area.

2.2. Interactions between financial and business cycles

Information on the relationship between FC and BC variables such as output gap provides policymakers with a key ingredient for assessing the state of the economy. Figure 3 depicts Thailand's FC in comparison with the corresponding BC as measured by output gap.[4] The following stylized facts can be seen:

[4] The series is obtained from the application of Laubach-Williams's method to real GDP (Laubach and Williams, 2003).

Stylized fact 1: In line with Borio (2014), our FC moves more slowly than BC. The duration and amplitude of the former are higher than those of the latter. Although this may be an artefact of our methodology, it has a crucial interpretation: the slow swing in FC represents vulnerabilities which tend to build up slowly, and are not influenced by other more volatile short-term factors. Indeed, financial crises, being the major driver of FC, do not occur frequently.

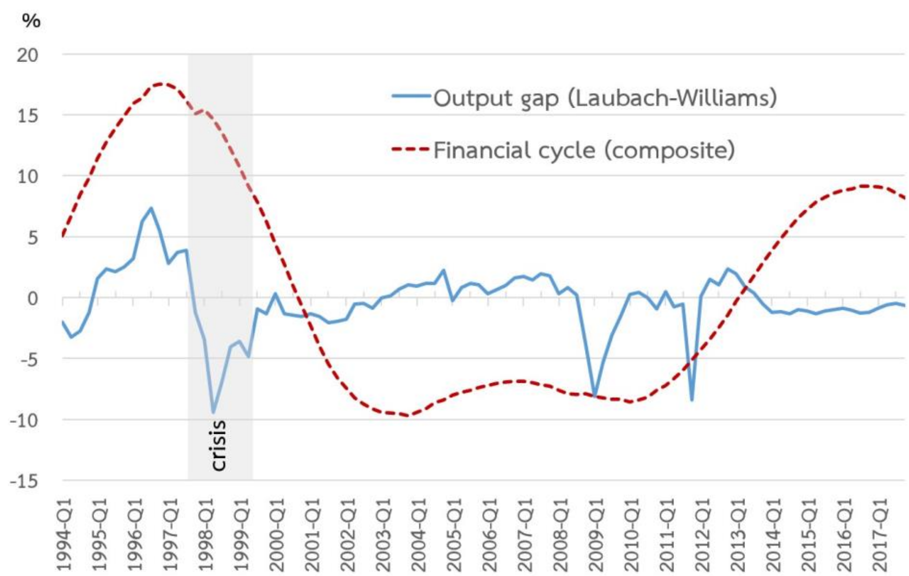

Figure 3. Financial Cycle vs. Business Cycle

At first glance, the correlation between FC and BC is weak. In line with the literature, the former appears to be moving at a much slower pace than the latter. However, there seems to be a non-linear relationship between the two variables. In particular, economic recessions tend to be more intense during financial crisis period.

Stylized fact 2: The interaction between FC and BC is more pronounced during downturns. To put it differently, economic recessions are more severe if they occur at the same time as financial crises. An intuition is that, during crises, financial institutions tend to face more difficulties in obtaining liquidity, putting a limit on credit extended to households and corporates. This type of distress makes recovery even harder. See detailed discussion in Jorda et al. (2013), who argue that recessions associated with crises lead to deeper recessions than during normal recessions. In the case of Thailand, the economy took almost two years to recover from the Asian financial crisis, while other recessions spent significantly shorter time.

2.3. FC and consequences on the economy

The above graphic (Figure 3) raises the question whether the higher magnitude of financial cycles, the more severe economic downturn. We verify this relationship by mean of quantile regression for panel data (with a country dummy variable) of 9 countries over the period 1993 Q1 - 2017 Q4.[5] In the analysis, the dependent variable is the one-year ahead GDP growth, while the regressor is the financial cycle constructed by the applying CF-filter on credit-to-GDP ratios and property prices (see Section 2.1). In Figure 4, our analysis reveals the negative impact of an increase in FC on future economic growth. During economic downturns (roughly around the 5th percentile of historical GDP growth[6]) a one-percentage point increase in FC will dampen growth in the following year by 0.27 percentage points. The size of the impact is inversely related to the size of GDP growth. Crucially, these numbers establish a novel trade-off between activities in financial and real sectors, in particular one which is inter-temporal. Further discussion of its implication on monetary policy decisions is postponed to Section 3.

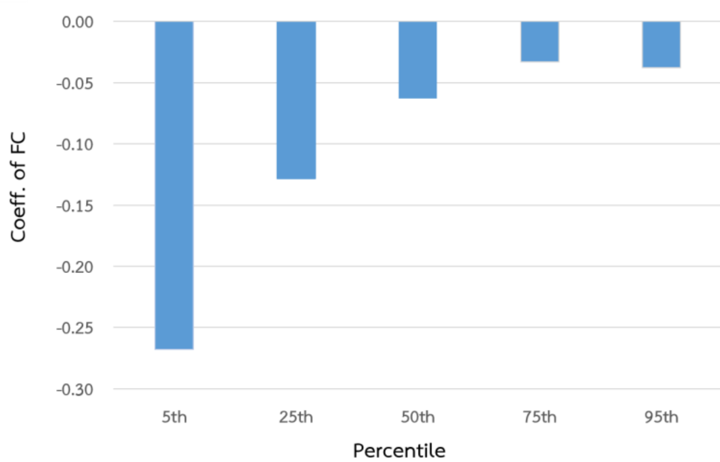

Figure 4. Quantile Coefficient of Regression of 1Yr-ahead GDP Growth on Financial Cycle

This figure shows coefficient values of regressions of one-year-ahead GDP growth on FC with respect to percentiles of the dependent variable. There appears to be an inverse relationship between the impact of FC and the percentile level of GDP growth. In particular, the negative impact of FC is more pronounced when GDP growth is relatively weak.

5 Data comprises two groups, namely (1) emerging economies: Thailand and Malaysia, and (2) advanced economies: France, Italy, Netherlands, Spain, Sweden, United Kingdom and United States. For comparability, each cross-country data is gathered from the same source: credit-to-GDP ratios and residential property prices from BIS and GDP annual growth rate from OECD and CEIC. Especially, the proxy for asset prices is now the residential property prices, see the Handbook on Residential Property Prices Indices (RPPIs).

6 The 5th percentile of Thailand's GDP annual growth rate over the period of 1994-2017 was -4.3% while its median was 4%.

2.4. FC and crisis probability

Another dimension where FC can be used to inform monetary policy decisions is its relationship with the probability of financial crises. As mentioned earlier, peaks in FC could signal systemic risks. On a closer inspection, however, the magnitude of the cycle is also likely to play an important role. As shown in Figure 3, for instance, the peak in 2016 may not give us a straightforward sign of crises as its size was considerably small compared to the pre-crisis peak in 1995. This problem calls for a more accurate assessment of the probability of future crises in relation to the current level of FC. Nevertheless, one inevitably faces data limitations since crises are rare events.[7] As a result, we have to employ a different identification strategy, and resort to a cross-country panel data to ensure adequate observations of financial crises for predictive analysis.

Following Anundsen et al. (2016), Bauer and Granziera (2017) and Gourinchas and Obstfeld (2012), we estimate a panel logistic regression using a cross-country dataset. The data used in this analysis were quarterly credit-to-GDP ratios and residential property prices of emerging and advanced economies.[8] Each data series is mapped individually to systemic crises identified by IMF staff as in Laeven and Valencia (2013) which covers both the Asian financial crisis in 1997 and the Global financial crisis in 2007-2008.

In order to provide policymakers time to put in place measures to prevent financial crises, the probability that a country will be in a pre-crisis state is defined to be 1 to 3 years prior to the crisis event. Therefore, the dependent binary variable of country i, $Y_{i,t}$, is 1 if the outbreak of systemic crisis occurred at time $t + k$, where $k \in [5, 12]$, and to be 0 otherwise. In the estimation, we omit observations lying on the crisis period, which is classified to be 4 quarters before and 6 quarters succeeding the crisis date. This crisis probability can then be used as an early warning signal (up to 1-3 years ahead). The forward-looking probability of a crisis is calculated according to the following logistic function:

7 In Thailand, there have been only two financial crises in its history, the first one was in 1983 (historical data is not available for the financial cycle analysis) and the latest one was the Asian financial crisis in 1997, see systemic crises database in Laeven and Valencia (2013).

8 These are the same data set as in the quantile regression analysis above.

$$\mathbb{P}(Y_{i,t} = 1) = \frac{\exp(a_i + bx_{i,t})}{1 + \exp(a_i + bx_{i,t})}$$

where a_i is a country-specific fixed effect; b is the coefficients of $x_{i,t}$ – FC of country i.[9] Figure 5 shows historical estimates of the likelihood of a crisis in Thailand. In 2017 Q4, the probability is around 0.07 which is significantly lower than 0.90 in the eve of the 1997 crisis.

In addition to the financial cycle, such a probabilistic evaluation facilitates policy discussion in terms of risk assessments, and should supplement the impact assessment on baseline economic growth discussed later. This result will fit comfortably into a risk management approach to monetary policy a´la Greenspan (2004) where decision makers seek to under- stand the many sources of risks, and quantify them when possible. Alternatively, one could investigate the level of critical thresholds in order to come up with an early warning system (see Box 1).

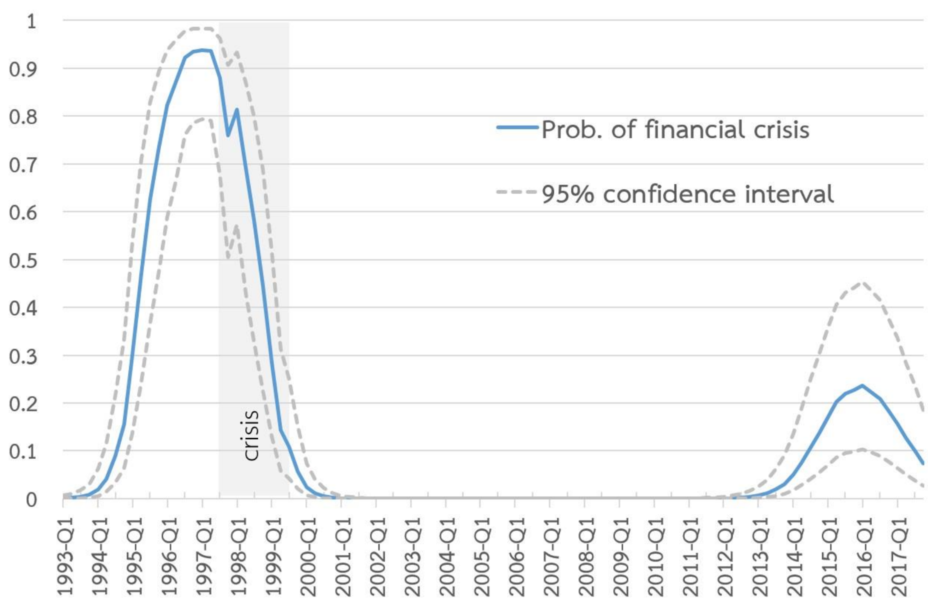

Figure 5. Forward-looking Crisis Probability in Thailand (1-3 Years Ahead)

Thailand's crisis probability is calculated by a panel logistic regression based on cross-country credit-to-GDP and residential property price data. This likelihood is used as an early warning indicator for systemic crisis up to 1-3 years ahead.

9 The CF-filter is applied to the credit-to-GDP ratio and residential property price index so as to get the deviation from their trend, analogously to the calculation of FC. The individual financial cycle is then the simple average of these two components.

Box 1: A Derivation of Early Warning State for Crisis Probability

The forward-looking probability of financial crisis derived in Section 2 facilitates policymakers in assessing financial stability risk. However, one might ask what level of crisis probability should trigger policy makers to start implementing measures to prevent significant economic slowdowns. Based on historical data, we apply a statistical method to set a threshold for an early warning state.

By specifying a threshold, two types of errors occur: (i) missed crisis calls (type I error) and (ii) false alarms (type II error). If the threshold is set too high, the former will increase whereas the latter will decline, i.e. setting too high threshold will increase missed crisis chance, but signal less false alarm, and vice versa.

Therefore we need to deal with the trade-off between these two types of errors by adjusting the threshold such that the so-called noise-to-signal ratio – defined to be the ratio of a false positive rate (FPR) and a true positive rate (TPR) – is minimized.[10] Moreover, the desired threshold should historically predict at least two thirds of the occurrence of crises correctly. See Aldasoro et al. (2018).

Figure A shows the mapping between TPR and FPR by adjusting the threshold ranging from 0 to 1. In fact, this curve is called a Receiver Operating Characteristic (ROC) curve which contains information about signaling quality for an indicator. Intuitively, it shows whether the distributions of the two samples –crisis group sample and non-crisis group sample – are well separated. Under our criteria the point of interest is the one which is lying above the dashed red horizontal line (predicting at least two thirds of crisis events) and has the steepest slope from the origin (maximizing signal-to-noise ratio).[11] The optimal threshold given by our analysis is equal to 0.24 which gives the minimum noise-to-signal ratio.

We evaluated the performance of this early warning indicator in the case of Thailand. The threshold of 0.24 performs well since it signals a pre-crisis state in 1995 Q1, about 2 years before the Asian

10 We define FPR to be the ratio of false alarm, i.e. the number of negative (non-crisis) events wrongly categorized as positive (crisis) group, while TPR is denoted to be the ratio of correctly predicted crises.

11 The slope is the ratio of TPR and FPR, therefore maximizing this slope is equivalent to minimizing noise-to-signal ratio.

financial crisis in 1997. The threshold enables policymaker to get an idea of early warning state of financial booms.

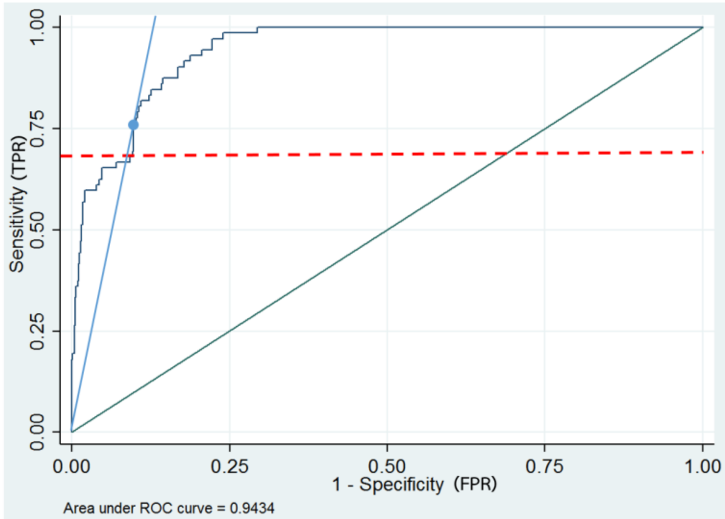

Figure A. Receiver Operating Characteristic (ROC) Curve

3. Input into Monetary Policy Decisions

A key challenge faced by policymakers, especially those under flexible inflation targeting, is they need to strike a balance between PS and FS mandates. In the preceding section, we have shown how FC can be characterized, along with its association with real economic activities, as well as with the occurrence of financial crisis. Now we will discuss their implication on monetary policy, and how these pieces of information may be submitted to the rate setting committee. We will suggest a number of formats – with increasing degrees of complexity – that central bank staff may choose to present empirical evidence regarding FS considerations to cater for different needs of the policymakers.

3.1. Groundwork for FS considerations

At the fundamental level, the MPC shall be presented with data for FC which is a summary measure of financial imbalances in the economy. A monetary policy framework with FS objective should take FC into consideration akin to key indicators of the real economy's health such as inflation, GDP growth, and unemployment rates. Figures 2 and 3 above are examples of time series data for FC that form part of MPC briefing at the BOT. This is a simple yet powerful step to incorporate FS considerations into policy decision making systematically.

The MPC shall discuss the latest movement and magnitude of this indicator, and may also form a view about its trajectory. Staff should be mindful, however, not to prompt the rate setting committee to target FC – as a variable to stabilize – instead of inflation rate. Failing to do so risks losing the primacy of PS, and the credibility of monetary policy in the longer term. The publication of FC, furthermore, could facilitate monetary policy communication. On one hand, being a rather well-established metric, FC supports the MPC's narratives about systemic risk assessments. On the other hand, it would well complement issue-based assessments of FS risks in general.

Policymakers in a small open economy might also be interested in movements of FC elsewhere. Figure 6 depicts Thailand's credit-to-GDP gap whose movements are quite in line with those of other ASEAN countries (Malaysia, Indonesia and Malaysia) in contrast to those of the G3 countries (United States, Euro area and Japan).[12] This finding provides some evidence for the existence of 'de-coupling thesis' in the aftermath of the global financial crisis. The MPC could debate on the influence of the global factors with more credit inflows fueling domestic FC, together with the bearing on monetary policy in the same fashion as the proposition put forth by Rey (2015). Consequently, the MPC could discuss optimal policy responses with respect to the underlying sources of FC movements. For instance, the interest rate policy may be deemed appropriate for managing such movements arising from domestic factors, as opposed to external ones.

[12] Data source: BIS. We applied Christiano-Fitzgerald-filter with frequency domain of 8-30 years to the credit-to-GDP series from 1993 Q1 to 2016 Q4.

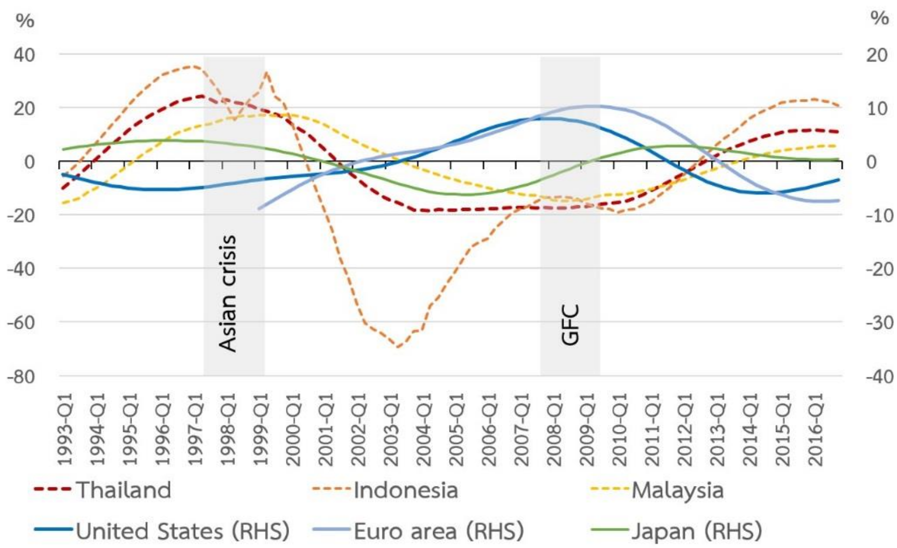

Figure 6. (De-) Synchronization of Credit-to-GDP gaps

This figure shows evolution of credit-to-GDP gaps for selected economies. Thailand's financial cycle seems to be moving in line with those of other ASEAN countries, but decouples from those of G3 countries.

3.2. Qualitative policy analysis

In the next step, staff might present the evolution of FC in conjunction with BC. The simplest format is a contemporaneous plot of FC and BC to straightforwardly depict a potential trade-off in preserving PS vis-a-vis FS. A more complicated inter-temporal relationship could be explored such as lagged FC against current BC, depending on the staff's view on macro-financial dynamics. We do not recommend a plot of FC against inflation though for two main reasons. First, inflation should receive priority under flexible inflation targeting. Second, the relationship between FC and BC is better established in the literature, despite the fact that one could still figure out an implicit relationship between FC and inflation by using the Phillips curve.

A simple illustration for Thailand's case is shown in Figure 7. We say that macro-financial dynamics is 'complementary' when FC and BC are in the same direction [Quadrant I & III or the green zone]. Under such circumstances, a policy action that addresses PS would also benefit FS. For example, when a financial crisis strikes, monetary policy easing will not only stimulate economic growth, but also support credit and stabilize asset price. On the other hand, monetary policy tightening may be desirable when both the economy and the financial sector are showing signs of overheating. In retrospect, monetary policy in Thailand should have been tightened more aggressively during 1995-

1996 in order to divert or help dampen the impact of the Asian financial crisis. When FC and BC are in the opposite directions [Quadrant II & IV or the red zone], on the other hand, policymakers will face a policy dilemma. At this juncture, there is a trade-off between PS and FS mandates. Further analyses are required accordingly such that the MPC would be able to carefully weigh benefits of each policy option against its costs. We will discuss a sample procedure for quantifying the policy trade-off shortly.

As previously mentioned, at this stage MPC members may form view about trajectories for the variables of interest. The main concern here would be the macro-financial dynamics, i.e. the co-trajectories of FC and BC. The projected path could base on either the market forecast or the central bank's own econometric models. Such forecasts would enable a forward-looking assessment of the evolving state of the economy, and an appropriate policy response accordingly. The latest data (2017 Q4) for Thailand sees FC and BC in the red zone. The projection, nevertheless, shows the pairs gradually move into the green zone as output gap slowly closes and credit and asset prices moderate.[13] With the economic outlook strengthening while concerns about financial instability receding, the situation is supportive of policy normalization in 2019. However, if FC is projected to accelerate, the MPC may use it as a ground to 'lean against the wind' (LAW), thereby increasing the pace of policy normalization.

13 Credit, house price, and land price are projected to grow by 5%, 2%, and 5% respectively. These are consistent with consensus forecasts. The path for BC, on the contrary, is based on BOT's macroeconomic projection.

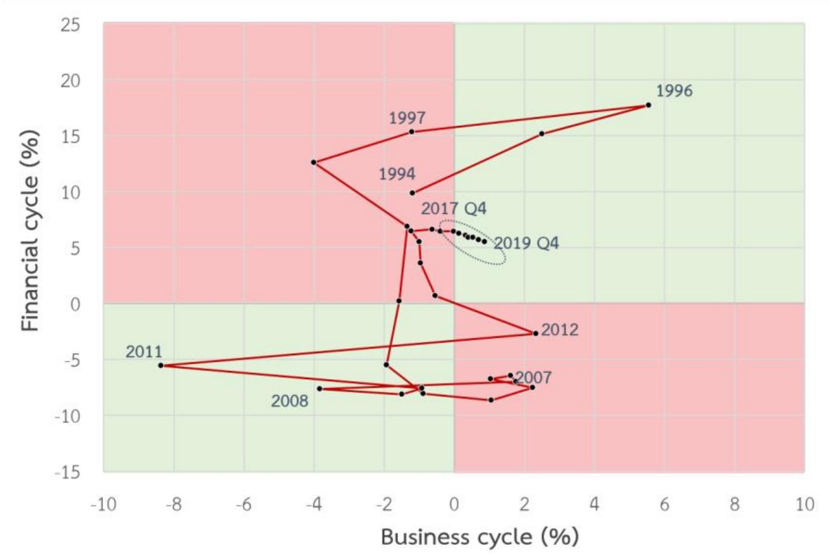

Figure 7. Path of Thailand's Financial Cycle and Business Cycle

This figure shows a contemporaneous plot of FC and BC. The macro-financial dynamics is said to be 'complementary' when the two variables are in the same direction (green zone), and there is a 'trade-off' otherwise (red zone). The densely dotted line represents projection (2018 Q1 to 2019 Q4) based on the same set of information as the economic projection presented to the rate setting committee.

3.3. Quantitative policy analysis

Our central analysis is the quantification of the trade-off between preserving PS and FS. In this endeavor, one requires, first of all, a 'core' economic model that encapsulate linkages between macroeconomic and financial variables. While some progress has been made in this regard – see e.g. Bernanke et al. (1999); Bernanke and Gertler (2000); Christiano et al. (2010); Rigobon and Sack (2003); Juselius et al. (2017) – to the best of our knowledge there is no consensus on the "standard" model in the literature as yet. The current practice in central banking is to resort to a model suite consisting of a core model and multiple satellite models to capture the complex macro-financial dynamics (e.g. Anundsen et al., 2016; Burgess et al., 2013; Burrows et al., 2012; Dees et al., 2017; Gerdrup and Nicolaisen, 2011). A more complicated modeling strategy is indeed encourage provided that it better represents a country's macro-financial linkages.

In the study of macro-financial linkages, we follow a VAR approach of Disyatat and Vongsinsirikul (2003) which is prior work on monetary policy transmission in Thailand. We construct SVAR in a compact system, comprising real output (GDP), headline consumer price index (CPI), private credit (CREDIT), land price index (LAND), and the policy rate or 1-day repurchase rate (RP1). Based on a literature survey, the ordering of endogenous variables is as follows: CPI, GDP, RP1, LAND and

CREDIT, which implies that financial variables have lagged implications on rate-setting decisions, but they respond contemporaneously to an interest rate shock. We also include two exogenous variables: Dubai Crude Oil Price (DUBAI) and Real Effective Exchange Rate (REER) in order to capture effects from external sectors. All data are quarterly from 2000 Q1 to 2017 Q4,[14] and are transformed to quarter-on-quarter growth in order to achieve stationarity (except the policy rate which is its first-difference). The optimal lag length of two was chosen based on information criteria. Cholesky decom- position is employed to identify structural shocks based on the ordering above.[15]

The main advantage of using VAR-type models in policy analysis is that an impulse-response function (IRF) is readily available. This technique conveniently enables scenario-based policy simulation, which is more informative than a standard impact assessment. For instance, when evaluating the cost of LAW, staff normally reports the baseline reduction in credit growth as a result of monetary policy tightening. Nevertheless, they might additionally present the confidence interval (e.g. ± 2SD) of the impact on credit growth to the MPC too. The lower bound of the IRF could correspond to 'Effective LAW' scenario (reduction in credit growth is larger than baseline), and the upper bound 'Ineffective LAW' (reduction in credit growth is smaller than baseline). As a consequence, policymakers can fully appreciate a range of possible outcomes.

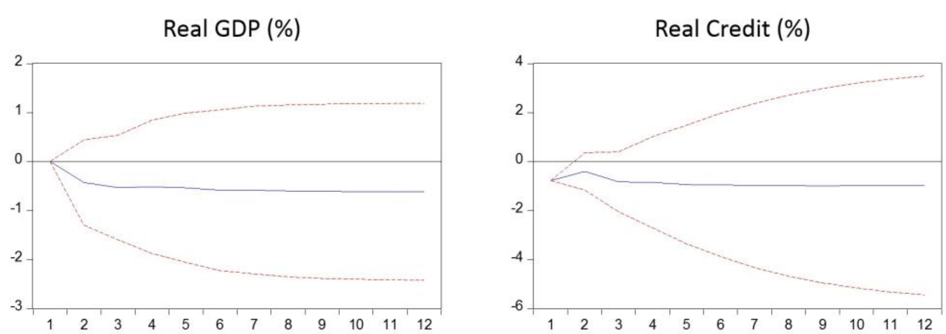

Figure 8. Effects of Policy Rate Shock on Real GDP and Real Credit Growth

The panel shows three different lines – ineffective LAW line, baseline and effective LAW line (from top to bottom respectively) – of responses on GDP and CREDIT to monetary shock. The bounds correspond to ± 2SD.

[14] We use the same data set as in Section 2.1

[15] We also experimented with time-varying parameters (Primiceri, 2005; Aastveit et al., 2017), and coeffi- cient restrictions (Arias et al., 2017). However, such variation in core models does not pose any departure from the main analytical framework.

For Thailand's policy simulation, we assume that credit and land price will grow by about 5% per annum during the next few years [market forecasts]. Under the baseline scenario, credit growth is expected to soften by slightly above 1% per annum in response to a one percentage point increase in the policy interest rate. On the other hand, the 'Effective LAW' sees the impact of around 4%, while 'Ineffective LAW' faces accelerating loan growth. The latter might arise because of a shift in expectations where agents perceive the rate hike as a sign of robust growth outlook.

Based on the above IRF results, we can then calculate the corresponding changes in FC, their impact on future GDP growth, and the probability of financial crises accordingly by using the methodologies described in Section 2.

- In the short run, such monetary policy tightening is expected to cut down GDP growth by 0.60% but adds a non-statistically significant 0.16% to headline inflation [core model].[16]
- In the longer run (about 2-4 years), the softer growth of credit and land price is expected to improve future GDP growth by a 0.01% rate [quantile regression], and lower the probability of financial crises by 0.91% [panel logistic regression]. In the Effective LAW case, however, future growth could improve by 0.07%, and the crisis probability drops markedly by 4.62%. Under the Ineffective LAW scenario, on the other hand, the impact is reversed.

These figures represent a novel inter-temporal trade-off between using monetary policy to address FS vis-a-vis PS. The exercise, therefore, provides the MPC with information to carefully weigh the costs and benefits of LAW policy. Our analytical framework is summarized in Figure 9 below. Such a procedure shall be integrated into a monetary policy framework that takes FS considerations into account systematically. Although our framework shares the same spirit as the simple cost-benefit analysis of Svensson (2016) and Pescatori and Laseen (2016), we account for a detailed analysis of macro-financial linkages which gives us an insight into the impact of FC to future economic growth.

[16] We humbly acknowledge the presence of 'price puzzle', which we have been unsuccessful at resolving.

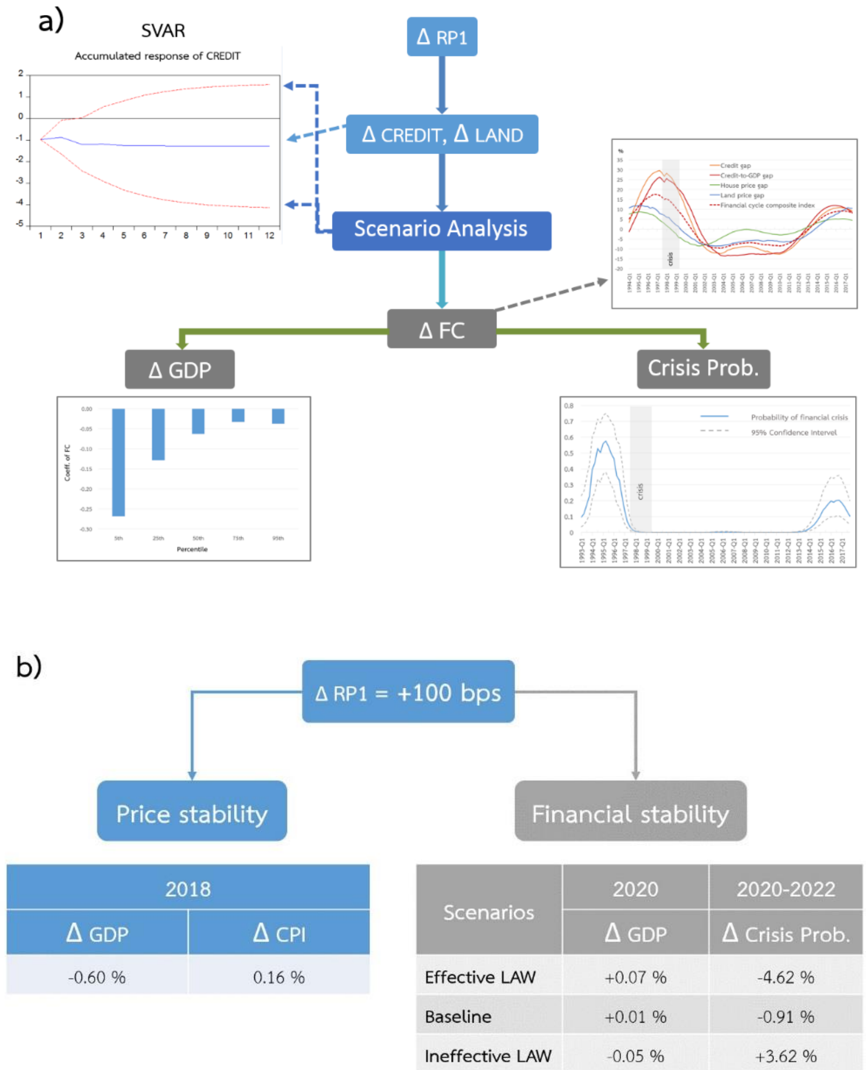

Figure 9. Analytical Framework for FS-oriented Monetary Policy (a) and Policy Simulation Results (b)

Panel a) shows a procedural diagram to quantify the impact of monetary policy actions on financial cycle (FC), which in turn affects growth dynamics and the probability of financial crises. A change in monetary policy will affect credit and land price growth in the scenario analysis via the 'core' SVAR model. In the longer run, an increase in policy rate, leading to a decrease in FC, will also lower the likelihood of a crisis and raise growth as shown by our quantile regression results. However, this interest rate hike will cut down the GDP growth in the short run. We acknowledge the presence of 'price puzzle' in our SVAR analysis. **Panel b)** is an example of the quantified trade-off presented to the Monetary Policy Committee.

4. FS Dashboard for Comprehensive Risk Surveillance

To successfully incorporate FS into monetary policy formulation, a set of tools to continually evaluate and monitor FS risks is indispensable. So far, our attention has centered around FC. However, being an aggregate measure, FC can at best reflect the overall financial imbalances – it does not offer granular views of the country's financial stability. To comprehensively capture all pockets of vulnerabilities therefore requires a look into disaggregate indicators.

At the BOT, a working group brings together experts from various departments across the bank to explore and prototype a sectoral dashboard which would complement FC in risk surveillance. The dashboard aims to serve three main objectives: (1) to ensure that all pockets of risks are under the radar; (2) to shed some light on which sectors are at risk and which types of vulnerabilities are building up. This will facilitate an appropriate policy mix between monetary and macroprudential policies discussed later in section 4; (3) to systematize and improve an existing FS monitoring process which tends to rely rather substantially on expert judgment. Our design follows four steps below.

Step 1 Indicator selection. Since the adoption of flexible inflation targeting in 2000, BOT staff have regularly monitored FS risks in seven key sectors, namely households, corporates, financial institutions, fiscal sector, real estate, financial markets, and external sector. The working group decided not to include fiscal sector in the dashboard as fiscal sustainability assessment has a separate process at the bank, while financial institutions are sub-categorized into banks and non-banks due to the different natures of their businesses. Nonbank financial institutions have recently played more prominent role in our credit markets, especially in low-income groups who are more susceptible to macroeconomic shocks. Candidate indicators for each sector were proposed and debated by the experts. For instance, households' debt to GDP could be easily agreed upon as a prime risk indicator for household sector. On the contrary, the validity of certain financial market indicators were challenged on grounds of the lack of depth in the relevant segments. All in all, the chosen set of indicators conforms to the literature on an early warning system, see IMF (2014), BIS (2017).

Step 2 Risk classification. To articulate meaning out of the pre-selected indicators, we follow the FRBNY FS monitoring framework (Adrian et al., 2015) that classifies vulnerability into four types, namely 'price of risk', 'leverage', 'mismatch', and 'interconnectedness'. Some of them share the same rationale as FC, where overleverage could lead to default, while underpricing of risk could result in asset price bubbles which are prone to sharp corrections. In addition, risk underpricing tends to weaken credit standards and lead to low risk premium. Mismatch in terms of liquidity, maturity, and currency could also be a source of financial instability. Excessive mismatch exposes banks to liquidity risk that could trigger bank runs and fire sales. Furthermore, structural features of the financial system itself could generate vulnerabilities. Coupled with complexity to assess information and insufficient transparency, interconnection between entities could cascade and amplify shocks on much larger scales.

The working group also proposed two more vulnerability types, viz. 'risk appetite' which captures behavior that may lead to underpricing of risk, and 'vulnerability in debt serviceability and cushion' which helps identify borrowers' propensity to default and lenders' shock-absorption capacity. They are particularly relevant to Thailand in the current context as search-for-yield behavior in the prolonged low rate environment warrants continued monitoring. Finally, the indicators are compiled into a FS risk matrix of sectoral risks as shown in Table 1. In this paper, we will focus on the four cyclical risks only, for they have direct implication on the conduct of monetary policy as mentioned above.

Step 3 Risk scoring. The next step is to come up with a systematic approach to assess the degree of riskiness. In so doing, we adopt 'Ms.Muffet' (Cervantes et al., 2014) – which is a simple yet robust methodology – to calculate risk scores. It begins with computing z-score for each indicator from 5-year historical rolling window. Next, the numerical ranking from 1 to 10 is assigned to each normalized variable. The last step is to equally weigh each numerical ranking to get the final score. The consolidation by type of risks is also permissible. (See Figure 10 for an example of FS Dashboard). While FS seems sound overall, [under] pricing of risk and vulnerability in debt serviceability and cushion exacerbated from five years back, and hence warranted close monitoring.[17] While the use of statistical techniques should make risk assessment more consistent over time, there is room to incorporate expert opinions, for instance, by fine-tuning the relevant window, or by leaving some remarks to policymakers. Indeed, the selection of appropriate benchmarks – instead of using historical average – as well as reference period is an empirical issue which bank staff could explore further.

[17] The working group later changed the name from 'price of risk' to '[under] price of risk' to better indicate the direction of concern.

Step 4 Robustness check. Since Normality is the critical underlying assumption of Ms. Muffet, we validate the final scores by using average probabilities based on empirical distributions (for detail see e.g. Lichtendahl et al., 2013). This method yields a similar result to Ms.Muffet, but the new scores show greater degree of dispersion due to the relaxation of normality assumption. Overall, the working group concluded that the dashboard produced by Ms.Muffet methodology provided satisfactory results.

a) FS risk matrix

t1		Type of Risk			
		[Under] Pricing of risk	Risk appetite	Leverage	Vulnerability in debt serviceability and cushion
Entity	Household				
	Corporate				
	Bank + SFIs				
	Non-bank FIs				
Market	Real Estate				
	Monetary and Financial Market				
	External				

b) Spidergram of FS risks

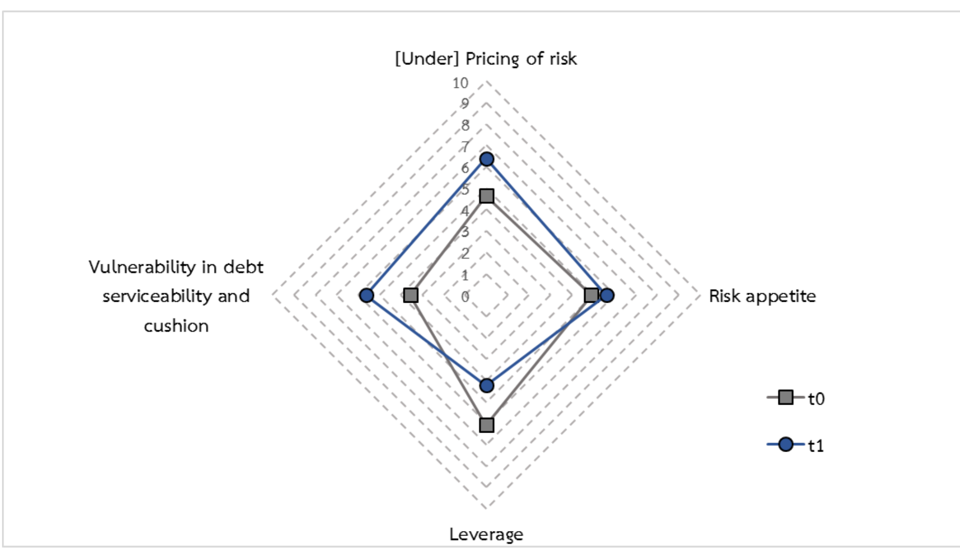

Figure 10. Final Scores Illustrated by Two Formats:

A score ranging from 0 to 10 represents the lowest to the highest level of risk respectively. Panel a) shows risk scores in matrix format (a score ranging from 0 to 10 is converted into a heat-map for better visualization). While financial stability appears sound overall, [under] pricing of risk seems prevalent in many sectors. This risk type, along with vulnerability in debt serviceability and cushion, warranted close monitoring. Panel b) shows the consolidation by type of risks that allows for comparison across time. In fact, both issues exacerbated from the previous period.

5. Calibrating Monetary and Macroprudential Policies

Our discussion will not be complete without considering the optimal policy mix for the MP framework that systematically takes FS considerations into account. As the well-known Tinbergen rule dictates, each policy target requires at least one policy tool. Therefore, preserving both PS and FS simultaneously probably requires, in addition to monetary policy tools like the policy interest rate, other available tools that can address FS concerns such as macroprudential policy (MaP). The formulation of a suitable policy package should draw on the merits of these policies in close coordination. The literature on interactions between MP and MaP is in an early stage though. Here, we will contribute to it by discussing a high-level framework and presenting some practical issues that need to be considered when policymakers calibrate these tools.

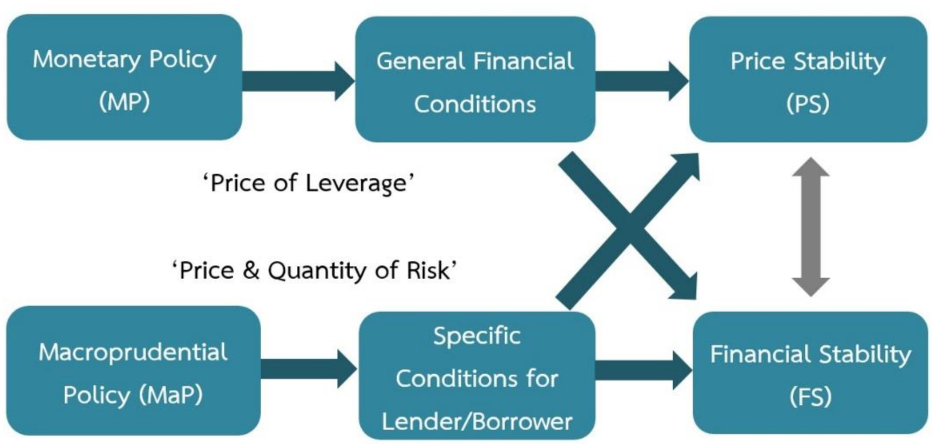

Figure 11. Transmission of Monetary and Macroprudential Policies

MP sets a benchmark domestic interest rates, which determine costs of borrowing ('price of leverage'). The impact of MaP, on the contrary, is transmitted via balance sheet components of banks/companies/households. These tools could influence both PS and FS objectives.

Figure 11 illustrates the standard transmission mechanism of these policies. MP influences economic activities by affecting general financial conditions since the policy interest rate serves as a benchmark of domestic interest rates. An increase in the benchmark rate raises costs of borrowing ('price of leverage'), and the economy's overall financial activities are likely to be dented. Being a blunt tool, MP seems to be able to 'get in all the cracks', as Stein (2013) puts it. MaP, on the contrary, targets financing activities of a particular group of borrowers and lender, where transmission is made via balance sheet components of economic agents. For example, tightening the loan-to-value ratio is likely to deter financing activities in the real estate sector, but shall not, at least in theory, deter other types of activities. Thus, MaP is usually viewed as a prime candidate to counter pockets of FS risk. Along the above line of reasoning, one might be obliged to use MP to address systemic risks as captured by FC, while pockets of risks presented in the dashboard are left for MaP. IMF (2015) recommends that policy actions be taken only when financial risks are 'excessive', i.e. there is a significant likelihood of large disturbances to future macroeconomic conditions originating in financial variables (crises). We argue, on the contrary, that such systemic risks as captured by FC are not mutually exclusive from those in the dashboard as large financial imbalances could translate into underpricing of risk, higher risk appetite or vulnerability in debt serviceability, to name a few. MP and MaP should therefore be calibrated together, particularly when the economy is in the 'red zone' (FC and BC in opposite directions). In case of Thailand, even though FC has recently peaked (Figure 2) – which signals subsiding systemic risk – [under] pricing of risk still seems prevalent in many sectors according to disaggregate data (Figure 10). In such circumstances, MP easing to shore up output should be accompanied by MaP tightening in multiple sectors to contain FS risks. Even in the presence of effective MaP, such a policy strategy may be most costly than using MP to LAW so as to manage the 'price of leverage' in general.

Indeed, an appropriate policy sequencing is still a hotly debated topic among academics and central bankers (for detail see Smets, 2014). A camp led by the BIS supports the use of MP to addresses financial imbalance, while the other led by the IMF believes that MP should be the last line of defense against FS risks. To aid policymakers' discussion, bank staff shall provide additional information which includes, but not limited to, transmission analysis of MP and MaP to BC and FC, the interactions between MP and MaP, and also a risk management plan in case of unintended consequences.

In practice, there are additional considerations that policymakers need to factor into their decisions.

- **Institutional arrangements MaP** might not be under the jurisdiction of the central bank; or fragmented institutional arrangements might make it difficult for the MPC to deploy such policies. In Thailand, for instance, FS falls under the responsibility of four main agencies, namely the Ministry of Finance, the BOT, the Securities and Exchange Commission, and the Office of Insurance Commission. Although these regulators do meet regularly, not all MaP measures will be promptly available.

- **Availability of MaP** There is no MaP available for certain segments of the economy. Non-banks such as credit cooperatives tend to be more loosely regulated than banks which means that MaP to target this particular businesses may not exist. In the extreme, the grey economy requires structural policies and appropriate interventions.
- **Implementation concerns** MaP tightening is usually an unpopular directive, and might have some political repercussion. This not only makes the implementation itself challenging, but also the right timing difficult to gauge.

Under the above circumstances, it might be necessary for the rate setting committee to LAW slightly by keeping the key rate at a marginally higher level than otherwise warranted by developments in the real economy in order to safeguard FS.

6. Conclusion

In this paper, we consider a systematic approach to incorporate financial stability considerations into monetary policy framework, and supports our case by looking at the experience at the Bank of Thailand. In summary, our attempt is not to propose a new monetary policy framework, but to make some modifications to the flexible inflation targeting framework. As an initial step, the conduct of monetary policy can be made more oriented toward financial stability when staff includes financial cycle data in the information pack for the rate setting committee. Additional materials, e.g. the estimated cost of leaning against the wind, shall be supplemented if required. We also presented an example of a dashboard which should further facilitate discussion of the policymakers.

While the proposed analytical framework is rather generic, more works need to be done to ensure successful implementation. Obviously, the applicability of our approach will also depend largely on the country context such as the economic and financial structure, the suitable measurement of financial imbalance, and institutional setups of different policy tools. Nevertheless, we believe that technical research and model development are key to enhance quantitative policy analysis. The analysis of macro-financial dynamics could be strengthened by utilizing micro and balance sheet data. Moreover, a platform of model should be developed to facilitate realistic policy simulation.

Table 1: List of Core Indicators by Sector and Type of Vulnerability

Sector/Vulnerability		[Under] Pricing of risk	Risk appetite	Leverage	Vulnerability in debt serviceability and cushion	Mismatch	Interconnectedness
Entity	Household		▪ % of risky financial asset to total financial asset	▪ Household debt to GDP ▪ Household debt growth	▪ Debt service ratio (DSR) ▪ New entry NPL rate (retail loan) ▪ % Special mention loans (SM) + NPL (retail loan)	Structural dimension	
	Corporate	▪ Hurdle rate (proxy by Weighted Average Cost of Capital: WACC)		▪ Corporate debt to GDP ▪ D/E ratio of The Stock Exchange of Thailand (SET) ▪ Corporate debt growth	▪ Interest coverage ratio (ICR) ▪ New entry NPL rate (business loan) ▪ % SM + NPL (business loan)		
	Bank + Specialized financial institutions (SFIs)	▪ Change in new loan rate* - Change in policy rate • > 1,000 mn THB • < 1,000 mn THB	▪ Risk-weighted asset growth ▪ Loan to deposit + borrowing ▪ Credit to GDP gap ▪ Credit standard from senior loan officer survey (SLOS)	▪ Bank D/E ratio ▪ SFI leverage (D/E ratio)	▪ Liquidity coverage ratio ▪ Capital adequacy ratio (CAR) ▪ Actual to regulatory loan loss provision		
	Non-bank financial institutions	▪ Average cooperatives' loan rate – Average cooperatives' deposit rate	▪ Non-bank FI's loan growth ▪ Saving cooperatives' deposit growth ▪ Money market fund +daily fixed income / Saving commercial banks' deposit + SFI ▪ Foreign investment fund growth	▪ Non-bank FI's Leverage (D/E ratio) ▪ Saving cooperatives' Leverage (D/E ratio) ▪ Insurance D/E ratio	▪ Non-bank FI's ICR (listed company only)		
Market	Real Estate	▪ Housing price growth ▪ Land price growth	▪ Loan-to-value ratio (LTV) ▪ Condominium's reservations (average of the past 20 months) to transferred properties by unit (latest month)	▪ Pre-finance loan + bond (% growth) ▪ Pre-finance loan + bond (% to GDP) ▪ Post-finance loan (% growth) ▪ Post-finance loan (% to GDP)	▪ ICR of SET's developers • ICR P25 • ICR P75 ▪ Mortgage borrowers' debt service ratio ▪ % SM + NPL pre finance ▪ % SM + NPL post finance		
	Monetary and Financial Market	▪ 12-month forward P/E ratio ▪ 2 - 10 spread of govt bond ▪ 1-3Y corporate bond spread by rating • A group • B group	▪ VIX Index ▪ Outs of unrated + non-investment grade bonds to total bond outstanding ▪ SET turnover ratio ▪ % Non-resident (NR) bond holding ▪ % NR stock holding ▪ % margin loan to SET total market value				
	External	▪ 5Y CDS premium • 10Y govt bond spread over G3		▪ External debt growth ▪ External debt to annualized export ▪ External debt to foreign reserve	▪ DSR (foreign debt to export's income (goods & services)) ▪ ST debt to foreign reserve		

This dashboard is an attempt on classifying our core indicators into a 7 × 6 table –seven key sectors and six types of vulnerabilities– which enables us to comprehensively monitor all pockets of FS risks. The first four columns are time-dimensional type of vulnerabilities, which are known to be conducted by monetary policy, whereas the last two columns are of structural-dimension (under on-going investigation).

*New loan rate is calculated from interest payments on new loan contracts by 14 Thai commercial banks excluding loans to households and financial intermediaries and is weighted by loan size.

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