Are Market Views on Banking Industry Useful for Forecasting Economic Growth?*

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Abstract

Using two market-view variables, namely the regulatory forbearance fraction imbedded in the bank capital and the market-valued of the bank equity-to-assets ratio, derived from market equity and total liabilities from listed commercial banks in the U.S. and three countries (Japan, China, India) and a region (Southeast Asia) in Asia, we show compelling evidence that market views on banking industry have significant predictive power on economic growth after controlling for stock, bond, and inflation variables. The current paper further contributes to the literature on interaction between the financial intermediation and the economic growth by showing evidence of market perceptions of the banking industry impacting the real economic activities.

Keywords: Bank regulation, Regulatory forbearance, Forecasting, Economic growth

JEL classification: G17, G21, G28

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1 Introduction

The financial intermediaries by their nature efficiently allocate resources between lenders and borrowers. Firms in real sectors, especially those heavily relying on external financing, benefit from financial intermediaries due to reduced financing costs, and thus grow faster than those without accessing to the same resources. Many studies demonstrate that the development and the structure of financial intermediaries, especially the banks, have impacts on economic activities with both single-country and cross-country evidence (e.g. Chava et al., 2013; Fernandez de Guevara and Maudos, 2011; Mitchener and Wheelock, 2013 and etc.). According to the World Development Indicators (WDI) published by the World Bank, credit provided by financial sector to GDP increases from 140.6% (145.2%) in 1990 to 184.1% (241.9%) in 2016 world wide (in the U.S.), which indicates the rising importance of the banking industry worldwide. During the 2007-2009 financial crisis, the insolvency of U.S. banks not only caused the deterioration of the global financial markets, but also spilled over to other industries. Consequently, the economic output fluctuated in align with the changing health and insolvency conditions of the banking industry.

Traditionally in the literature, the financial health and soundness of a bank is assessed by accounting-based measures. Without market and regulatory intervention and discipline, banks increase the leverage in case of risk reduction (Bushman and Williams, 2012). Tabak et al. (2012) document positive impacts of capital ratio (equity to asset ratio) on the stability of large banks in a competitive market. Adrian and Boyarchenko (2015) and Geanakoplos (2010) develop theoretical frameworks advocating the procyclical leverage of financial intermediaries. Adrian and Shin (2013) empirically show that the financial intermediaries' book leverage, measured by the ratio of total assets to equity, is a procyclical variable that is high in boom times with low risk premiums. However, the accounting-based measures possess static and backward-looking nature. They provide no information on how the market expectation reacts to the changing banking health and soundness conditions and regulatory policies.

Based on stock market information, the market perception of the bank regulatory closure rules, represented by a regulatory policy parameter which is first introduced by Ronn and Verma (1986), can be inferred. A parameter less than one implies the existence of the regulatory capital forbearance with a value equal to that of the capital assistance. Most existing literature adopts a fixed regulatory policy parameter to estimate bank asset values and volatility (Flannery and Sorescu, 1996; Hassan et al., 1994). However, the time-varying feature of the bank closure rules is not taken into consideration by assuming a fixed policy parameter. To compensate the practical shortcoming, Lai and Ye (2017) develop a more realistic framework to infer the time-varying policy parameter reflecting market views from more than 700 U.S. listed banks' market value of equity and estimate the capital forbearance value given bank-specific risk and business cycle variables. They find a negative relation between forbearance fraction in capital and the GDP growth, which indicates that the market expects banks to obtain more (less) forbearance during recessions (expansions). Therefore, the forbearance value, which reflects the market perception of banks' equity value and risks, i.e. banks' financial health, is a countercyclical variable. In light of the banking industry' prominent role on the U.S. economy, we expect that the gross domestic product (GDP) growth rate can be predicted by the market-view of the banking industry health embedded in the forbearance value. The Asian banking industry differs from that of the U.S. in terms of developing level and economic stage, governance structure, and regulatory oversight among other factors such as law and culture. The role played by the market view on the safety and soundness of the banking industry in the economic growth in Asia is worth studying to test whether our framework also works outside of the U.S. Dictated by the availability of data, we retain three countries namely Japan, China, India and a region, Southeast Asia (composed of Singapore, Malaysia, Philippines, Indonesia, Thailand, and Vietnam), and their major public listed banks for estimating the capital forbearance value and its capacity in predicting GDP growth rates.

Following Lai and Ye (2017), we derive two market-viewed factors from their bank regulatory capital forbearance model. The Forbearance Fraction in Capital ($\mathbb{FFC}$) measures the market evaluation of a bank's health, and the "Market Cap / Implied Asset Value" measures the market assessment on the capital adequacy of a bank. We expect the first moment, which is calculated as the cross-sectional median over time, of the factors to be able to predict short-term GDP growth, as they measure the aggregate status of the whole banking industry. In addition, we also select the second moment of the cross-sectional distribution of the factors, which measures the cross-sectional dispersion of the market views, to forecast GDP growth rate, as they provide information on imbalanced shocks in the market views of the banking industry. These variables are particularly influential during the recessions. For instance, the bailout or failure of large public banks could induce overall market panic and contagion, negatively impact related industries, and consequently lower the market expectations of future economic growth.

Among the macroeconomic factors that influence the economic growth, the inflation is generally proved to have a negative impact on the medium to long-run economic growth when it is above certain threshold which is determined by country characteristics (Ashraf et al., 2013; Bruno and Easterly, 1998; Kremer et al., 2013; Vaona, 2012). In addition, the Chicago Fed National Activity Index (CFNAI) has been documented as an effective measure of U.S. real economic activity which can be used as an early indicator of business cycle (Brave et al., 2009; Evans et al., 2002; Lang and Lansing, 2010). In our models, we add the two variables and find that the CFNAI performs much better than the lagged GDP in predicting the GDP growth while the inflation does not contribute to the quarterly GDP growth forecasting within the in-sample period. A similar business cycle forcasting measure Leading Economic Index (LEI) published by the Conference board is used as our Asian counterpart of the CF-NAI.

To test the robustness of our forecast models, we take into consideration the bond and stock market factors which have been proved to significantly influence the real economic activity. Harvey (1989) finds that over the period of 1953 to 1989 30% and 5% of the variation in economic growth can be explained by bond yield spreads (both medium- and long-term bond yields) and stock market returns (both short-term and long-term returns), respectively.[1] The curvature utilizes more yield curve information on short-, medium- and long-horizon bond yields. Therefore, it possesses much better predictive power than the term spread in forecasting GDP growth (Møller, 2014).

In this article, we construct and compare three GDP forecast models: a simple regression model using CFNAI/LEI as an explanatory variable without any banking industry indicators, a model with accounting/market-based banking variables, and a model with model-derived market-view banking variables. After controlling stock and bond market factors, and inflation that potentially predict the GDP growth, we find that the forecasting power of our model-derived market-viewed banking variables is obviously superior to that of the accounting/market-based banking variables. The models are improved noticeably in terms of adjust R^2s, Akaike information criterion (AIC), and Bayesian information criterion (BIC) for the U.S., but only marginally for Asia. The significant predictive variables including lagged CFNAI, inflation and asset market factors in the first two models become insignificant in the third model, which indicates that our market-view banking variables contain information on contemporaneous macro economy and financial asset markets. In general, the Asian GDP growth cannot be well predicted by business cycle indicators, inflation and asset market factors. However, the short-term GDP growth can be predicted by market-

[1] Stock and Watson (1989) also add the term spread, the stock market return, and corporate credit spread in the construction of their leading business cycle indictor index. Many other researchers explain GDP growth with term spreads (e.g., Bernard and Gerlach, 1998; Estrella and Mishkin, 1998; Hamilton and Kim, 2002, and etc.).

evaluated bank's health variables $\mathbb{FFC}$. Overall, our model-derived variables reflecting the market view of the banking industry health exhibit a strong predictive power on the future GDP growth in the short run. In the U.S. case, a healthier banking sector, indicated by lower aggregated $\mathbb{FFC}$, higher aggregated "Market Cap / Implied Asset Value", more left-skewed $\mathbb{FFC}$, and lower dispersion in "Market Cap / Implied Asset Value", tends to lead to subsequent higher GDP growth. Unlike the U.S., in many of the Asian countries, the government often intervenes directly into the banking industry by injecting more cash credit to stimulate real economic activities. Higher value of capital forbearance entails more additional expected credit granted by the government. Therefore, we expect the opposite results in the Asian case on realizing the impact of regulatory forbearance into economic growth.

The remainder of the article is organized as follows. Section 2 derives the two market-viewed banking factors from the regulatory capital forbearance model of Lai and Ye (2017). Section 3 provides insights and mechanism of the relationship between market-viewed banking factors and the GDP growth. Section 4 presents the forecast models with the analysis of empirical results. Section 5 concludes.

2 Market view factors: Lai and Ye (2017) model

This section briefly reviews the equity pricing model with time-varying policy parameter developed by Lai and Ye (2017). This section keeps the derivations minimal and limited to a conceptual understanding necessary for this article. Please see Lai and Ye (2017) for more detailed derivations.

2.1 The model

Let us define a 2×1 column vector of state variables

$$X_t = \begin{pmatrix} x_1(t) \\ x_2(t) \end{pmatrix}$$

which, under the risk-neutral measure Q, follows the stochastic differential equations (SDE)

$$dX_t = d\begin{pmatrix} x_1(t) \\ x_2(t) \end{pmatrix} = \left[\begin{pmatrix} \kappa\theta \\ \mu \end{pmatrix} + \begin{pmatrix} -\kappa & 0 \\ 0 & 0 \end{pmatrix}\begin{pmatrix} x_1(t) \\ x_2(t) \end{pmatrix}\right] dt + \begin{pmatrix} \sigma_1\sqrt{x_1(t)} & 0 \\ 0 & \sigma_2 \end{pmatrix} d\begin{pmatrix} w_1(t) \\ w_2(t) \end{pmatrix}. \quad (1)$$

where $w_1(t)$ and $w_2(t)$ are independent Wiener processes under the measure Q. Note that we model exogenously the stochastic policy parameter as $\rho_t = e^{-x_1(t)}$, so that ρ_t lies between zero and one as x_1 is non-negative, and ρ_t is mean reverting. Since we model the value of a bank as $V_t = e^{x_2(t)}$, the dynamic of V_t is given by,

$$dV_t = de^{x_2(t)} = \mu_V V_t dt + \sigma_2 V_t dw_2(t)$$

where

$$\mu_V = \mu + \frac{\sigma_2^2}{2}.$$

At time t, the equity value of a bank represented by the market cap, E_t, which is a call option on V_t with maturity T, has the following pay-offs at time T:

$$E_T = \begin{cases} V_T - D & \text{if } V_T > D \\ V_T - \rho_T D & \text{if } \rho_T D \leqslant V_T \leqslant D \\ 0 & \text{if } V_T < \rho_T D. \end{cases} \quad (2)$$

The stock market assessment of the supervisory forbearance is captured by this pay-off function with a random strike price. Then, with $\mathbb{E}_t^Q[.]$ denoting the expectation, under the measure Q conditional on the information up to t, we have[2]

$$\begin{aligned}
E_t &= B_t(T)\,\mathbb{E}_t^{Q}(E_T) \\
&= B_t(T)\,\mathbb{E}_t^{Q}\left[(V_T - D)\,\mathbb{1}_{\{V_T>D\}} + (V_T - \rho_T D)\,\mathbb{1}_{\{\rho_T D\le V_T\le D\}}\right] \\
&= B_t(T)\left\{\mathbb{E}_t^{Q}\left[(V_T - \rho_T D)\,\mathbb{1}_{\{V_T>\rho_T D\}}\right] - D\mathbb{E}_t^{Q}\left[(1-\rho_T)\,\mathbb{1}_{\{V_T>D\}}\right]\right\} \\
&= B_t(T)\left\{\mathbb{E}_t^{Q}\left[\left(e^{x_2(T)} - e^{-x_1(T)}D\right)^{+}\right]\right. \\
&\qquad\qquad \left. - D\mathbb{E}_t^{Q}\left[\left(1-e^{-x_1(T)}\right)\mathbb{1}_{\{x_2(T)>\log D\}}\right]\right\},
\end{aligned} \tag{3}$$

where $B_t(T) = e^{-r(T-t)}$ is the discount factor, r is the assumed-constant interest rate, and $\mathbb{1}_{\{\cdot\}}$ is an indicator function equal to one when $\{\cdot\}$ holds, and zero otherwise. In the implementation, we set $D = F/B_t(T)$ where F is the book value of the debt level at time t. The model can be solved in closed-form using affine techniques developed in Duffie et al. (2000) and calibrated to bank market equity data using Unscented Kalman Filter (see Lai and Ye, 2017, for details).

2.2 The two market-view variables

Given the model described above, $\mathbb{FFC}$ is defined as

$$\mathbb{FFC}_t = \frac{E_t - E_t^{\rho=1}}{E_t},$$

where $E_t^{\rho=1} = B_t(T)\,\mathbb{E}_t^{Q}\left[(V_T - D)^{+}\right]$ corresponding to the model value of the equity when assuming $\rho_t = 1$, i.e., the intrinsic market cap that is devoid of the forbearance subsidy. By construction, $\mathbb{FFC}$ measures the market value of forbearance in terms of total equity. The lower $\mathbb{FFC}$, the healthier is a bank. We call $\mathbb{FFC}$ a market-view variable that reflects market view of forbearance given to a bank. The reason $\mathbb{FFC}$ can

[2] The risk-free interest rate is assumed to be constant. As in Ronn and Verma (1986), it is also assumed that the effects of interest rate changes are captured in the assets value and associated volatility, i.e., the present value of assets are brought about by anticipated changes in both the investment opportunity set and the interest rate. Unanticipated changes in interest rates are accounted for in the asset risk.

somewhat represent the market view is due to our modeling approach: we explicitly model the policy parameter as a stochastic process and embed market expectation of this process in the bank's equity pricing.

The other variable we consider is Market Cap to Implied asset value ratio, $\frac{MC}{IA}$, defined as $\frac{E_t}{V_t}$ using the symbols in this section. This variable measures the market equity capital ratio, i.e., the model counterpart of the book equity ratio defined as Book Equity / Total Assets. The lower is this ratio, the lower is the owner-contributed equity ratio, and the higher is the leverage level.

To estimate the regulatory forbearance parameter and implied asset values, one-year risk free interest rates, banks' total liabilities, and market caps are used to calibrate the model. Please refer to Section 3.4 in Lai and Ye (2017) for more descriptions about the market-view factors.

3 The economic growth and the market views of banking industry

Take $\mathbb{FFC}$ as an example, because the individual $\mathbb{FFC}$s reveal how the market evaluates the forbearance premium for individual banks, the aggregate $\mathbb{FFC}$ is a nice measure of the market assessment of the health of the whole banking sector. Similarly, the aggregate equity ratio "Market Cap / Implied Asset Value" measures how the market assesses the capital adequacy of the whole banking sector.

If we regard the aggregate factor as first moment information (cross-sectional distribution) from our model-derived panel data, we can also look at second moment information, which measures the cross-sectional dispersion of the market views. This second moment information would be very different from its first moment counterpart: the aggregate factor. The first moment in general measures the macro economic shocks that affect the whole sector relatively evenly, while the second moment is meant to capture imbalanced shocks and/or shocks that have uneven or opposite impacts on the different segments of the whole sector. Therefore, the second moment information provides new insights on how the market evaluates the banking sector. Calmès and Théoret (2014) also find that the cross-sectional dispersion of certain variables, such as loan to asset and non-interest income share, does co-move with business cycle, although they do not explore the usefulness of the cross-sectional dispersion in predicting GDP growth. There is also a view that a greater ability to trade ownership of an economy's productive technologies facilitates efficient resource allocation, physical capital formation, and faster economic growth (Levine and Zervos, 1998). Therefore, the information from stock market and banking industry predicts economic growth. Given this view, in our paper, we combine stock market information with banking industry health measure into the market-view variables to which could potentially provide combined predictive power on economic growth.

In view of the above intuition, we conjecture that our model-derived variables are able to provide incremental information useful for predicting real economic activities. To verify our conjecture, we construct four variables from our panel data: a) the cross-sectional standard deviation of $\mathbb{FFC}$ over time denoted by $\mathbb{FFC}\text{-std}_t$, b) the cross-sectional standard deviation of "Market Cap / Implied Asset Value" over time denoted by $\frac{\mathrm{MC}}{\mathrm{IA}}\text{-std}_t$,[3] c) the cross-sectional median of $\mathbb{FFC}$ over time denoted by $\mathbb{FFC}\text{-median}_t$, and d) the cross-sectional median of "Market Cap / Implied Asset Value" over time, being adjusted to be orthogonal to $\mathbb{FFC}\text{-median}_t$, denoted by $\frac{\mathrm{MC}}{\mathrm{IA}}\text{-median}_t^{\perp}$.[4] Dynamics of these four variables are shown in the upper panels in

[3] We use "Market Cap / Implied Asset Value" instead of "Intrinsic Market Cap / Implied Asset Value" here to avoid potential multicollinearity caused by the highly negative correlation between "Intrinsic Market Cap / Implied Asset Value" and $\mathbb{FFC}$. Nevertheless, "Market Cap / Implied Asset Value" together with $\mathbb{FFC}$ should provide same amount of information as "Intrinsic Market Cap / Implied Asset Value" together with $\mathbb{FFC}$ by their definitions.

[4] The orthogonality here is to ensure, in addition to avoiding multicollinearity, that the coefficients in subsequent regressions reflect clear measures of the impact of the RHS on the LHS. When only the lagged $\mathbb{FFC}$-median and $\mathbb{FFC}$-std are included in the regression, the coefficient of $\mathbb{FFC}$-median is 0.0385* with standard error of 0.015. Similarly, when only the lagged $\frac{\mathrm{MC}}{\mathrm{IA}}$-median and $\frac{\mathrm{MC}}{\mathrm{IA}}$-std are included, the coefficient of $\frac{\mathrm{MC}}{\mathrm{IA}}$-median is 0.0747* with standard error of 0.032. These indicate that the results from using the orthogonal variable are consistent with the genuine relations between GDP growth and $\mathbb{FFC}$ and $\frac{\mathrm{MC}}{\mathrm{IA}}$.

Figure 1 and in all panels in Figure 3.

4 GDP growth prediction analysis

In this section, we first discuss our regression models and control variables that are typically predictive about the GDP growth, then present the empirical results with quarterly data and analyze the implications. Both the US and Asian countries results are discussed.

4.1 U.S. case

4.1.1 Regression models

We now formally test whether our model-derived variables are able to improve the GDP prediction. Specifically, we run the following time series regressions to test how much improvement the four model-derived variable would offer on top of control variables that are typically predictive about the GDP growth. We measure the incremental predictive power by the adjusted R^2s, AIC, and BIC.[5]

$$
\begin{aligned}
\text{GDPG}_t &= \alpha_0 + \alpha_1 \text{CFNAI}_{t-\frac{1}{4}} + \text{Control variables} + \varepsilon_t && (4)\\
\text{GDPG}_t &= \alpha_0 + \alpha_1 \text{CFNAI}_{t-\frac{1}{4}} + \alpha_2 \frac{\text{BE}}{\text{TA}}\text{-std}_{t-\frac{1}{4}} + \alpha_3 \frac{\text{MC}}{\text{TA}}\text{-std}_{t-\frac{1}{4}} \\
&\quad \alpha_4 \frac{\text{BE}}{\text{TA}}\text{-median}_{t-\frac{1}{4}} + \alpha_5 \frac{\text{MC}}{\text{TA}}\text{-median}_{t-\frac{1}{4}} + \text{Control variables} + \varepsilon_t && (5)\\
\text{GDPG}_t &= \alpha_0 + \alpha_1 \text{CFNAI}_{t-\frac{1}{4}} + \alpha_2 \mathbb{FFC}\text{-std}_{t-\frac{1}{4}} + \alpha_3 \frac{\text{MC}}{\text{IA}}\text{-std}_{t-\frac{1}{4}} \\
&\quad \alpha_4 \mathbb{FFC}\text{-median}_{t-\frac{1}{4}} + \alpha_5 \frac{\text{MC}}{\text{IA}}\text{-median}^{\perp}_{t-\frac{1}{4}} + \text{Control variables} + \varepsilon_t && (6)
\end{aligned}
$$

where $\frac{\text{BE}}{\text{TA}}$ and $\frac{\text{MC}}{\text{TA}}$ denote "Book Equity / Total Assets" and "Market Cap / Total Assets", respectively. "Book Equity / Total Assets" is the book-based equity ratio while

[5] Regressions with more lag structures have also been tested in our unreported results. However, none of the lags more than one have significant coefficients. These results are available from the authors upon request.

"Market Cap / Total Assets" is a "hybrid" equity ratio as "Market Cap" is market-based but "Total Assets" is book-based. Both variables are common and model-free measures of the capital ratio and leverage risk. It is worth noting that the construction of the accounting/market-based variables follows standard format in the literature and does not reflect (or is not intended to reflect) market-view. We use these two variables as a benchmark to see how our model-derived market-view variables can improve from this benchmark. Dynamics of the standard deviation and median of the these variables are shown in the lower panel of Figure 1. We also try the models with $\text{CFNAI}_{t-\frac{1}{4}}$ replaced by $\text{GDPG}_{t-\frac{1}{4}}$. All empirical interpretations remain the same. However, the coefficients of $\text{CFNAI}_{t-\frac{1}{4}}$ are highly significant while those of $\text{GDPG}_{t-\frac{1}{4}}$ are much less so, and also the models with $\text{GDPG}_{t-\frac{1}{4}}$ have lower adjusted R^2's. We therefore present results with $\text{CFNAI}_{t-\frac{1}{4}}$.

Since our model-derived variables are constructed based on the model parameters calibrated using the full sample period, one might suspect that the incremental gain of the R^2, if any, would be due to the future information captured in the parameters. To ease this concern, we conduct both in sample and out of sample regressions. Specifically, in the out of sample regression, we calibrate all the parameters using partial data, then part of model-derived variables are constructed based on the information only available up to that point. In the out of sample regression, the full sample is up to 2017Q4 and the model-derived variables before 2012Q4 are estimated only using data up to 2012Q4.

4.1.2 Data

CFNAI is constructed by the Federal Reserve Bank of Chicago. It employs economic indicators that belong to the categories production and income (23 series), employment and hours (24 series), personal consumption and housing (15 series), and sales, orders, and inventories (23 series). The data are inflation adjusted, and freely available at the website of the Federal Reserve Bank of Chicago.

For the control variables, we consider stock and bond market variables. Specifically, for the stock market variable, we use quarterly S&P 500 stock index return, *SP500 Return*, which is the most standard variable for controlling stock market information, the data is obtained from Bloomberg; for the bond market variable, we follow Møller (2014) and consider the curvature of the treasury bond yield curve, *Curvature* is defined as two times five-year yield minus the sum of 10-year and one-year yields $(2 * 5yr - (10yr + 1yr))$; *Curvature* is calculated using the data downloaded from Bloomberg. We also include the inflation rate, which is generally believed to have negative impact on the medium to long-run economic growth (see, e.g., Ashraf et al., 2013, and others), downloaded from the website of Trading Economics. The sample period covers 1990Q2 to 2017Q4, where the data after 2012Q4 is used for out-of-sample test.

4.1.3 Empirical results and analysis

We report in sample regression results in Table 1 and out of sample results in Table 2. In the in sample regression, the full sample is up to 2012Q4 and the model derived variables are estimated using the full sample. In the out of sample regression, the full sample is up to 2017Q4 and the model-derived variables before 2012Q4 are estimated only using data up to 2012Q4. Since the out of sample results are consistent with the in sample results, we focus on the out of sample results only.

From Table 2 we can see with one quarter lagged CFNAI, Model (4) has an adjusted R^2 of 34%. By adding four more model-free variables: $\frac{\text{BE}}{\text{TA}}$-std, $\frac{\text{MC}}{\text{TA}}$-std, $\frac{\text{BE}}{\text{TA}}$-median, and $\frac{\text{MC}}{\text{TA}}$-median to the RHS, the adjusted R^2 increases by 3% and AIC only improves marginally (BIC even becomes worse). We also notice that among the four variables in Model (5), only $\frac{\text{MC}}{\text{TA}}$-std and $\frac{\text{MC}}{\text{TA}}$-median are significant. This means the book-based variable $\frac{\text{BE}}{\text{TA}}$ (both the first and second moments) and the second moment of $\frac{\text{MC}}{\text{TA}}$ provide little power in predicting the GDP growth.

Let's now look at the results of Model (6). When we add the four model-derived variables: $\mathbb{FFC}$-std, $\frac{\text{MC}}{\text{IA}}$-std, $\mathbb{FFC}$-median, and $\frac{\text{MC}}{\text{IA}}$-median$^{\perp}$ to the RHS in addition to the lagged CFNAI and the control variables, we find the adjusted R^2 increases significantly: from 34% to 42%. AIC also improves noticeably. BIC improves as well although the improvement is less prominent. Therefore, we confirm that our model-derived variables are able to provide a significant amount of incremental information useful for predicting real economic activities. Since these are out of sample results, this incremental gain is not due to the future information captured in the calibrated parameters.

The significant coefficients of $\mathbb{FFC}$-median and $\frac{\text{MC}}{\text{IA}}$-median$^\perp$ well match our intuition. As we mentioned previously, $\mathbb{FFC}$-median measures the market view of the health status of the whole banking sector. The significantly negative coefficient of $\mathbb{FFC}$-median indicates when the market thinks the sector is healthier, the subsequent GDP growth tends to improve. The significantly positive coefficient of $\frac{\text{MC}}{\text{IA}}$-median$^\perp$ indicates that higher aggregate capital adequacy ratio of the banking sector well accommodates improvement in the GDP growth.

We also have significant coefficients of $\mathbb{FFC}$-std and $\frac{\text{MC}}{\text{IA}}$-std. The significantly positive coefficient of $\mathbb{FFC}$-std implies that the imbalanced shocks to $\mathbb{FFC}$ typically induce a better GDP growth. To understand this observation, we refer to the histogram of $\mathbb{FFC}$ plotted in the left panel of Figure 2. Since $\mathbb{FFC}$'s distribution is highly skewed to the left, when $\mathbb{FFC}$-median keeps constant, a higher $\mathbb{FFC}$-std means there are more banks having lower $\mathbb{FFC}$s. This is a sign of improved health of the banking sector. Therefore, given the same level of $\mathbb{FFC}$-median, a higher $\mathbb{FFC}$-std generally improves the GDP growth. A higher $\frac{\text{MC}}{\text{IA}}$-std typically indicates an higher capital concentration cross-sectionally, as $\frac{\text{MC}}{\text{IA}}$ has a relatively symmetric distribution, which is shown in the right panel of Figure 2. The significantly negative coefficient of $\frac{\text{MC}}{\text{IA}}$-std might indicate that this trend of capital shifting is not propitious for the GDP growth due to a higher banking (capital) concentration, see, e.g., Bikker and Haaf (2002). In Table 3 we also present results of a robustness test where we replace the lagged CFNAI with the lagged GDP growth. Even though the R^2s are lower in the robustness test, the significance and signs of the coefficients remain the same. In sum, our results are consistent with Levine and Zervos (1998)'s view about the predictive power of information from the stock market and banking industry on the economic growth.

4.2 Asian case

4.2.1 Data

To compare with the U.S. case, we use the Leading Economic Index (LEI) from the Conference Board to replace the CFNAI in Model (4) to (6) as the CFNAI is not available for Asian countries. The index calculated from key economic indicators aims to predict future economic activity of a country. All the control variables are collected for each of the three Asian countries and a region including Japan, China, India, and Southeast Asia. Each variable for the Southeast Asia region weights equally corresponding variables of the six countries - Singapore, Malaysia, Philippines, Indonesia, Thailand, and Vietnam.[6] In total, Japan, China, India, and Southeast Asia data consist of 69, 17, 13, and 18 banks, respectively. The overall stock market information is captured by quarterly stock market index returns, including NIKKEI 225 for Japan, CSI 300 for China, SENSEX for India, STI for Singapore, KLCI for Malaysia, SET index for Thailand, PSEi for Philippines, VN index for Vietnam, and JCI for Indonesia. We obtain LEI and inflation rates from the website of Trading Economics.[7] Stock market indices, as well as one-year, five-year, and ten-year bond yields of each country to calculate curvature are downloaded from Bloomberg. Limited by the availability of the data, the sample periods start in 2004Q3, 2010Q4, 2005Q2, and 2003Q1 for Japan, China, India, and Southeast Asia, respectively, and all end in 2017Q4. Given the short sample periods, we use all the data to calibrate our model-based variables. Therefore, only in-sample analysis is conducted for Asian countries.

[6] We have tried other weighting schemes in our unreported tests, but the results here are robust to the weighting schemes. However, we are aware of the other other factors, e.g., political structure, currency policy, etc, entering the picture of economy growth prediction. We leave these for future studies.

[7] The LEI is not available for India on the website of Trading Economics.

4.2.2 Empirical results and analysis

The model specifications remain the same as these of Model (4) to (6), where all variables are replaced by their Asian counterparts. The fixed effect panel data regressions are applied to the panel data with four groups: Japan, China, India, and Southeast Asia. The quarterly GDP of Asian countries is generally less predictable than that of the U.S. in the three models. Table 4 shows the results of three panel regressions. All independent variables in Model (4) with one quarter lagged LEI and control variables are insignificant with 10.16% adjusted R^2. Adding model-free variables: $\frac{\text{BE}}{\text{TA}}$-std, $\frac{\text{MC}}{\text{TA}}$-std, $\frac{\text{BE}}{\text{TA}}$-median, and $\frac{\text{MC}}{\text{TA}}$-median to the RHS does not improve Model (4). All the four accounting/market-based variables are insignificant, indicating their lack of predictive power on GDP growth rates. The adjusted R^2 of Model (5) declines by 1.4% although AIC and BIC improve slightly. In Model (6), we replace the four model-free variables in Model (5) by the four model-derived variables: $\mathbb{FFC}$-std, $\frac{\text{MC}}{\text{IA}}$-std, $\mathbb{FFC}$-median, and $\frac{\text{MC}}{\text{IA}}$-median$^{\perp}$ on the RHS. The adjusted R^2 increases from 8.73% to 10.53%, and meanwhile both AIC and BIC improve. From the results we find that our model-derived variables provide some incremental information useful for predicting real economic activities in Asian markets. In Table 5 we present results of a robustness test where we replace the lagged LEI with the lagged GDP growth. Even though the R^2s are lower in the robustness test, the significance and signs of the coefficients remain the same.

To better understand the difference in results for the US and Asia, it is helpful to look at some institutional differences in the US and Asia banking sectors. Allen et al. (2004) document that banks in the US have much smaller loan to GDP ratio than in Asian countries, while banks in the Asian countries have much higher deposit to GDP ratio than in the US. Also, as mentioned by Walsh (2014), the relative size of the financial sectors to GDP in Asian countries tend to be larger than in the US. But they are not yet as sophisticated as that in the US. The capital financing market is dominated by banks in most Asian countries, but this is not the case in the US where equity and bond markets also have an equally important if not larger role. Very importantly, government plays a critical role in banking in many Asian countries, especially in China and India, than in the US. In China, the five largest commercial banks are state-owned, while in India, public banks account for about three-quarters of system assets.[8] Therefore, it is understandably normal to see obvious trace of government intervention in the Asian banking sector. The amount of government granted credit can influence the future economic growth. Under such circumstance, $\mathbb{FFC}$-median measures the market view of the extra credit which the government provides to the banking sector. The significant positive coefficient of $\mathbb{FFC}$-median suggests that the GDP growth tends to be higher after the market expects more credit in the sector. Asian banks' $\mathbb{FFC}$ is also highly skewed to the left, which can be seen in the left panel of Figure 4. When $\mathbb{FFC}$-median keeps constant, a higher $\mathbb{FFC}$-std means less credit by way of capital forbearance in the banking sector, the subsequent GDP growth tends to decline. Therefore, the significant coefficient of $\mathbb{FFC}$-std is negative.

We can also see that the results of Asian countries suggest much less improvement of Model (6) over Model (4) when compared to the results of the US. The difference in the results lies in the fact that the banking sectors in Asia are dramatically different from that in the US in various aspects, which we mention above. Specifically, in the US market, the market view variables carry important information about the efficiency of the banking sector. The banking sector in the US is also less dependent on government than in the Asian countries. The fact that government plays a much bigger role in banking in many Asian markets makes the efficiency of the banking sector less important for the economic growth. This somewhat explains the much less significant results we see in the Asian countries.

[8] See Sahay et al. (2015); Remolona and Shim (2015); Madhu Sudan et al. (2010) for more general discussions on Asian banking/financial sector.

5 Conclusion

Based on the time-varying policy parameter model developed by Lai and Ye (2017) and market equity of more than 600 listed commercial banks in the U.S. and more than 100 banks in Asia, we derive market-view variables that reflect the market perceptions of the banking industry. Our empirical results show that these variables have predictive power on GDP growth after controlling asset market variables that are traditionally believed to predict the economic growth.

In particular, on the aggregate level, we find in the U.S. that the median of the fraction of forbearance in capital ($\mathbb{FFC}$-median), which measures the market view of the health status of the whole banking industry, is significantly and negatively related to future economic growth, indicating when the market thinks the sector is healthier, the subsequent GDP growth tends to improve. We also find that the market-valued bank equity-to-asset ratio median ($\frac{\text{MC}}{\text{IA}}$-median$^{\perp}$) is significantly and positively related to future growth, meaning that higher aggregate capital adequacy ratio of the banking sector helps improve the GDP growth.

With respect to cross-sectional dispersion level in the U.S., $\mathbb{FFC}$-std being positively linked with future growth implies that the imbalanced shocks to $\mathbb{FFC}$ induce a better GDP growth. Given the left-skewed distribution of $\mathbb{FFC}$, a higher $\mathbb{FFC}$-std depicts a signal of improved health of the banking sector, therefore, an improvement in the GDP growth. Similarly, a higher $\frac{\text{MC}}{\text{IA}}$-std indicates an imbalanced shock that shifts the capital away from low capital banks to high capital banks. The capital shifting induces banking concentration, thereby hinders economic growth. This is consistent with the negative relation between $\frac{\text{MC}}{\text{IA}}$-std and future growth shown in the results.

Given the different regulatory policy, economic development level and economic and governance structure of the banking industry in Asia, the $\mathbb{FFC}$-median instead measures the market view of the extra credit injected to the banking sector by the government. On aggregate level, more credit, or higher $\mathbb{FFC}$-median, leads to higher subsequent GDP growth, buttressed by the significant positive coefficient. On the cross-sectional dispersion level, the Asian $\mathbb{FFC}$-std is significantly negatively related to the future GDP growth in the short run, as less credit in the sector implied by a higher $\mathbb{FFC}$-std is not a good sign for the real economic activities.

These findings suggest that intelligently monitoring and analyzing the market information of the banking industry can be very useful not only for forecasting but also for guiding and accommodating economic activities in an effective way.

Figure 1: Model-derived and market/accounting-based variables v.s. GDP Growth: the US case

This figure plots the dynamics of the standard deviation and median values of the US $\mathbb{FFC}$ (upper left panel), $\frac{\mathrm{MC}}{\mathrm{IA}}$ (upper right panel), $\frac{\mathrm{BE}}{\mathrm{TA}}$ (lower left panel), and $\frac{\mathrm{MC}}{\mathrm{TA}}$ (lower right panel) against the GDP Growth from the beginning of 1990 to the end of 2017. Note that the median of $\frac{\mathrm{MC}}{\mathrm{IA}}$ is adjusted to be orthogonal to the median of $\mathbb{FFC}$.

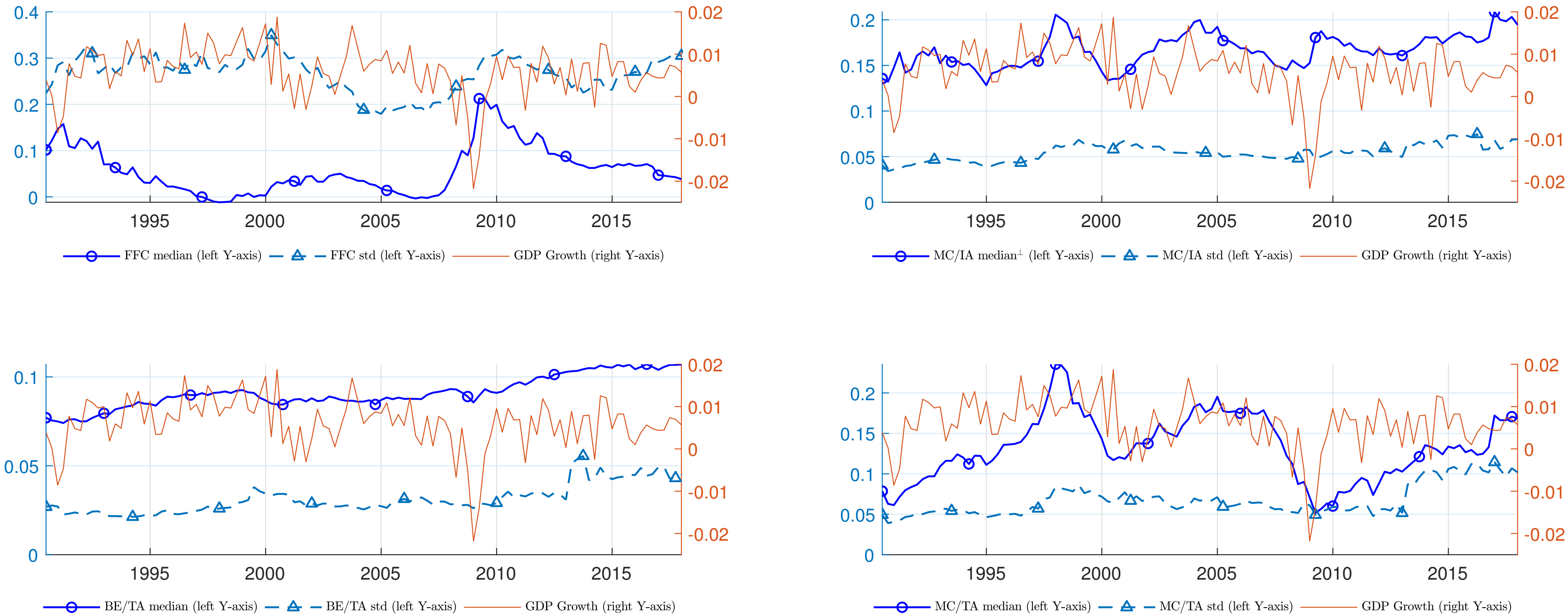


Figure 2: Normalized histogram of the Forbearance Fraction in Capital ($\mathbb{FFC}$) and $\frac{\mathrm{MC}}{\mathrm{IA}}$: the US case

This figure shows the normalized histograms of the Forbearance Fraction in Capital ($\mathbb{FFC}$) in the left panel and $\frac{\mathrm{MC}}{\mathrm{IA}}$ in the right panel (the bars). For the sake of comparison, nonparametric density curves (the solid line marked with circles) are also plotted.

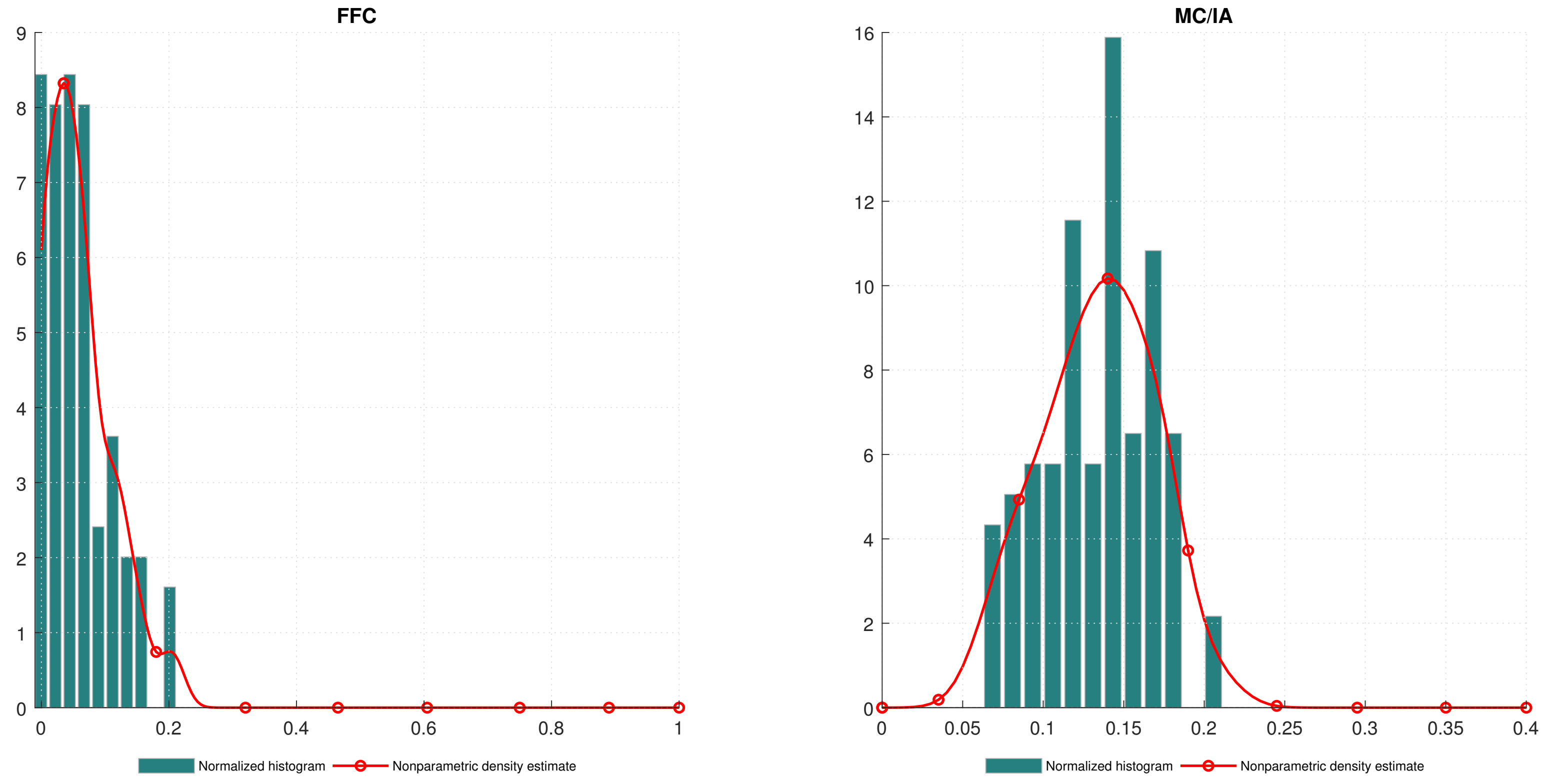
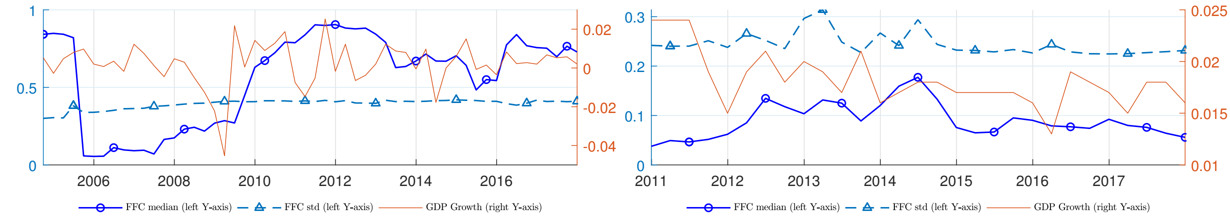
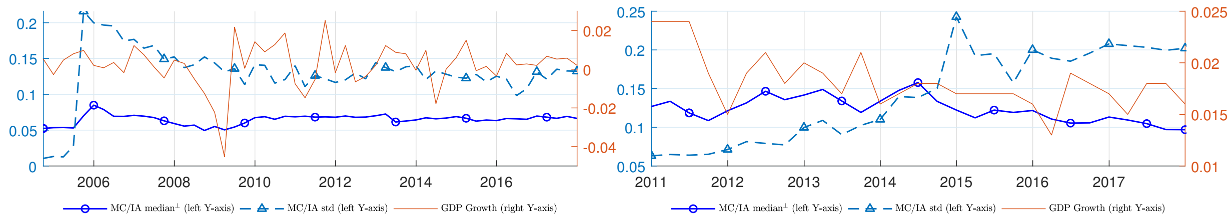


Figure 3: Model-derived variables v.s. GDP Growth: the Asian countries case

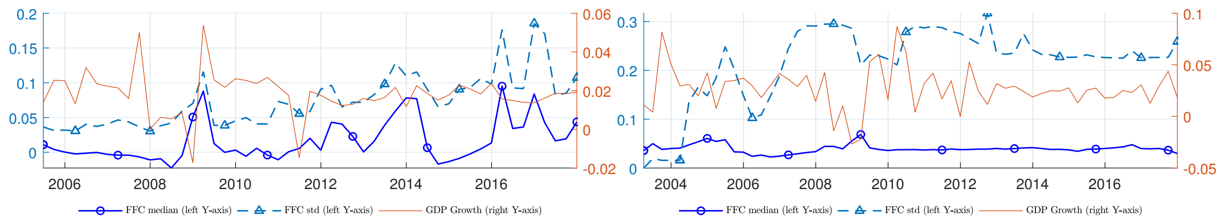
This figure plots the dynamics of the standard deviation and median values of $\mathbb{FFC}$ and $\frac{MC}{IA}$ against the GDP Growth from various starting years (depending the data availability of each country) to the end of 2017. Note that the median of $\frac{MC}{IA}$ is adjusted to be orthogonal to the median of $\mathbb{FFC}$. Four Asian countries/regions are included here: Japan (panel a), China (panel b), India (panel c), and Southeast Asia (panel d).

(a) Japan (b) China





(c) India (d) Southeast Asia



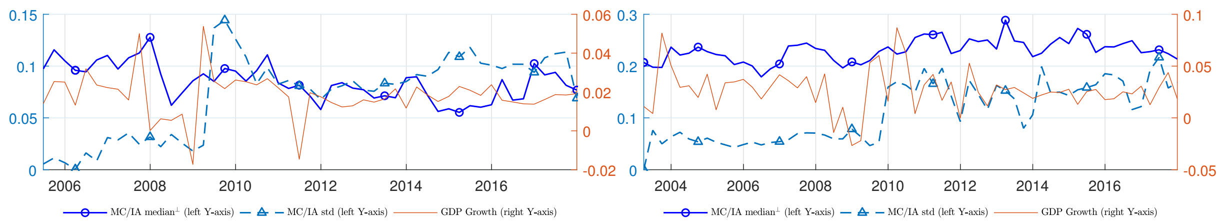


Figure 4: Normalized histogram of the Forbearance Fraction in Capital ($\mathbb{FFC}$) and $\frac{\mathrm{MC}}{\mathrm{IA}}$: the Asian countries case

This figure shows the normalized histograms of the Forbearance Fraction in Capital ($\mathbb{FFC}$) in the left panel and $\frac{\mathrm{MC}}{\mathrm{IA}}$ in the right panel (the bars). For the sake of comparison, nonparametric density curves (the solid line marked with circles) are also plotted.

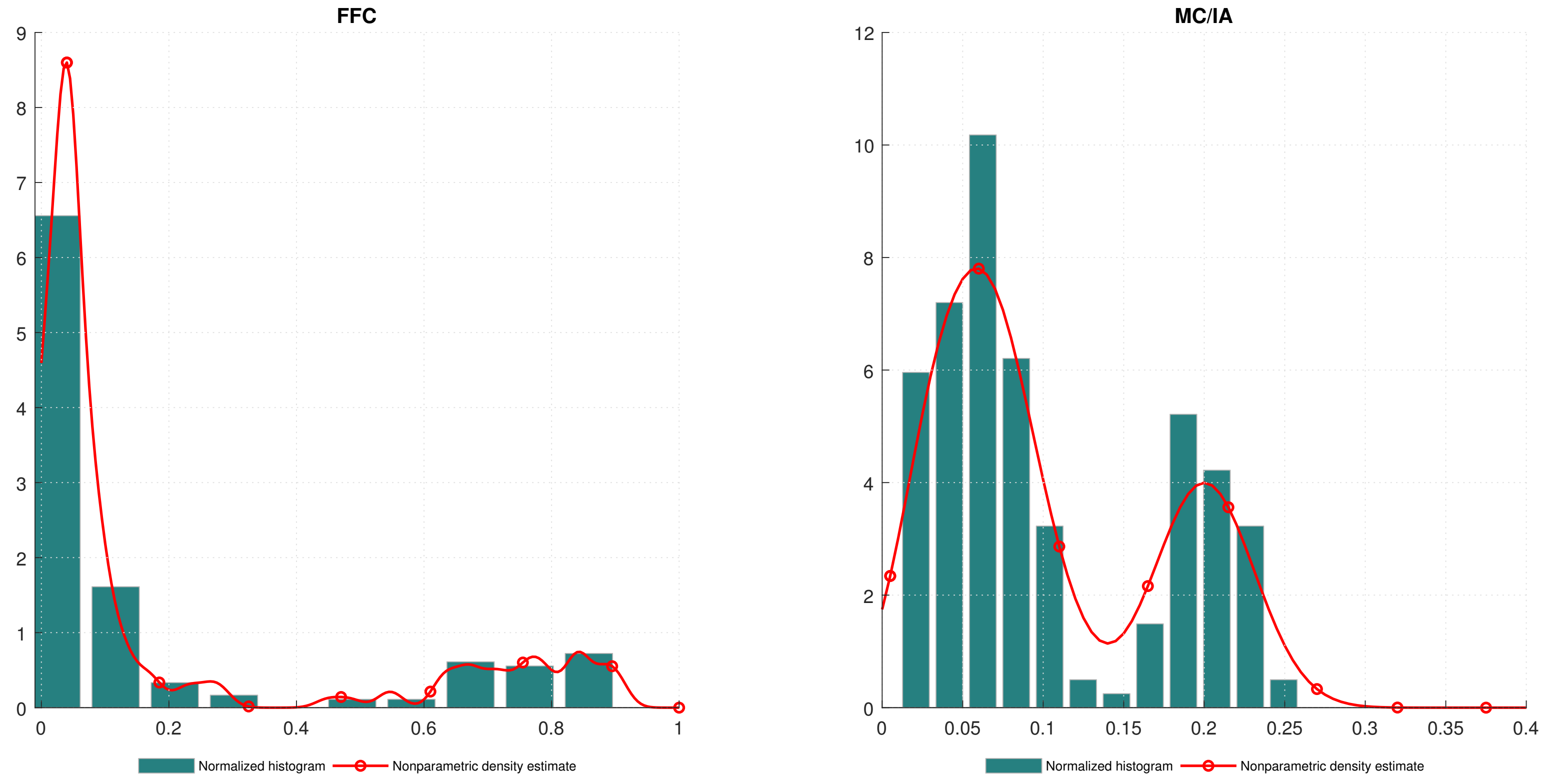


Table 1: In sample results of the GDP growth prediction: the US case

This table reports the in sample results of regressions (4), (5), and (6). The results use data up to the end of 2012. OLS coefficient estimates, significance, Newey-West standard errors (in parentheses), AIC, and BIC are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Model (4)	Model (5)	Model (6)
Intercept	0.0069***	-0.0034	-0.0239***
	(0.0009)	(0.0095)	(0.0084)
$\text{CFNAI}_{t-\frac{1}{4}}$	0.3944***	0.3236***	0.3230***
	(0.0754)	(0.0797)	(0.0716)
$\frac{\text{BE}}{\text{TA}}\text{-std}_{t-\frac{1}{4}}$	-	0.0974	-
	-	(0.2349)	-
$\frac{\text{MC}}{\text{TA}}\text{-std}_{t-\frac{1}{4}}$	-	-0.0776	-
	-	(0.1000)	-
$\frac{\text{BE}}{\text{TA}}\text{-median}_{t-\frac{1}{4}}$	-	0.0677	-
	-	(0.1124)	-
$\frac{\text{MC}}{\text{TA}}\text{-median}_{t-\frac{1}{4}}$	-	0.0417**	-
	-	(0.0189)	-
$\mathbb{FFC}\text{-std}_{t-\frac{1}{4}}$	-	-	0.0724***
	-	-	(0.0193)
$\frac{\text{MC}}{\text{IA}}\text{-std}_{t-\frac{1}{4}}$	-	-	-0.2491***
	-	-	(0.0942)
$\mathbb{FFC}\text{-median}_{t-\frac{1}{4}}$	-	-	-0.0354***
	-	-	(0.0132)
$\frac{\text{MC}}{\text{IA}}\text{-median}^{\perp}_{t-\frac{1}{4}}$	-	-	0.2071***
	-	-	(0.0602)
$\text{SP500 Return}_{t-\frac{1}{4}}$	0.0094	0.0090	-0.0021
	(0.0064)	(0.0066)	(0.0075)
$\text{Curvature}_{t-\frac{1}{4}}$	0.0759	0.1594*	-0.0422
	(0.0641)	(0.0879)	(0.0722)
$\text{Inflation}_{t-\frac{1}{4}}$	-0.1180	-0.1060	-0.0542
	(0.0839)	(0.0693)	(0.0688)
AIC	-683.64	-680.89	-705.73
BIC	-668.65	-655.89	-680.74
Adj R squared	0.3528	0.3593	0.5138

Table 2: Out of sample results of the GDP growth prediction: the US case

This table reports the out of sample results of regressions (4), (5), and (6). The results use data up to the end of 2017. The data before the end of 2012 are the same as those in Table 1. OLS coefficient estimates, significance, Newey-West standard errors (in parentheses), AIC, and BIC are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Model (4)	Model (5)	Model (6)
Intercept	0.0067***	-0.0063	-0.0153
	(0.0008)	(0.0061)	(0.0121)
$\text{CFNAI}_{t-\frac{1}{4}}$	0.3927***	0.3145***	0.3369***
	(0.0647)	(0.0641)	(0.0807)
$\frac{\text{BE}}{\text{TA}}\text{-std}_{t-\frac{1}{4}}$	-	0.1585	-
	-	(0.1362)	-
$\frac{\text{MC}}{\text{TA}}\text{-std}_{t-\frac{1}{4}}$	-	-0.1430**	-
	-	(0.0568)	-
$\frac{\text{BE}}{\text{TA}}\text{-median}_{t-\frac{1}{4}}$	-	0.1038	-
	-	(0.0819)	-
$\frac{\text{MC}}{\text{TA}}\text{-median}_{t-\frac{1}{4}}$	-	0.0561***	-
	-	(0.0134)	-
$\mathbb{FFC}\text{-std}_{t-\frac{1}{4}}$	-	-	0.0447**
	-	-	(0.0197)
$\frac{\text{MC}}{\text{IA}}\text{-std}_{t-\frac{1}{4}}$	-	-	-0.1656***
	-	-	(0.0617)
$\mathbb{FFC}\text{-median}_{t-\frac{1}{4}}$	-	-	-0.0244**
	-	-	(0.0116)
$\frac{\text{MC}}{\text{IA}}\text{-median}^{\perp}_{t-\frac{1}{4}}$	-	-	0.1258**
	-	-	(0.0616)
$\text{SP500 Return}_{t-\frac{1}{4}}$	0.0075	0.0068	0.0014
	(0.0066)	(0.0068)	(0.0069)
$\text{Curvature}_{t-\frac{1}{4}}$	0.1151	0.3046***	0.0224
	(0.0697)	(0.1140)	(0.0897)
$\text{Inflation}_{t-\frac{1}{4}}$	-0.1095	-0.1188*	-0.1033
	(0.0765)	(0.0697)	0.0706
AIC	-850.19	-851.91	-861.22
BIC	-833.99	-824.91	-834.21
Adj R squared	0.3414	0.3732	0.4240

Table 3: Robustness results of the GDP growth prediction: the US case

This table reports the robustness results (out of sample) of regressions (4), (5), and (6). The lagged GDP growth is used in replace of the lagged CFNAI in the models. The results use data up to the end of 2017. OLS coefficient estimates, significance, Newey-West standard errors (in parentheses), AIC, and BIC are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Model (4)	Model (5)	Model (6)
Intercept	0.0037***	-0.0150*	-0.0171
	(0.0012)	(0.0076)	(0.0111)
$GDPG_{t-\frac{1}{4}}$	0.3716***	0.2019*	0.2360*
	(0.1153)	(0.1028)	(0.1255)
$\frac{BE}{TA}$-std$_{t-\frac{1}{4}}$	-	0.2651	-
	-	(0.1728)	-
$\frac{MC}{TA}$-std$_{t-\frac{1}{4}}$	-	-0.1989***	-
	-	(0.0739)	-
$\frac{BE}{TA}$-median$_{t-\frac{1}{4}}$	-	0.1435	-
	-	(0.0880)	-
$\frac{MC}{TA}$-median$_{t-\frac{1}{4}}$	-	0.0797***	-
	-	(0.0204)	-
$\mathbb{FFC}$-std$_{t-\frac{1}{4}}$	-	-	0.0486**
	-	-	(0.0189)
$\frac{MC}{IA}$-std$_{t-\frac{1}{4}}$	-	-	-0.1952***
	-	-	(0.0712)
$\mathbb{FFC}$-median$_{t-\frac{1}{4}}$	-	-	-0.0387***
	-	-	(0.0127)
$\frac{MC}{IA}$-median$^{\perp}_{t-\frac{1}{4}}$	-	-	0.1320**
	-	-	(0.0565)
SP500 Return$_{t-\frac{1}{4}}$	0.0123	0.0115	0.0068
	(0.0080)	(0.0076)	(0.0068)
Curvature$_{t-\frac{1}{4}}$	0.1046	0.4006***	0.0378
	(0.0637)	(0.1336)	(0.0842)
Inflation$_{t-\frac{1}{4}}$	-0.0910	-0.0845	-0.0866
	(0.1005)	(0.0847)	(0.0994)
AIC	-825.97	-832.74	-838.85
BIC	-809.77	-805.73	-811.84
Adj R squared	0.1792	0.2539	0.2942

Table 4: Results of the GDP growth prediction: the Asian countries case

This table reports the results of regressions (4), (5), and (6). The fixed effect panel data regressions are applied. The results use data up to the end of 2017. Panel data regression coefficient estimates, significance, robust standard errors (in parentheses), AIC, and BIC are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Model (4)	Model (5)	Model (6)
Intercept	0.0160***	0.0196***	0.0171***
	(0.0006)	(0.0028)	(0.0027)
$\text{LEI}_{t-\frac{1}{4}}$	-0.0550	-0.0530	-0.0490
	(0.0488)	(0.0482)	(0.0479)
$\frac{\text{BE}}{\text{TA}}\text{-std}_{t-\frac{1}{4}}$	-	0.0135	-
	-	(0.0083)	-
$\frac{\text{MC}}{\text{TA}}\text{-std}_{t-\frac{1}{4}}$	-	0.0000	-
	-	(0.0014)	-
$\frac{\text{BE}}{\text{TA}}\text{-median}_{t-\frac{1}{4}}$	-	-0.0166	-
	-	(0.0138)	-
$\frac{\text{MC}}{\text{TA}}\text{-median}_{t-\frac{1}{4}}$	-	-0.0427	-
	-	(0.0305)	-
$\mathbb{FFC}\text{-std}_{t-\frac{1}{4}}$	-	-	-0.0357**
	-	-	(0.0089)
$\frac{\text{MC}}{\text{IA}}\text{-std}_{t-\frac{1}{4}}$	-	-	0.0028
	-	-	(0.0187)
$\mathbb{FFC}\text{-median}_{t-\frac{1}{4}}$	-	-	0.0102**
	-	-	(0.0021)
$\frac{\text{MC}}{\text{IA}}\text{-median}^{\perp}_{t-\frac{1}{4}}$	-	-	0.0383
	-	-	(0.0286)
$\text{SP500 Return}_{t-\frac{1}{4}}$	0.0332	0.0359	0.0297
	(0.0226)	(0.0230)	(0.0215)
$\text{Curvature}_{t-\frac{1}{4}}$	0.0678	0.0638	0.0620
	(0.2215)	(0.2120)	(0.2879)
$\text{Inflation}_{t-\frac{1}{4}}$	-0.0400	-0.0387	-0.0378
	(0.0680)	(0.0699)	(0.0915)
AIC	-1104.82	-1105.98	-1109.77
BIC	-1095.08	-1096.23	-1100.02
Adj R squared	0.1016	0.0873	0.1053

Table 5: Robustness results of the GDP growth prediction: the Asian countries case

This table reports the results of regressions (4), (5), and (6). The fixed effect panel data regressions are applied. The lagged GDP growth is used in replace of the lagged LEI in the models. The results use data up to the end of 2017. Panel data regression coefficient estimates, significance, robust standard errors (in parentheses), AIC, and BIC are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Model (4)	Model (5)	Model (6)
Intercept	0.0166***	0.0218**	0.0206***
	(0.0006)	(0.0045)	(0.0032)
$\text{GDPG}_{t-\frac{1}{4}}$	-0.0294	-0.0239	-0.0504
	(0.0447)	(0.0389)	(0.0405)
$\frac{\text{BE}}{\text{TA}}\text{-std}_{t-\frac{1}{4}}$	-	0.0139*	-
	-	(0.0056)	-
$\frac{\text{MC}}{\text{TA}}\text{-std}_{t-\frac{1}{4}}$	-	0.0004	-
	-	(0.0022)	-
$\frac{\text{BE}}{\text{TA}}\text{-median}_{t-\frac{1}{4}}$	-	-0.0217	-
	-	(0.0208)	-
$\frac{\text{MC}}{\text{TA}}\text{-median}_{t-\frac{1}{4}}$	-	-0.0599	-
	-	(0.0411)	-
$\mathbb{FFC}\text{-std}_{t-\frac{1}{4}}$	-	-	-0.0478**
	-	-	(0.0126)
$\frac{\text{MC}}{\text{IA}}\text{-std}_{t-\frac{1}{4}}$	-	-	0.0088
	-	-	(0.0268)
$\mathbb{FFC}\text{-median}_{t-\frac{1}{4}}$	-	-	0.0112**
	-	-	(0.0031)
$\frac{\text{MC}}{\text{IA}}\text{-median}^{\perp}_{t-\frac{1}{4}}$	-	-	0.0343
	-	-	(0.0324)
$\text{Stock Market Return}_{t-\frac{1}{4}}$	0.0350	0.0383	0.0312
	(0.0275)	(0.0285)	(0.0255)
$\text{Curvature}_{t-\frac{1}{4}}$	0.1749	0.1689*	0.1272
	(0.1159)	(0.0716)	(0.1802)
$\text{Inflation}_{t-\frac{1}{4}}$	-0.0936	-0.0886*	-0.0813
	(0.0422)	(0.0372)	(0.0387)
AIC	-1098.35	-1100.00	-1105.14
BIC	-1088.61	-1090.26	-1095.40
Adj R squared	0.0705	0.0581	0.0833

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