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The Use of Financial Market Variables in Forecasting

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Financial market indicators can provide valuable information for forecasting macroeconomic developments. In response to the global financial crisis of 2007/2008, the role of financial variables for forecasting has been revisited, and new empirical and theoretical forecasting methods able to explicitly incorporate financial market information have been developed. This roundup discusses characteristics of financial variable movements and the relation to business cycles. It furthermore summarizes some of the new theoretical and empirical approaches at hand for forecasting macroeconomic variables with financial market information, and highlights main challenges forecasters willing to consider financial market information in forecasting exercises have to face.

Understanding the link between financial and business cycles

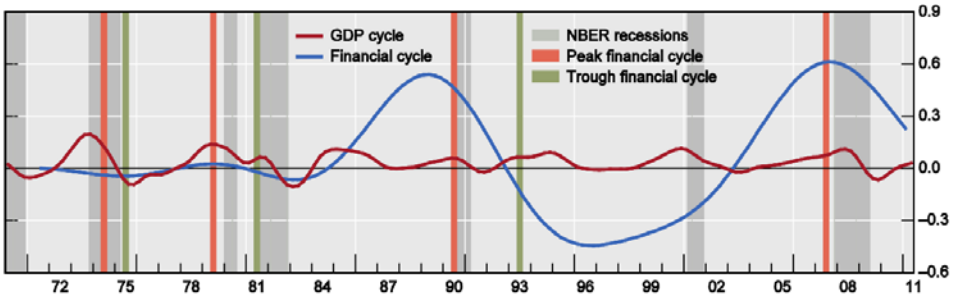
Prior to the recent global financial crisis, financial markets were not perceived as important drivers of real macroeconomic developments. For instance, state-of-the-art macroeconomic models used for business cycle analyses and forecasting often lacked financial sectors completely or at best incorporated stylized financial intermediaries to introduce features aimed at improving the response of real economic variables to real economic shocks in the model (e.g. Bernanke et al. 1999, Woodford 2003). This view has changed dramatically over the last decade, as the experiences of the Great Recession have led to an acknowledgement of the importance of financial disturbances, both as a source and amplification mechanism of shocks that can affect the real economy. The acknowledged link between financial variables and business cycles has ultimately triggered extensive research on how to incorporate their interplay in standard macroeconomic models and tools used for forecasting.

Evaluating the importance of financial variables for business cycle analyses requires a thorough understanding of 1) which variables should be considered in a respective forecasting model and 2) how these indicators are linked to the macroeconomy. A promising starting point for discussing the role of financial variables for real economic forecasting depicts the financial cycle literature (Drehmann et al. 2012, Borio 2014), which extensively evaluates the movement of financial variables and their relation to the business cycle.

Several studies define financial cycles in terms of movements in a set of key financial variables – most prominently in terms of credit growth (Aikman et al. 2015, Schularick and Taylor 2012, Jordà et al. 2011, Jordà et al. 2016, Bakker et al. 2012, Chen and Ranciere 2016, Claessens et al. 2011, IMF 2009, Mendoza and Terrones 2008, or Gourinchas and Obstfeld 2012) or asset price movements (English et al. 2005, Ng 2011, Claessens et al. 2011). Even though most studies differ in terms of financial cycle definitions, as well as on the methodology and sample period employed, some key findings emerge from the empirical literature on financial cycles and their link to

business cycle movements (Figure 1). First, financial cycles appear to be characterized by substantially lower frequencies than business cycles (Drehmann et al. 2012, Borio 2014, Claessens et al. 2012). Second, financial cycle swings are often more pronounced than business cycle fluctuations, a finding in line with earlier studies on the high volatility of asset prices compared to economic fundamentals (Campbell 2003, Claessens et al. 2012). Third, business cycle recessions that coincide with a financial recession tend to be longer and deeper than recessions without contemporaneous disruptions in financial markets, and recovery from double recessions tends to be more sluggish (Claessens et al. 2012, Borio 2014). Claessens et al. (2012) not only evaluate the interplay of financial and economic downturns, but furthermore look at the relation of both cycles over boom periods, i.e. when economic expansions are associated with strong growth in credit and/or asset prices compared to booms without significant developments in financial markets. They find that economic expansions associated with strong financial upswings tend to be shorter but more pronounced in terms of output growth than other booms.

Figure 1: The Financial and Business Cycles in the United States



Source: Drehmann et al. (2012): "Characterising the Financial Cycle: Don't Lose Sight of the Medium Term!". BIS Working Papers, No. 380, June.

Financial variables in forecasting – theoretical models

Building on the insights drawn on the interplay of financial and macroeconomic variables, a multitude of forecasting models – both structural and reduced-form frameworks - explicitly accounting for financial variables and frictions have been proposed over recent years. On the theoretical side, financial frictions and their linkages to macroeconomic outcomes and policy design have been extensively evaluated with the help of financial sector-augmented dynamic stochastic general equilibrium (DSGE) models. Whereas these models have been used for various purposes, some studies evaluate to what extent incorporating financial intermediaries explicitly and allowing for feedback from financial variables to macroeconomic variables within a general equilibrium framework enhances the forecasting performance of state-of-the-art DSGE models. Christiano et al. (2011) use a medium-size DSGE model for the Swedish economy and find that augmenting the model with a financial sector setup as in Bernanke et al. (1999) increases the accuracy of point forecasts of macroeconomic variables, especially of CPI inflation and the nominal interest rate. In a similar way, Del Negro et al. (2013) and Del Negro and Schorfheide (2013) extend the standard Smets and Wouters (2007) DSGE model with a financial sector, which improves forecasts for the Great Recession period of the US economy. By considering both crisis and non-crisis periods, Kolasa and Rubaszek (2015) find that extending a standard New-Keynesian DSGE model by one of the two leading financial friction setups – the financial accelerator setup (Bernanke et al. 1999, Gilchrist et al. 2009) or the collateral constraint framework

(Kiyotaki and Moore 1997, Iacoviello 2005, Iacoviello and Neri 2010) – separately does not result in an overall improvement of macroeconomic forecasts during normal times, but can have statistically and economically significant positive effects for the prediction of several macroeconomic variables during periods of financial turmoil. Relying on the same modelling approaches for financial frictions, Pagan and Robinson (2014) evaluate two macroeconomic models, each featuring one of those setups, in terms of their ability to replicate business cycle movements. They do so by using turning point analyses (Bry and Boschan 1971) to compare business cycle characteristics of data generated with the respective model to those in the actual data. While they do find that financial factors can play a role in explaining some of the business cycle features, the average cycle characteristics generated by the model are not strongly affected by adding financial friction information to the model. Finally, Cardani et al. (2015) compare the forecast performance of a version of the Smets and Wouters (2007) model with and without a banking sector modelled as in Gertler and Karadi (2011) and confirm the improvement in output and inflation forecasts for the US economy in the banking-augmented model.

Financial variables in forecasting – empirical models

In addition to structural models, a multitude of (non-structural) econometric frameworks able to explicitly account for financial indicators in the forecast of macroeconomic variables have been proposed since the outbreak of the Great Recession. Incorporating information stemming from financial indicators in statistical forecasting models is promising for several reasons. For instance, as financial asset prices are affected by market expectations about economic developments and thus set in a forward-looking manner, they should be considered in macroeconomic forecasting (Chen and Ranciere 2016). Furthermore, timely available financial market data can improve both nowcasting and forecasting outcomes whenever macroeconomic data is collected with a considerable time lag (Andreou et al. 2013). However, two particular challenges when combining real and financial variables emerge. First, given the vast amount of financial market data available to forecasters, adequate methods for either pre-selecting financial indicators relevant for forecasting a specific macroeconomic indicator, or for efficiently compiling a large set of financial indicators in a comprehensive way need to be applied. Furthermore, econometric methods used for forecasting real economic variables need to be capable of capturing differences in the frequencies at which financial and macroeconomic variables are usually measured.

In practice, several non-structural empirical frameworks have been developed to incorporate financial data in business cycle forecasts. For instance, financial variables play a prominent role as leading indicators in recession forecast models. Studies relying on probit models for recession forecasting often find that including financial variables such as the yield curve or stock market returns increases the predictive power of these models significantly (Nyberg 2010, Erdogan et al. 2015, Fornari and Lemke 2010). By employing Bayesian model averaging techniques, Faust et al. (2013) and Berge (2015) find that financial as well as housing market indicators are particularly powerful for forecasting real economic developments, particularly over longer horizons. Similar results are drawn by Espinoza, Fornari and Lombardi (2012) in a vector autoregression (VAR) framework for the US and the Euro Area.

To deal with the issue of frequency mismatch when financial variables available in real time are used to forecast lower-frequency economic variables, mixed-frequency forecasting models have been developed. Using financial data in Mixed Data Sampling (MIDAS) regression models (Ghysels et al. 2004, 2006) for macroeconomic variables often reduces the forecast errors compared to models lacking the

information stemming from high-frequency financial data (Ghysels and Wright 2009, Monteforte and Moretti 2013, Andreou et al. 2013, Kuzin et al. 2011, Ferrara et al. 2014). Furthermore, increasing the frequency of the data used - for instance daily financial data instead of monthly data to forecast quarterly economic variables - reduces the forecast error of the MIDAS model further.

Alternatively, (dynamic) factor models can deal with the issue of consolidating information from a vast array of financial indicators in macroeconomic forecasts. Including high-frequency financial data generally increases the statistical and forecasting properties of these models (Breitung and Schumacher 2008, Angelini et al. 2011). Finally, Marcellino and Schumacher (2010) combine both factor models and the MIDAS framework to deal with both frequency mismatch and large sets of financial and macro variables contemporaneously and find that including high-frequency data in such a framework improves the adequacy of nowcasts and short-term forecasts of German GDP.

Conclusion

Over the last decade, the role of financial variables in forecasting has been revisited. Based on findings on the nature of financial cycles and their relation to business cycles, both theoretical and empirical methods have been adjusted so that information from financial markets can be incorporated. Generally, considering information on financial markets – such as credit or asset price movements –in forecasting exercises can significantly improve the quality of forecasts. However, the vast amount of financial market data at hand requires adequate empirical tools for either pre-selecting information relevant for forecasting a specific macroeconomic indicator, or for consolidating information in a tractable and efficient way. Furthermore, theoretical models incorporating financial sectors and frictions are potentially able to produce more accurate macroeconomic forecasts, particularly in times of financial distress, but only few studies have structurally evaluated the forecast performance of macroeconomic models featuring financial markets so far.

References

Aikman, D., Haldane, A. G., Nelson, B. D. (2015). „Curbing the credit cycle". The Economic Journal, 125(585), 1072-1109.
http://onlinelibrary.wiley.com/doi/10.1111/ecoj.12113/full

Andreou, E., Ghysels, E., Kourtellos, A. (2013), "Should macroeconomic forecasters use daily financial data and how?". Journal of Business & Economic Statistics, 31(2), 240-251.
http://www.tandfonline.com/doi/abs/10.1080/07350015.2013.767199

Angelini, E., Camba-Mendez, G., Giannone, D., Reichlin, L., Rünstler, G. (2011), „Short-term forecasts of euro area GDP growth". The Econometrics Journal, 14(1).
http://onlinelibrary.wiley.com/doi/10.1111/j.1368-423X.2010.00328.x/full

Bakker, B., Dell' Arriccia, G., Igan,D. , Laeven, L., Tong, H., Vandenbussche, J., (2012), "Policies for Macrofinancial Stability: How to Deal with Credit Booms". IMF Discussion Note, April.
http://www.imf.org/en/Publications/Staff-Discussion-Notes/Issues/2016/12/31/Policies-for-Macrofinancial-Stability-How-to-Deal-with-Credit-Booms-25935

Berge, T. J. (2015), "Predicting recessions with leading indicators: model averaging and selection over the business cycle". Journal of Forecasting, 34(6), 455-471.
http://onlinelibrary.wiley.com/doi/10.1002/for.2345/full

Bernanke, B., Gertler, M., Gilchrist, S., (1999), „The financial accelerator in a quantitative business cycle framework". In: Taylor, J., Woodford, M. (Eds.), Handbook of Macroeconomics, Amsterdam, pp. 1341–1393.
http://www.sciencedirect.com/science/article/pii/S157400489910034X?via%3Dihub

Borio, C. (2014), "The financial cycle and macroeconomics: What have we learnt?". Journal of Banking & Finance, 45, 182-198.
http://www.sciencedirect.com/science/article/pii/S0378426613003063?via%3Dihub

Breitung, J., Schumacher, C. (2008), "Real-time forecasting of German GDP based on a large factor model with monthly and quarterly data". International Journal of Forecasting, 24(3), 386-398.
http://www.sciencedirect.com/science/article/pii/S0169207008000393

Bry, G., Boschan, C., (1971), "Cyclical Analysis of Time Series: Selected Procedures and Computer Programs". Technical Paper No. 20. National Bureau of Economic Research, New York.
http://www.nber.org/books/bry_71-1

Cardani, R., Paccagnini, A., Villa, S. (2015), "Forecasting in a DSGE Model with Banking Intermediation: Evidence from the US".
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2563310

Chen, S., Ranciere, R., (2016), "Financial Information and Macroeconomic Forecasts", IMF Working Paper WP/16/251.
http://www.imf.org/en/Publications/WP/Issues/2016/12/31/Financial-Information-and-Macroeconomic-Forecasts-44496

Campbell, J. Y. (2003), "Consumption-based asset pricing". Handbook of the Economics of Finance, 1, 803-887.
http://www.sciencedirect.com/science/article/pii/S1574010203010227

Christiano, L. J., Trabandt, M., & Walentin, K. (2011), "Introducing financial frictions and unemployment into a small open economy model". Journal of Economic Dynamics and Control, 35(12), 1999-2041.
http://www.sciencedirect.com/science/article/pii/S0165188911001710

Claessens, S., Kose, M.A., Terrones, M.E., (2011), „Financial Cycles: What? How? When?" IMF Working Paper WP/11/76.
http://www.imf.org/en/Publications/WP/Issues/2016/12/31/Financial-Cycles-What-How-When-24775

Claessens, S., Kose, M.A., Terrones, M.E. (2012), „How do business and financial cycles interact?" J. Int. Econ., 87 (1) (2012), pp. 178-190
http://www.sciencedirect.com/science/article/pii/S0022199611001462

Del Negro, M., Schorfheide, F. (2013), "DSGE model-based forecasting". G. Elliott, A. Timmermann (Eds.), Handbook of economic forecasting, Vol. 2, Elsevier (2013), pp. 57-140
https://www.elsevier.com/books/handbook-of-economic-forecasting/elliott/978-0-444-62732-2?author=&cat0=&categoryrestriction=&imprintname=&producttype=&q=timmermann%20elliott&sort=relevance

Del Negro, M., Giannoni, M. P., & Schorfheide, F. (2013), "Inflation in the Great Recession and New Keynesian models". Staff reports 618. Federal Reserve Bank of New York.
https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr618.pdf

Drehmann, M., Borio, C., Tsatsaronis, K., (2012), "Characterising the Financial Cycle: Don't Lose Sight of the Medium Term!". BIS Working Papers, No. 380, June.
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2084835

English, W., Tsatsaronis, K., Zoli, E., (2005), "Assessing the Predictive Power of Measures of Financial Conditions for Macroeconomic Variables". BIS Papers, No. 22, pp. 228–252.
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1188602#page=238

Erdogan, O., Bennett, P., Ozyildirim, C. (2014), „Recession prediction using yield curve and stock market liquidity deviation measures". Review of Finance, 19(1), 407-422.
https://academic.oup.com/rof/article/19/1/407/1630574/Recession-Prediction-Using-Yield-Curve-and-Stock

Espinoza, R., Fornari, F., Lombardi, M. J. (2012), "The role of financial variables in predicting economic activity". Journal of Forecasting, 31(1), 15-46.
http://onlinelibrary.wiley.com/doi/10.1002/for.1212/full

Faust, J., Gilchrist, S., Wright, J. H., Zakrajšsek, E. (2013), "Credit spreads as predictors of real-time economic activity: a Bayesian model-averaging approach". Review of Economics and Statistics, 95(5), 1501-1519.
http://www.mitpressjournals.org/doi/pdfplus/10.1162/REST_a_00376

Ferrara, L., Marsilli, C., Ortega, J. P. (2014), „Forecasting growth during the Great Recession: is financial volatility the missing ingredient?". Economic Modelling, 36, 44-50.
http://www.sciencedirect.com/science/article/pii/S0264999313003581

Fornari, F., Lemke, W. (2010), "Predicting recession probabilities with financial variables over multiple horizons". ECB Working Paper No. 1255.
https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1255.pdf?17faf3181cddc6090d149d4c62a35f55

Gertler, M., Karadi, P. (2011), "A model of unconventional monetary policy". Journal of Monetary Economics, 58(1), 17-34.
http://www.sciencedirect.com/science/article/pii/S0304393210001261

Ghysels, E., Santa-Clara, P., Valkanov, R. (2004), "The MIDAS touch: mixed data sampling regression models". University of North Carolina. Mimeo.
http://escholarship.org/uc/item/9mf223rs

Ghysels, E., Santa-Clara, P., Valkanov, R. (2006), "Predicting volatility: getting the most out of return data sampled at different frequencies". Journal of Econometrics, 131, pp. 59-95
http://www.sciencedirect.com/science/article/pii/S0304407605000060?via%3Dihub

Ghysels, E., Wright, J. (2009), "Forecasting professional forecasters". Journal of Business and Economic Statistics, 27, pp. 504-516
http://www.tandfonline.com/doi/abs/10.1198/jbes.2009.06044

Gilchrist, S., Yankov, V., Zakrajšek, E. (2009), "Credit Market Shocks and Economic Fluctuations: Evidence From Corporate Bond and Stock Markets," Journal of Monetary Economics 56, 471–493.
http://www.sciencedirect.com/science/article/pii/S0304393209000440

Gourinchas, P.-O. and Obstfeld, M. (2012), "Stories of the Twentieth Century for the Twenty-First", American Economic Journal: Macroeconomics, 4(1), 226–265.
http://www.jstor.org/stable/41426394

Iacoviello, M. (2005), "House prices, borrowing constraints, and monetary policy in the business cycle". American Economic Review, 95 (3), pp. 739-764
http://www.jstor.org/stable/4132738

Iacoviello, M., Neri, S. (2010). "Housing market spillovers: evidence from an estimated DSGE model". American Economic Journal: Macroeconomics, 2(2), 125-164.
http://www.jstor.org/stable/25760299

International Monetary Fund (2009), "From Recession to Recovery: How Soon and How Strong?", World Economic Outlook.
https://www.imf.org/external/pubs/ft/weo/2009/01/pdf/c3.pdf

Jordà, O., Schularick, M., Taylor, A.M., (2011), "When Credit Bites Back: Leverage, Business Cycles and Crises". Federal Reserve Bank of San Francisco Working Paper Series 2011-27.
http://www.nber.org/papers/w17621.pdf

Jordà,O., Schularick, M., Taylor, A.M. (2016). "Macrofinancial History and the New Business Cycle Facts," NBER Macroeconomics Annual 31 (2016)
http://www.nber.org/chapters/c13776.pdf

Kolasa, M., & Rubaszek, M. (2015), "Forecasting using DSGE models with financial frictions". International Journal of Forecasting, 31(1), 1-19.
http://www.sciencedirect.com/science/article/pii/S0169207014000910

Kiyotaki, N., Moore, J. (1997), "Credit cycles". Journal of political economy, 105(2), 211-248.
http://www.journals.uchicago.edu/doi/abs/10.1086/262072

Kuzin, V., Marcellino, M., Schumacher, C. (2011), "MIDAS Versus Mixed-Frequency VAR: Nowcasting GDP in the Euro Area". International Journal of Forecasting, 27: 529–542.
http://www.sciencedirect.com/science/article/pii/S0169207010000427

Marcellino, M., Schumacher, C. (2010), "Factor MIDAS for Nowcasting and Forecasting with Ragged-Edge Data: A Model Comparison for German GDP". Oxford Bulletin of Economics and Statistics, 72(4), 518-550.
http://onlinelibrary.wiley.com/doi/10.1111/j.1468-0084.2010.00591.x/full

Mendoza, E. G. and Terrones, M. E. (2008), "An Anatomy of Credit Booms: Evidence from Macro Aggregates and Micro Data", NBER Working Paper No. 14049.
http://www.nber.org/papers/w14049

Monteforte, L., Moretti, G. (2013), "Real-Time Forecasts of Inflation: The Role of Financial Variables". Journal of Forecasting, 32(1), 51-61.
http://onlinelibrary.wiley.com/doi/10.1002/for.1250/full

Ng, T., (2011), "The predictive content of financial cycle measures for output fluctuations". BIS Quarterly Review June, 53–65.
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1864708

Nyberg, H. (2010), "Dynamic probit models and financial variables in recession forecasting". Journal of Forecasting, 29(1-2), 215-230.
http://onlinelibrary.wiley.com/doi/10.1002/for.1161/full

Pagan, A., Robinson, T. (2014). "Methods for assessing the impact of financial effects on business cycles in macroeconometric models". Journal of Macroeconomics, 41, 94-106.
http://www.sciencedirect.com/science/article/pii/S016407041400055X

Schularick, M., Taylor, A., (2012), “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008”. American Economic Review; 102(2), 1029–61.
http://www.jstor.org/stable/23245443

Smets, F., Wouters, R. (2007), “Shocks and frictions in US business cycles: a Bayesian DSGE approach”. American Economic Review, 97 (3), pp. 586-606
http://www.jstor.org/stable/30035013

Woodford, M., (2003), Interest and prices: foundations of a theory of monetary policy”. Princeton University Press, Princeton.
https://press.princeton.edu/titles/7603.html

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