The Econometric Analysis of Mixed Frequency Data with Macro/Finance Applications

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Structure of Course

It is easy to collect and store large data sets, particularly of financial series. Nevertheless, many real activity series have maintained the traditional monthly or quarterly collection and release scheme. As a result, interest in the econometric analysis of mixed-frequency data has emerged as an important topic. One of the important areas of application is the linkages between macroeconomic time series (GDP growth, inflation, etc.) and financial market series (equity returns/volatility, term structure, etc.).

MIDAS Regressions

We start the course with an introduction to MIDAS regressions, meaning Mi(xed) Da(ta) S(ampling), regressions. It is a regression framework that is parsimonious - notably not requiring to model the dynamics of each and every daily predictor series - in contrast to the system of equations in Kalman filter based state space models that require imposing many assumptions and estimating many parameters, for the measurement equation, the state dynamics and their error processes. We follow the analysis of Andreou, Ghysels, and Kourtellos (2010a), who study regressions with mixed frequency data and revisit temporal aggregation issues. We study the effects of mis-specification imposed by the typical aggregation schemes on the asymptotic properties of regression parameter estimates. Finally, we explore various specifications, including the class of ADL-MIDAS regressions.

Kalman Filter and Mixed Frequency Data

Bai, Ghysels, and Wright (2009) and Kuzin, Marcellino, and Schumacher (2009) discuss in detail the connections between the Kalman filter and MIDAS regressions. The setup treats the low-frequency data as *"missing data"* and the Kalman filter is a convenient computational device to extract the missing data. The approach has many benefits, but also some drawbacks. State space models can be quite involved, as one must explicitly specify a linear dynamic model for all the series involved: the high-frequency data series, the latent high-frequency series treated as missing and the low-frequency observed processes. The system of equations therefore typically requires a lot of parameters, namely for the measurement equation, the state dynamics and their error processes. The steady state

Kalman filter gain, however, yields a linear projection rule to (1) extract the current latent state, and (2) predict future observations as well as states. The Kalman filter can then be used to predict low frequency macro series, using both past high and low frequency observations.

Forecasting and nowcasting GDP growth

Theory suggests that the forward looking nature of financial asset prices should contain information about the future state of the economy and therefore should be considered as extremely relevant for macroeconomic forecasting. There are a huge number of financial times series available on a daily basis. However, since macroeconomic data are typically sampled at quarterly or monthly frequency, the standard approach is to match macro data with monthly or quarterly aggregates of financial series to build prediction models. Overall, the empirical evidence in support of forecasting gains due to the use of quarterly or monthly financial series is rather mixed and not robust. To take advantage of the data-rich financial environment one faces essentially two key challenges: (1) how to handle the mixture of sampling frequencies i.e. matching daily (or weekly or potentially intra-daily) financial data with quarterly (or monthly) macroeconomic series when one wants to predict over relatively long horizons, like one year ahead, and (2) how to summarize or extract the relevant information from the vast cross-section of daily financial series. We address both challenges.

Not using the readily available high frequency data such as daily financial predictors to perform quarterly forecasts has two important implications: (1) one foregoes the possibility of using real time daily, weekly or monthly updates quarterly macro forecasts and (2) one looses information through temporal aggregation. Regarding the loss of information through aggregation, there are a few studies that addressed the mismatch of sampling frequencies in the context of macroeconomic forecasting.

The gains of real-time forecast updating, sometimes called nowcasting when it applies to current quarter assessments, have been documented in the literature and are of particular interest to policy makers. Nowcasting typically uses a state space setup - and therefore face the same computational complexities pointed out earlier. MIDAS regressions provide a relatively easy to implement alternative. The simplicity of the approach allows us to produce nowcasts with potentially a large set of real-time data feeds. More importantly, we show that MIDAS regressions can be extended beyond nowcasting the current quarter to forecast multiple quarters ahead.

Mixed frequency VAR models

Macroeconomic data are typically available at a quarterly or monthly frequency, while financial data, from which financial expectations can be retrieved, are available at a daily frequency. This sampling disparity causes a dilemma about whether to focus exclusively on monthly data, which is what VARs do, or on daily financial data, which is what more recent papers on monetary policy shocks have done. Some studies have suggested using the daily effective fed funds rate or the daily (or monthly) fed funds futures rate when studying monetary policy. There is clearly a tension between the low-frequency phenomenon of the policy impact we want to measure and the availability of high-frequency (daily) data on policy surprises. We use MIDAS regressions to combine low-frequency macroeconomic time-series data (recording the effect of monetary policy shocks) with daily high-frequency time series data (pertaining to the timing of monetary policy shocks).

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The original work on MIDAS focused on volatility predictions; see for instance, Alper, Fendoglu, and Saltoglu (2008), Chen and Ghysels (2009), Engle, Ghysels, and Sohn (2008), Forsberg and Ghysels (2006), Ghysels, Santa-Clara, and Valkanov (2004), León, Nave, and Rubio (2007), Clements, Galvo, and Kim (2008) among others. In addition a number of recent papers have documented the advantages of using such MIDAS regressions in terms of improving quarterly macro forecasts with monthly and daily data. For instance, Bai, Ghysels, and Wright (2009), Kuzin, Marcellino, and Schumacher (2009), Armesto, Hernandez-Murillo, Owyang, and Piger (2009), Clements and Galvão (2009), Clements and Galvão (2008), Galvão (2006), Schumacher and Breitung (2008), Tay (2007), for the use of monthly data to improve quarterly forecasts. Similarly, quarterly and monthly macroeconomic predictions are improved by daily financial series, see e.g.Ghysels and Wright (2009), Hamilton (2006), Tay (2006), Monteforte and Moretti (2009), and Andreou, Ghysels, and Kourtellos (2010b).

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