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High-Frequency Credit Spread Information and Macroeconomic Forecast Revision

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High-Frequency Credit Spread Information and Macroeconomic Forecast Revision

We examine whether professional forecasters incorporate high-frequency information about credit conditions when revising their economic forecasts. Using Mixed Data Sampling regression approach, we find that daily credit spreads have significant predictive ability for monthly forecast revisions of output growth, at both aggregate and individual forecast levels. The relations are shown to be notably strong during ‘bad’ economic conditions, suggesting that forecasters anticipate more pronounced effects of credit tightening during economic downturns, indicating the amplification effect of financial developments on macroeconomic aggregates. Forecasts do not incorporate the totality of financial information received in equal measures, implying the presence of information rigidities in the incorporation of credit spread information.

Keywords: Forecast Revision, GDP Forecast, Credit Spread, High-Frequency Data, Mixed Data Sampling (MIDAS).

JEL Classification: C53, E32, E44

I . Introduction

The prediction of future economic activity is of great interest to individuals and policy makers, as economic activities are in fact influenced by the expectations of market participants. Policy makers in central banks and governments produce forecasts of the main macroeconomic variables upon which they base monetary and fiscal policy responses, while at the same time the published predictions provide useful information for economic agents making everyday economic decisions. Among sources of economic predictions, professional forecast surveys are widely reported as they integrate a number of individual forecasters' predictions of several variables and are regularly updated, usually published on a monthly or quarterly basis.

Through sequences of updated surveys, forecasters make and revise their forecasts by reflecting on actual data outcomes and incorporating newly available information. This structure of economic surveys, in which initial forecasts are followed by periodic updates, has initiated a large literature examining the expectations formation process and finding that survey forecasts fail the full-information rational expectations hypothesis.

Nordhaus (1987) demonstrated the failure of forecast efficiency by showing forecast errors and revisions are correlated with past forecast revisions. Forecast efficiency has been tested in numerous studies, most of which have rejected weak-form efficiency in consensus forecasts (see, for example, Isiklar et al. 2006; Ager et al. 2009; Capistrán and López-Moctezuma 2014) and also in individual forecasts (Gallo et al. 2002; Dovern and Weisser 2011; Deschamps and Ioannidis 2013; Andrade and Le Bihan 2013). With only a few exceptions such as Clements (1997), most studies have found positive coefficients on lagged revisions, implying that forecasts are not sufficiently updated when new information is received.

Recent studies have focused on the linkages between forecast smoothing and models of information rigidities. Dovern et al. (2015), for

example, examine information rigidities in GDP growth forecasts and show that forecast revision dynamics are in line with the predictions of noisy information models (Woodford 2001; Sims 2003). A similar conclusion is reached by Coibion and Gorodnichenko (2012, 2015a).¹⁾

Instead of testing the informational rigidities for weak-form forecast efficiency, in this paper we directly examine how forecasters incorporate high-frequency information from financial markets as they make predictions at both the consensus and individual levels. Specifically, we explore whether forecasts respond to changes in credit spreads and test whether this relation is consistent with what theory and empirical studies imply. We use the survey forecasts data set for the US by Consensus Economics, which comprises monthly predictions made by a panel of professional forecasting institutions.

To use high-frequency financial market data in a model explaining low-frequency forecast revisions, we adopt the framework of mixed data sampling (MIDAS) proposed by Ghysels et al. (2004, 2007). This framework uses weighting functions with only a few hyper-parameters, such as distributed lag polynomials. By reducing the number of parameters to estimate, the MIDAS regression enables us to relate variables with different frequencies. The method, initially focused on financial applications (see, for example, Ghysels et al. 2007; Alper et al. 2008; Chen and Ghysels 2010), has recently been applied to improving forecasts of low-frequency macroeconomic variables, such as GDP growth, with the aid of higher-frequency macroeconomic and financial data. For instance, Clements and Galvão (2008) demonstrate a significant reduction in RMSE by using monthly indicators in a MIDAS specification to forecast quarterly output growth.²⁾ Andreou et al. (2013) incorporate information

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1) Other studies examining information rigidities in survey forecasts include Dräger and Lamla (2012), Andrade and Le Bihan (2013), Loungani et al. (2013), and Hur and Kim (2016).

2) Other articles linking low-frequency macroeconomic series with high-frequency macroeconomic or financial data include Schumacher and Breitung (2008), Hamilton (2008), Armesto et al. (2009), Marcellino and Schumacher (2010), Kuzin et al. (2011), Monteforte and Moretti (2013), Modugno (2013), Galvão (2013), Foroni and Marcellino (2014), and Breitung and Roling (2015).

from daily financial data in forecasting quarterly GDP, and they demonstrate that adding high-frequency financial information to the model delivers superior forecasting performance. There are two reasons for using high-frequency daily asset prices with the MIDAS framework. First, even though the information sources and methodologies that underlie the survey forecasts are largely unknown, it is reasonable to expect that forecasters who update their forecasts at short intervals (in our case, on a monthly basis) will endeavor to utilize information from high-frequency economic news. As financial asset prices are forward-looking in nature and reflect expectations about future economic activity, they incorporate all high-frequency information in a timely manner. The common methods of time-aggregating higher-frequency variables, such as averaging or taking only the latest value, may result in loss of efficiency with respect to the use of past information.

Second, due to incomplete information about the timing of the surveys, *a priori* aggregation schemes summarising the high-frequency data may ignore respondents' forecast behaviour in forming predictions upon arrival of newly available information. Indeed, as discussed in Ghysels and Wright (2009), there may exist gaps among the dates when the forecasters information set are formed, the dates when the surveys are actually submitted, and the dates set as the submission deadlines.³⁾ The adoption of MIDAS regression resolves these issues, as it relies on a flexible aggregation function with minimal restrictions, allowing a data-generated weighting scheme (see Andreou et al. 2010 for a detailed discussion).

Our study is related to a large body of literature on the predictive information in financial asset prices for future economic activity.⁴⁾ For example, in the tradition of Estrella and Hardouvelis (1991), the ability of

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3) We know the dates of the survey deadlines, which do not exactly match the dates the forecasters made their forecasts and answered the surveys.

4) See Stock and Watson (2003) for a comprehensive survey on the role of asset prices in forecasting macroeconomic variables.

spreads between long- and short-term government bonds to predict output growth and recession has been regarded as a stylised fact among economists (see also Harvey 1989; Stock and Watson 1989; Dotsey 1998; Wright 2006; Ang et al. 2006; Rudebusch and Williams 2009).

A large empirical literature has shown that credit spreads have predictive power for real activity. Gertler and Lown (1999) and Mody and Taylor (2004) show that credit spreads based on high-yield corporate bonds forecast US GDP growth. Gilchrist et al. (2009) document that the predictive power of credit spreads is more prominent when the corporate bonds of intermediate-risk rather than high-risk firms are used. The most recent works by Gilchrist and Zakrajšek (2012), Faust et al. (2013), Krishnamurthy and Muir (2015), and Bleaney et al. (2016) support the earlier findings that credit spreads have substantial predictive content, and find that a component in credit spreads attributable to deviations from the usual compensation for default risk strongly predicts a decline in economic activity.

Our paper is also linked to the growing interest in recent studies examining the differences in forecasting behaviour under different states of the business cycle.⁵⁾ For instance, Coibion and Gorodnichenko (2015b) and Loungani et al. (2013) find that the degree of information rigidity is lower in recessions than in normal years. Dovern and Jannsen (2017) find that the forecast errors turn positive as the economy recovers from recessions and disappear during expansions, implying a differential treatment of information depending on the phase of the business cycle.

Our findings can be summarised as follows. First, forecasts are negatively impacted by credit spreads, consistent with the predictions of the theory. An increase in daily credit spreads – the difference between the yields on an index of seasoned long-term Aaa-rated corporate bonds and on constant maturity 10-year Treasuries – is associated with significant negative revisions in consensus forecast revisions of US GDP

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5) Other exercises examining state-dependent forecast errors include Sinclair et al. (2010), Sheng and Wallen (2014), Messina et al. (2015), Xie and Hsu (2016), and El-Shagi et al. (2016).

growth. Second, weighting functions in MIDAS regressions show hump-shaped weights. Forecast revisions respond more strongly to 10- to 15-day-old credit spread information than to the most recent information, indicating that forecasts are slow to incorporate high-frequency financial information. This result is consistent with models of information rigidities (Coibion and Gorodnichenko 2012; 2015a), and with models of sticky information in particular (Mankiw and Reis 2002).

Third, testing these relations at the individual forecast level, we find that forecasters broadly agree in the direction of revision as they update their information sets using the news from financial asset prices. Most individual forecasters (more than 90%) revise their forecasts downward as the daily credit spread increases. There is however substantial cross-section variability in the individual estimates, indicating that forecasters interpret credit spread information differently.

Fourth, we provide evidence as to whether forecasters exhibit state-dependent forecasting behaviour when they revise their GDP predictions in light of new information from financial asset prices. Proxying the state of the economy using a real-time daily measurement of business conditions built by Aruoba et al. (2009), we find that the effect of credit spreads on revisions of output growth forecasts is more prominent during bad economic states. This result is consistent both with the finding that information acquisition is faster during recessions (Loungani et al. 2013), and with the finding that credit shocks have larger effects on output during periods of weak economic growth (Barnichon et al. 2017).

The rest of the paper is organised as follows: Section 2 explains the structure of Economic Consensus and other data. Section 3 explains the MIDAS methodology for analysing mixed-frequency data. Section 4 discusses the empirical findings regarding the effect of credit spreads on forecast revisions. Finally, Section 5 concludes.

II. Data

1. Consensus Economics

We examine the effect of credit spreads on GDP forecast revisions using the Consensus Economics data set. Every month, Consensus Economics Inc. publishes macroeconomic forecasts provided by a panel of professional forecasters comprising financial institutions, research centres and large industrial firms. We use the fixed-event GDP forecasts for the United States between 1991 and 2016. Panellists predict GDP for both the current and following year every month, i.e. each forecaster makes the initial forecast for a target year on January of the previous year and then updates the forecast monthly, making a total of 24 forecasts for the target year. This fixed-event structure of the survey gives a three-dimensional panel structure (formalised by Davies and Lahiri 1995), comprising 26 target years, 24 forecast horizons, and N forecasters. As characterised by Capistrán and Timmermann (2009), forecasters frequently enter, exit, and reenter with a period of absence. The average number of submitted forecasts in each survey is 26.0 for both the current and following year, which gives us 16,213 observations in total.

In measuring revisions, we count only the differences between consecutive revisions, but consider submitted but unchanged forecasts as zero revisions.⁶⁾ To prevent the inclusion of non-consecutive forecast values in the calculation of consensus revisions, we first calculate individual revisions, and then average the revisions across the individual forecasts.⁷⁾ Each target year has 24 forecasts and thus a maximum of 23

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6) It is possible that forecasters do not respond when their predictions are unchanged. Dovern and Weisser (2011) interpolate the data when an observation is missing but two adjacent forecasts are the same by setting the missing value with the adjacent value. We tried increasing the number of observations with the interpolation method and confirmed that it does not affect our main findings.

7) For preventing small sample problems, several studies (such as Dovern and Weisser 2011; Deschamps and Ioannidis 2013) exclude panellists who made too few forecasts. Occasional participation may produce outliers in forecasts. As we only consider the revisions rather than the values of forecasts, we include all the forecasters when calculating consensus forecasts, regardless of the forecasters' participation rates.

revisions.

Figure 1 illustrates the means and standard deviations of forecast revisions across horizons ($h = 23, 22, \dots, 1$). The first row ('All States') shows that forecast revisions tend to be negative at long horizons, as GDP forecasts begin with somewhat optimistic numbers that are gradually corrected and revised down as the horizon shortens. The average standard deviation of revisions among forecasters is highest at middle horizons, when the forecasts are actively revised. Forecasts at shorter horizons are revised less frequently, resulting in lower standard deviations of revisions among forecasters. It can also be seen from the bottom row that forecasts in bad states overpredict GDP at all horizons.

Matching monthly revisions with daily credit spread data, we take forecast revisions from 7th to 18th updates, as we expect the relationship between output forecasts and credit spread information should be most relevant.⁸⁾ Dovern et al. (2015) find that the average size of revision is larger at mid-horizons than at very long or short forecast horizons. Sheng and Wallen (2014) also document that the professional forecasters included in Consensus Forecasts data revise their medium-term forecasts (10 to 17 months ahead) most frequently.⁹⁾

2. Credit Spreads

Credit spreads (also called quality spreads or default spreads) are the differences between the interest rates on matched maturity debt with different default risks. The predictive content of credit spreads has been examined in a number of articles focusing on the US economy, where the private debt market is most active. For example, Bernanke (1983) documents the usefulness of the Baa-Treasury bond spread as a predictor

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However, the results are robust even when we exclude the panellists with only a small number of forecasts.

8) Testing the relations with different sets of forecast horizons, such as the first 12 or the last 12 revisions, however, gives qualitatively the same results (the results are available on request).

9) Sheng and Wallen (2014) explain that forecasters' inattentiveness at very long and short forecasting horizons is due to noisier signals and the observation of actual outcomes, respectively.

Figure 1. Means and Standard Deviations of Revisions

Notes: The figure illustrates the means and standard deviations of individual forecast revisions across revision horizons ($h = 23, 22, \dots, 1$). The first row (All States) reports the statistics for the entire sample, whereas the bottom two rows report the split sample statistics for good states and bad states separately. Economic states are identified by averaging daily Aruoba-Diebold-Scotti (ADS) index values matched to monthly survey cycles. The sample period is from January 1991 to December 2016.

of industrial production growth during the Great Depression. Guha and Hiris (2002) show that the same spread contains useful information about the turning points of business cycles. The spread between commercial paper and Treasury bills (paper-bill spread) has also shown to be a significant predictor of real growth (see, for example, Stock and Watson 1989; Friedman and Kuttner 1993; Emery 1996; Ewing et al. 2003; Bordo and Haubrich 2004), and Gertler and Lown (1999) demonstrate that the high-yield spread outperforms other financial indicators.¹⁰⁾

We obtain daily observations of interest rates and credit spreads from Federal Reserve Economic Data (FRED). The credit spread is calculated as the difference between the Moody's Seasoned Aaa Corporate Bond and the 10-year Treasury constant maturity rate. Using the preliminary MIDAS regression exercises based on different measures of credit spreads from the literature, we choose the spread between Aaa-rated corporate bonds and 10-year Treasury notes (Aaa-spread) as our main high-frequency financial variable, as it has exhibited the most significant effects on forecast revisions. The Aaa-spread has fluctuated markedly, widening notably around the early 2000s recession and the recent Great Recession.

The predictive power of the Aaa-spread has been tested in several recent studies (see Mody and Taylor 2004; Gilchrist et al. 2009; Mueller 2009; Buchmann 2011; Schumacher 2014). Specifically, Gilchrist et al. (2009) find that the forecasting ability of bond spreads is closely associated with information about the bonds of intermediate-risk rather than those of high-risk firms.

3. Other Variables

To test differences in how forecasters' expectations are formed as they incorporate financial information in different economic conditions, the identification of economic states is required. Literature analysing the state dependence of forecasting behaviour (for example, Sinclair et al. 2010, 2015; Dovern et al. 2012; Lougani et al. 2013; Messina et al. 2015) uses recessions identified ex-post by institutions such as National Bureau of Economic Research (NBER) or Economic Cycle Research Institute (ECRI). A notable exception is Dovern and Jannsen (2017) who identify recession years at annual frequency using the most recent data vintage.

Examining state-dependent forecasting behaviour based on an ex-post

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10) Compared to corporate-Treasury spreads, the spreads across corporate bond categories (such as High yield-Aaa and Baa-Aaa) are mostly related to default risk premia, and thus their relationship with the business cycle is stronger during recessions (Duca 1999).

measure of business conditions may be problematic as forecasters do not know the state of the economy at the time they make forecasts.¹¹⁾ Instead of using ex-ante defined recessions, we adopt a real-time measure of aggregate business conditions developed by Aruoba, Diebold, and Scotti. (2009, ADS index hereafter). The ADS index is an indicator that uses a set of macroeconomic and financial variables to track business conditions. It is constructed using a dynamic factor model that permits extraction of the latent state of macroeconomic activity. Positive values of the ADS index indicate better-than-average conditions, whereas negative values indicate worse-than-average conditions; the average value is zero. The index is updated by the Federal Reserve Bank of Philadelphia and has been proven to be a useful indicator of economic conditions in real time.¹²⁾

We assume that forecasters decide the current economic state using all the available real-time information summarised in the ADS index. Then the economic states perceived by the forecasters at the time of each survey are measured by the average values of the daily ADS index between the previous and current survey deadlines. This method makes for a more transparent and straightforward rule which might be close to agents' recognition of the economic conditions, using a broad information set in real-time.

III. MIDAS Regressions

The MIDAS regression approach involves data sampled at different frequencies. Applying parsimonious but flexible distributed lag polynomials, the MIDAS framework allows us to use the information in high-frequency explanatory variables, avoiding probable issues from an a priori data aggregation scheme.¹³⁾ Our basic MIDAS model used to

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11) Determining the recessionary periods, matching ex-post identified recession months between the actual survey date or the target year is also questionable.

12) The index can be accessed online at <https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index>.

predict forecast revisions is given by

$$REV_{t+1,\tau} = \alpha + \beta \sum_{k=1}^K b(k; \theta) CS_{t-k/m} + \rho REV_{t,\tau} + \epsilon_{t+1,\tau}, \quad (1)$$

where $REV_{t,\tau}$ denotes a consensus forecast revision for US GDP growth rates for target year τ at time t . Consensus forecast revisions are calculated as the average of individual forecast revisions such that

$$REV_{t+1,\tau} = (1/n_t) \sum_i^{n_t} REV_{i,t+1,\tau}, \quad (2)$$

where n_t is the number of survey respondents at time t . K denotes the number of the lagged high-frequency explanatory variables, and m is the number of trading days in a month.

Individual forecast revisions are the differences between two consecutive GDP growth forecasts of individual i for target year τ at time t . Specifically,

$$REV_{i,t+1,\tau} = F_{i,t+1,\tau} - F_{i,t,\tau}, \quad (3)$$

where $F_{i,t,\tau}$ is individual i 's forecast of the GDP growth rate.¹⁴⁾ CS_t is the daily change in credit spreads. Our model specification is in the class of ADL-MIDAS regressions, introduced by Andreou et al. (2013), offering the structure of augmented distributed lag regression with mixed-frequency data. The inclusion of an autoregressive term of order one is from the literature testing the weak form of forecasting efficiency (Nordhaus 1987; Deschamps and Ioannidis 2013; Dovern et al. 2015).

Several previous studies proposed diverse functional forms of MIDAS polynomial weights aiming at parsimonious but flexible specifications.¹⁵⁾

13) For an overview of the MIDAS regression framework, see Armesto et al. (2010), Andreou et al. (2011), and Foroni and Marcellino (2013).

14) Notations for the revision horizons (h) are abstracted as each forecast time (t) matches to one corresponding consensus revision.

In this study, we employ four weighting schemes to test the robustness of the relations across different methods. The first weighting scheme we consider (denoted M1) is the normalised beta probability density function suggested by Ghysels et al. (2004, 2007). Specifically, we use

$$b(k; \theta_1, \theta_2) = \frac{x_k^{\theta_1-1} (1-x_k)^{\theta_2-1}}{\sum_{k=1}^K x_k^{\theta_1-1} (1-x_k)^{\theta_2-1}}, \quad (4)$$

where $x_k = k/(K+1)$. In M1, the parameters are estimated using non-linear least squares. Our second weighting scheme (M2) uses an Almon lag polynomial of order P , specified as

$$\beta b(k; \theta_0, \dots, \theta_P) = \sum_{p=0}^P \theta_p k^p. \quad (5)$$

In M2 the parameters are estimated with non-linear least squares, and we set $P=2$. We also use two alternative polynomial specifications, Step-Weighting (M3) and U-MIDAS (M4), that are estimated with OLS. The step-function allocates different coefficients to several intervals of high-frequency data as follows:

$$\beta b(k; \theta_1, \dots, \theta_P) = \theta_1 I_{k \in [a_0, a_1]} + \sum_{p=2}^P \theta_p I_{k \in (a_{p-1}, a_p]}, \quad (6)$$

where P is the number of steps, and $a_0 = 1 < a_1 < \dots < a_P = K$. I_k is an indicator which becomes 1 when k belongs to its corresponding interval and 0 otherwise. We set the number of steps in M3 to four, corresponding to the number of weeks in one month. Meanwhile, unrestricted MIDAS polynomials (U-MIDAS) use a simple regression estimating the individual coefficients without any constraints.¹⁶⁾

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15) Ghysels et al. (2007) present a discussion on various lag structures to parameterise MIDAS weighting functions.

16) U-MIDAS is particularly useful when m (the number of high-frequency data linked to one low-frequency

IV. Empirical Results

1. Credit Spread and Growth Forecasts Revisions

As discussed in the first section, studies have shown that higher credit spreads are associated with GDP growth. We estimate the four MIDAS regressions introduced in the previous section to test for the relation between credit spreads and forecast revisions. Our sample begins with the first forecast revision in 1991M01 for the growth rate of 1991 and ends with the revision in 2016M06 for the growth rate of 2016, making for a total number of 306 revisions. There are 6,505 Aaa-spread observations over 26 years, giving 20.8 observations on average for each month. Trading days per month (m) and the number of lagged daily series (K) in Equation (1) are each set to be 20. Most submission deadlines are the second Monday of the month, so 20 daily observations of credit spreads before the survey deadlines are selected to match for each forecast revision.¹⁷⁾

As deterioration in credit conditions works to propagate and amplify the effects of macroeconomic shocks and depress economic activity (Bernanke et al. 1999), we anticipate that survey respondents would make negative (positive) growth forecast revisions when credit spreads increase(decrease). Furthermore, we expect no clear patterns on MIDAS weighting polynomials on daily information, as there is no reason that credit spreads on specific days in a month react more strongly to future economic growth. A forecaster who is efficient in incorporating information from high-frequency asset prices may use every available observation, whether one day old or twenty. In other words, we would expect MIDAS weights to be equally negative for all days. Evidence that

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observation) is small, especially in the case of regressing quarterly series on monthly (Foroni et al. 2015). However, we estimate a U-MIDAS model to confirm whether we can find a specific daily lag formation as the forecasters use financial information.

17) An exercise with a larger number of lagged daily spreads, for example, 40 lags, gives similar results, as added lags do not affect the revisions significantly.

Figure 2. Estimated MIDAS Polynomials

Notes: This figure plots the estimated MIDAS polynomials from Equation (1) for the four weighting functions. Estimations are based on a normalised beta probability density function (M1), Almon lag polynomials (M2), a step-weighting function (M3), and U-MIDAS (M4). The dashed lines in M3 and M4 indicate two standard errors from the estimates.

the weights are larger for specific days would indicate that forecasts respond more strongly to information released on those days.

Figure 2 plots the estimated MIDAS polynomials for the four different weighting schemes across the 20 daily lags of credit spreads. The estimated parameters for M1 and M2 are reported in Table 1. In all four models, consensus GDP growth forecasts are revised negatively when credit spreads increase. For M1 and M2, the significance of the relationship can be seen from the t-statistics in Table 1. For M3, the confidence interval in Figure 2 shows significance for all steps, while the coefficient estimates of U-MIDAS (M4) are all negative but not always significant. Overall, our findings are largely consistent with the prediction that GDP forecasts incorporate credit spread information. Table 1 also reports the results for a model with only lagged revisions (M0). The estimates

Table 1. Parameter Estimates for MIDAS Regressions

$M1$	α	β	θ_1	θ_2	ρ	R^2
	-0.007 (-0.660)	-9.948 (-6.505)	3.026 (2.363)	1.824 (3.673)	0.503 (11.173)	0.392
$M2$	α	θ_0	θ_1	θ_2	ρ	R^2
	-0.009 (-0.833)	0.288 (1.042)	-0.192 (-3.308)	0.008 (3.232)	0.507 (11.095)	0.377
$M0$	α				ρ	R^2
	-0.008 (-0.781)				0.516 (7.960)	0.261

Notes: This table reports the Equation (1) coefficient estimates in MIDAS regression of the revisions of consensus GDP growth rates on a lag of revisions and changes in credit spreads (the difference between Aaa-rated corporate bond and 10-year Treasury rates). Estimations are based on a normalised beta probability density function (M1) and Almon lag polynomials (M2). M0 is a model without daily credit spreads. α is a constant, β is a slope coefficient in model M1 of high-frequency (daily) Aaa-spread, and ρ is a coefficient of the lag of revisions. θ 's are the parameters determining the shape of weighting polynomials on the daily credit spreads, and they are estimated using non-linear least squares. The adjusted R^2 is shown in the last column. See Equations (1), (4), and (5) for further details. The values in parentheses are t-statistics. The sample period covers 1991 to 2016.

for ρ are around 0.5 in all specifications, showing the existence of substantial information rigidities in consensus forecasts.¹⁸⁾ In Table 1, the MIDAS estimations including daily credit spreads give substantially higher adjusted R^2 , implying that forecasters update growth predictions in line with the developments in credit conditions.

Interestingly, we find that the weighting functions are not flat, as the polynomials in Figure 2 are clearly hump-shaped. The largest effects concentrated between 10 and 15 days, with some variability across models. The common pattern of the four weighting functions shows that consensus forecasts revisions are better associated with daily information lagged around two weeks prior to the submission deadlines rather than with the latest information.¹⁹⁾ This result indicates that, although

18) Our estimate of the rigidity parameter (ρ) is larger than those from previous studies with different sample periods. For example, Ager et al. (2009)'s estimated rigidity coefficient is 0.28 based on the data from 1996 to 2006, and Dovern et al. (2015) report a coefficient of 0.33 using a sample from 1989 to 2010.

19) The survey deadlines do not necessarily match the dates when surveys are actually submitted or the dates when the respondents form their predictions. However, we believe that professionals, who make monthly predictions consecutively, may form their predictions on a date close enough to observe the most up-to-date information.

forecasters incorporate credit spread information, they do not incorporate the totality of credit spread information received in equal measures.

The hump-shaped polynomials are indicative of information rigidities (see, for example, Coibion and Gorodnichenko 2012, 2015a), in the sense that forecasts are updated on the basis of 10- to 15-day-old information and are less responsive to the most recent information. Furthermore, hump-shaped polynomials are consistent with models of sticky information (Coibion and Gorodnichenko 2015a; Mankiw and Reis 2002). In sticky information models, forecasters update their information sets infrequently, and, in any given period, a fraction of the forecasts are based on outdated information. The finding that the consensus forecast places little weight on the most recent information suggests that some forecasters do not use the latest information. Consensus forecasts only partially incorporate the most recent information, which contributes to the formation of information rigidities in consensus forecasts.

Overall, our analysis suggests that the well-documented information rigidities in consensus forecasts can be partially attributed to the slow incorporation of high-frequency financial information.

2. Economic State and Forecast Revisions

Several recent studies have proposed theoretical explanations for the sluggishness in survey forecasts, including information frictions (Coibion and Gorodnichenko 2012), heterogeneity in loss aversion (Capistrán and Timmermann 2009), and forecasters' rational maximisation of their perceived abilities (Deschamps and Ioannidis 2013).

The origins of the forecast smoothness in these models, such as the variations in information rigidity and the role of revisions determining perceived ability, in fact, should be closely related to economic conditions. For example, in periods of high volatility, forecasters may confront larger costs of ignoring new information as well as smaller losses of reputation associated with deviations from their previous forecasts. Ribeiro and

Veronesi (2002) indeed find that agents' expectations are more influenced by current innovations in a recessionary state when their uncertainty about the current regime is high.

Following the recent literature studying state-dependent expectations formation in forecasting behaviour, we examine whether forecasters' responses to high-frequency information in asset prices differ according to the economic state. Specifically, our model modifying Equation (1) is

$$\begin{aligned} REV_{t+1,\tau} = & [\alpha_0 + \beta_0 \sum_{k=1}^K b(k; \boldsymbol{\theta}_0) CS_{t-k/m} + \rho_0 REV_{t,\tau}] \times (1 - \hat{s}_{t+1}) \\ & + [\alpha_1 + \beta_1 \sum_{k=1}^K b(k; \boldsymbol{\theta}_1) CS_{t-k/m} + \rho_1 REV_{t,\tau}] \times \hat{s}_{t+1} + \epsilon_{t+1,\tau}, \end{aligned} \quad (7)$$

where $\hat{s}_{t+1}$ is a dummy variable associated with the ADS index determining economic states between t and $t+1$. The value of $\hat{s}_{t+1}$ is zero when the averaged ADS index is above or equal to a certain threshold and one otherwise. We set the threshold so that the months with the lowest one-third of averaged ADS index values are identified as bad states. In determining the threshold, we consider the fact that economic expansions are usually longer than contractions. The identified bad states (bottom one-third) include all the months defined as recessions by the NBER, but cover more times of economic slowdown due to smaller business cycles.

In this modified version of the model, we allow both forecast smoothing and the effect of the credit spread to be state-dependent. A recent line of research focuses on the non-linear effects of credit shocks, and Barnichon et al. (2017) for instance find that credit shocks have a larger impact on economic activity during low-growth periods. By allowing for state-dependent effects, we investigate whether such non-linearities also apply to forecast data. If the effect of the credit spread on GDP growth is larger in bad states than in good states, we should expect professional forecasters to incorporate this relationship in their forecasts.

Figure 1 illustrates the means and standard deviations of individual

Table 2. Parameter Estimates for MIDAS Regressions in Good and Bad Economic States

Panel A. Good States						
$M1$	α_0	β_0	$\theta_{0,1}$	$\theta_{0,2}$	ρ_0	R^2
	0.020 (1.950)	−6.028 (−3.635)	1.795 (2.242)	1.025 (24.491)	0.461 (7.783)	0.268
$M2$	α_0	$\theta_{0,0}$	$\theta_{0,1}$	$\theta_{0,2}$	ρ_0	R^2
	0.020 (1.945)	−0.319 (−1.002)	0.018 (0.265)	−0.001 (−0.441)	0.469 (7.887)	0.270
$M0$	α_0				ρ_0	R^2
	0.018 (1.685)				0.473 (6.903)	0.228
Panel B. Bad States						
$M1$	α_1	β_1	$\theta_{1,1}$	$\theta_{1,2}$	ρ_1	R^2
	−0.054 (−2.430)	−13.530 (−5.245)	3.432 (2.170)	2.186 (3.257)	0.472 (6.244)	0.446
$M2$	α_1	$\theta_{1,0}$	$\theta_{1,1}$	$\theta_{1,2}$	ρ_1	R^2
	−0.060 (−2.602)	0.952 (2.004)	−0.403 (−4.041)	0.018 (4.027)	0.492 (6.296)	0.430
$M0$	α_1				ρ_1	R^2
	−0.074 (−2.169)				0.442 (4.342)	0.175

Notes: This table reports the Equation (7) coefficient estimates in MIDAS regression of the revisions of consensus GDP growth rates on a lag of revisions and changes in credit spreads (the difference between Aaa-rated corporate bond and 10-year Treasury rates). Estimations are based on a normalised beta probability density function (M1) and Almon lag polynomials (M2). M0 is a model without daily credit spreads. α is a constant, β is a slope coefficient in M1 of high-frequency (daily) Aaa-spread, and ρ is a coefficient of the lag of revisions. θ 's are the parameters determining the shape of weighting polynomials on the daily credit spreads, and they are estimated using non-linear least squares. See Equations (4), (5), and (7) for further details. The adjusted R^2 is shown in the last column. The values in parentheses are t-statistics. The sample period covers 1991 to 2016.

forecast revisions across revision horizons calculated for good and bad states. The plots in the first column show that forecasters made large positive errors in bad states, implying that they initially made moderate forecast values without much knowledge of the future states. Revisions in bad states peak between the 7th and 12th revisions, which is earlier than revisions in good states made between 10 and 16 months after the initial forecasts. The standard deviations of the revisions are larger in bad states, suggesting that forecasters disagree more in revising GDP forecasts under such economic conditions.

Figure 3 plots the estimated MIDAS weights using the four models.

Figure 3. Estimated MIDAS Polynomials between Good and Bad Economic States

Notes: This figure plots the estimated MIDAS polynomials from Equation (7) for the four weighting functions with good and bad economic states. Economic states are identified by averaging daily Aruoba-Diebold-Scotti (ADS) index values matched to monthly survey cycles. The estimates are based on normalised beta probability density function (M1), Almon lag polynomials (M2), Step-weighting function (M3), and U-MIDAS (M4). The dashed lines in M3 and M4 indicate two standard errors from the estimates.

The effects of daily credit spreads on monthly consensus forecast revisions are negative in both states, but the size of the relations are notably stronger in bad states. Comparing the slope coefficients on credit spreads in the M1 specification, Table 2 reports that $\hat{\beta}_1$ is larger than $\hat{\beta}_0$ in absolute value. The coefficients of M3 and M4 show that growth forecast revisions are more prominent in bad economic states and forecasters incorporate more recent information associated with the variations in credit spreads. These results are consistent with the findings of Loungani et al. (2013) that the acquisition of information is faster during recessions.

Gorodnichenko (2008) has also shown that macroeconomic shocks lower agents' inattention as information rigidity is endogenous to economic states. The adjusted R^2 in bad states is 0.45 (M1) and 0.43 (M2), higher than the R^2 from the regressions with only lagged revisions (0.18), indicating that in bad states regressing revisions on the credit spread substantially increases the model goodness-of-fit.

3. Forecast Revisions at Individual Level

Next, we test whether the effect of credit spreads on GDP forecast revisions found at the consensus forecast level exists for individual forecasts. The individual MIDAS regression model analogous to Equation (1) is

$$REV_{i,t+1,\tau} = \alpha_i + \beta_i \sum_{k=1}^K b(k; \theta_i) CS_{t-k/m} + \rho_i REV_{i,t,\tau} + \epsilon_{i,t+1,\tau}, \quad (8)$$

where $REV_{i,t,\tau}$ is the forecast revision of forecaster i for target year τ at time t . Equation (8) has five parameters to estimate for each individual forecaster in case of M1. We only test with the forecasters who made more than 50 revisions in total, leaving 41 forecasters with an average of 148.9 revisions each.

We report the results of individual-level estimation using model M1 as it provides the slope estimates ($\hat{\beta}_i$) related to the sign and size of forecast

Figure 4. Distributions of MIDAS Coefficients' at the Individual Level

Notes: This figure plots histograms of the slope coefficients ($\hat{\beta}_i$) on credit spreads and on lagged forecast revisions ($\hat{\rho}_i$) from Equations (8) and (9). The estimates are based on MIDAS regression M1 (using a normalised beta probability density function). The first row reports the results for all states, whereas the second and third rows report the results for good and bad states respectively. Forecasters with less than 50 revisions are excluded, leaving 41 forecasters in total.

updates associated with the developments of the credit spread. The estimated coefficients on the daily credit spread ($\hat{\beta}_i$) are negative for 36 out of 41 (87.8%) individuals. Counting only the significantly estimated coefficient at the 10% level, we find 28 (93.3%) among 30 individuals negatively responded to the change in Aaa-spread. The first row in Figure 4 plots the histogram of the estimated coefficients ($\hat{\beta}_i$), showing that the

estimates conform to the normal distribution, with an average value -10.3, close to the value (-9.9) from the coefficient of consensus revisions ($\hat{\beta}$).

This exercise shows that individual forecasters systematically revise their forecasts according to high-frequency information in asset markets, mostly agreeing on the sign of the impact of the developments in credit conditions. The range of the estimates displayed in Figure 4 however shows that forecasters disagree on the possible magnitude of the effects, which is consistent with the hypothesis that forecasters interpret public information differently (Lahiri and Sheng 2010; Manzan 2011).

The estimates of individual forecast rigidity ($\hat{\rho}_i$) are on average 0.14, and 37 out of 41 individual estimates are positive. The finding that forecast revisions are autocorrelated is strong evidence of forecast smoothing at the individual level. Individual forecasts are inefficient and therefore not optimal. The rigidity measure on average is much lower (0.14) compared to the estimate of consensus forecast revision, which is around 0.5. This result is consistent with the findings in previous studies that information rigidity in forecast surveys is a property largely related to the consensus forecast level and it is not as strong at an individual level (Coibion and Gorodnichenko 2015a; Doovern et al. 2015). Although forecasts are revised according to credit spread information, there are still inefficiencies in how forecasters use the information as they do not fully react to the latest developments in financial asset prices.²⁰⁾

We further examine how the forecast updating behaviour of individual forecasters differs depending on the economic state. Our model adjusting Equation (8) is

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20) Studies such as Gallo et al. (2002) have shown that the consensus made by other forecasters in the previous period affects individuals' current predictions. Our study is not directly connected to that issue, as we focus instead on forecast revisions. However, our findings at the individual forecaster level imply that revisions responding to the signals from credit conditions make the forecasters' herding less severe, as the majority of the forecasters revise in the same direction.

Table 3. Responses to Credit Spread and Forecasting Abilities

	δ_0	δ_1	R^2	N
All States	0.563 (37.298)	0.001 (0.577)	0.008	41
Good States	0.557 (39.095)	0.000 (0.110)	0.000	41
Bad States	0.571 (50.528)	0.002 (2.186)	0.109	41

Notes: This table reports the Equation (11) OLS estimates testing the relationship between the degree of responses to daily credit spreads ($\hat{\beta}_i$ in the model M1) and individual forecasting ability across economic states. Individuals' forecasting abilities are measured by the root mean squared forecast errors. δ_0 is a constant, and δ_1 is the relationship between forecasting ability and β_i . N is the number of forecasters, and the last column shows the R^2 . The values in parentheses are Newey-West t-statistics (Newey and West, 1987). The sample period covers 1991 to 2016.

$$REV_{i,t+1,\tau} = [\alpha_{i,0} + \beta_{i,0} \sum_{k=1}^K b(k; \theta_{i,0}) CS_{t-k/m} + \rho_{i,0} REV_{i,t,\tau}] \times (1 - \hat{s}_{t+1}) \\ + [\alpha_{i,1} + \beta_{i,1} \sum_{k=1}^K b(k; \theta_{i,1}) CS_{t-k/m} + \rho_{i,1} REV_{i,t,\tau}] \times \hat{s}_{t+1} + \epsilon_{i,t+1,\tau}, \quad (9)$$

where $\hat{s}_{t+1}$ is a dummy variable classified based on the ADS index defining economic states between t and $t+1$.

The second and the third row in Figure 4 illustrate the histogram of the estimates of (β_i) and ρ_i in good and bad economic states. A majority of forecasters revise output forecasts downward when credit spreads increase but exhibit substantial rigidities in updating forecasts as shown in positive $\hat{\rho}_i$. Estimates of both coefficients are more dispersed in bad states, showing that forecasters disagree more in the bad state in response to high-frequency financial information than in good states when they show more concentrated distributions. This result suggests that information from the market forecasters is more dispersed in troubled times, so policy makers such as monetary authorities should pay much attention to the signals from the financial markets.

As shown in this exercise, the degree to which forecasters incorporate high-frequency credit spread information varies substantially. In order to find a possible link between individuals' use of financial information when

making revisions and their forecasting ability, we initiate a simple regression connecting the individual forecasters' abilities and the degree of responses to daily credit spreads. Individuals' forecasting abilities are measured using the root mean squared forecast errors (Deschamps and Ioannidis 2013) over the entire period (1991-2016), defined as

$$RMSE_i = [(1/(26 \times 24))] \sum_{\tau=1991}^{2016} \sum_{h=1}^{24} e_{i,\tau,h}^2]^{1/2}, \quad (10)$$

where $e_{i,\tau,h}^2$ is the squared forecast errors for forecast i .²¹⁾ Forecast errors are calculated using the initial GDP releases rather than the revised GDP data as standard in the literature (Dovern and Weisser 2011; Chen et al. 2016; El-Shagi et al. 2016).²²⁾

We investigate whether a forecaster who strongly incorporates credit spread information shows higher overall forecast ability. Specifically, we estimate the relationship between individual $RMSE$ s and estimated slope coefficients on the daily credit spread ($\hat{\beta}_i$) using simple regression:

$$RMSE_i = \delta_0 + \delta_1 \hat{\beta}_i + \eta_i. \quad (11)$$

Figure 5 plots the relationship between the two variables. As $RMSE$ increases with higher forecast errors on average, lower $RMSE$ indicates higher ability. The coefficients on credit spreads ($\hat{\beta}_i$) are positively related with $RMSE_i$, but the relationship is statistically significant only when the economy is in bad states. We report the estimation results in Table 3, confirming that $\hat{\delta}_1$ is positive and significant in bad states. This result implies that responding more actively and consistently to the developments in credit market conditions enables forecasters to make

21) Using mean squared errors (MSE) instead of root mean squared errors (RMSE) to measure forecasters' abilities gives similar results.

22) The real-time macroeconomic data set of diverse vintages is provided by the Federal Reserve Bank of Philadelphia at <https://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data>.

Figure 5. Individual MIDAS Coefficients and Forecasting Abilities

Notes: This figure plots the linear relationship between the slope coefficients ($\hat{\beta}_i$) on credit spreads estimated using M1 and individuals' forecasting ability measured by the root mean squared error (RMSE). Each circle corresponds to one forecaster. Forecasters with less than 50 revisions are excluded, leaving 41 forecasters in total. The first row is for all economic states, while the second and third rows are for good and bad states respectively.

smaller forecasting errors on average, but this relationship is mostly dependent upon their strong responses during bad economic states.

V. Conclusion

This paper has explored the relationship between high-frequency credit spread information and forecast revisions. Using a MIDAS regression approach, we have provided empirical evidence that daily changes in credit spreads have a significant predictive ability for monthly revisions of GDP growth forecasts. Specifically, we have shown that increases in daily credit spreads, measured as the difference between the long-term Aaa-rated corporate bond rate and the constant maturity 10-year Treasury rate, are associated with significant downward forecast revisions both at the consensus and individual levels.

The weighting functions of all the four MIDAS regressions we examined have indicated hump-shaped polynomials, suggesting that forecasters do not respond in a sufficient and timely manner incorporating all high-frequency information in financial markets. Testing how the effect differs between economic states, we show that the effect of credit spreads on GDP forecast revisions is more prominent when the economy is in bad states, consistent with the previous literature studying state-dependent expectations formations in survey forecasts.

References

- Ager, P., M. Kappler, and S. Osterloh (2009). The accuracy and efficiency of the consensus forecasts: A further application and extension of the pooled approach. *International Journal of Forecasting* 25(1), 167–181.
- Alper, C. E., S. Fendoglu, and B. Saltoglu (2008). Forecasting stock market volatilities using MIDAS regressions: An application to the emerging markets. *MPRA Paper No.7460, University Library of Munich, Germany*.
- Andrade, P. and H. Le Bihan (2013). Inattentive professional forecasters. *Journal of Monetary Economics* 60(8), 967–982.
- Andreou, E., E. Ghysels, and A. Kourtellos (2010). Regression models with mixed sampling frequencies. *Journal of Econometrics* 158(2), 246–261.
- Andreou, E., E. Ghysels, and A. Kourtellos (2013). Should macroeconomic forecasters use daily financial data and how? *Journal of Business & Economic Statistics* 31(2), 240–251.
- Andreou, E., E. Ghysels, A. Kourtellos, et al. (2011). Forecasting with mixed-frequency data. *Oxford Handbook of Economic Forecasting*, 225–245.
- Ang, A., M. Piazzesi, and M. Wei (2006). What does the yield curve tell us about GDP growth? *Journal of Econometrics* 131(1), 359–403.
- Armesto, M. T., K. M. Engemann, M. T. Owyang, et al. (2010). Forecasting with mixed frequencies. *Federal Reserve Bank of St. Louis Review* 92(6), 521–36.
- Armesto, M. T., R. Hernández-Murillo, M. T. Owyang, and J. Piger (2009). Measuring the information content of the beige book: A mixed data sampling approach. *Journal of Money, Credit and Banking* 41(1), 35–55.
- Aruoba, S. B., F. X. Diebold, and C. Scotti (2009). Real-time measurement of

- business conditions. *Journal of Business & Economic Statistics* 27(4), 417–427.
- Barnichon, R., C. Matthes, and A. Ziegenbein (2017). Theory ahead of measurement? Assessing the nonlinear effects of financial market disruptions. *Unpublished Manuscript*.
- Bernanke, B. S. (1983). Nonmonetary effects of the financial crisis in the propagation of the Great Depression. *The American Economic Review*, 257–276.
- Bernanke, B. S., M. Gertler, and S. Gilchrist (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics 1*, 1341–1393.
- Bleaney, M., P. Mizen, and V. Veleanu (2016). Bond spreads and economic activity in eight European economies. *The Economic Journal* 126(598), 2257–2291.
- Bordo, M. D. and J. G. Haubrich (2004). The yield curve, recessions and the credibility of the monetary regime: Long run evidence 1875-1997. Technical report, National Bureau of Economic Research.
- Breitung, J. and C. Roling (2015). Forecasting inflation rates using daily data: A non-parametric MIDAS approach. *Journal of Forecasting* 34(7), 588–603.
- Buchmann, M. (2011). Corporate bond spreads and real activity in the euro area—Least angle regression forecasting and the probability of the recession. *ECB Working Paper*.
- Capistrán, C. and G. López-Moctezuma (2014). Forecast revisions of Mexican inflation and GDP growth. *International Journal of Forecasting* 30(2), 177–191.
- Capistrán, C. and A. Timmermann (2009). Forecast combination with entry

- and exit of experts. *Journal of Business & Economic Statistics* 27(4), 428–440.
- Chen, Q., M. Costantini, and B. Deschamps (2016). How accurate are professional forecasts in Asia? Evidence from ten countries. *International Journal of Forecasting* 32(1), 154–167.
- Chen, X. and E. Ghysels (2010). News—good or bad—and its impact on volatility predictions over multiple horizons. *The Review of Financial Studies* 24(1), 46–81.
- Clements, M. P. (1997). Evaluating the rationality of fixed-event forecasts. *Journal of Forecasting* 16(4), 225–239.
- Clements, M. P. and A. B. Galvão (2008). Macroeconomic forecasting with mixed-frequency data: Forecasting output growth in the United States. *Journal of Business & Economic Statistics* 26(4), 546–554.
- Coibion, O. and Y. Gorodnichenko (2012). What can survey forecasts tell us about information rigidities? *Journal of Political Economy* 120(1), 116–159.
- Coibion, O. and Y. Gorodnichenko (2015a). Information rigidity and the expectations formation process: A simple framework and new facts. *The American Economic Review* 105(8), 2644–2678.
- Coibion, O. and Y. Gorodnichenko (2015b). Is the Phillips curve alive and well after all? Inflation expectations and the missing disinflation. *American Economic Journal: Macroeconomics* 7(1), 197–232.
- Davies, A. and K. Lahiri (1995). A new framework for testing rationality and measuring aggregate shocks using panel data. *Journal of Econometrics* 68(1), 205–227.
- Deschamps, B. and C. Ioannidis (2013). Can rational stubbornness explain forecast biases? *Journal of Economic Behavior & Organization* 92,

141–151.

- Dotsey, M. (1998). The predictive content of the interest rate term spread for future economic growth. *Federal Reserve Bank of Richmond Economic Quarterly*.
- Dovern, J., U. Fritsche, P. Loungani, and N. Tamirisa (2015). Information rigidities: Comparing average and individual forecasts for a large international panel. *International Journal of Forecasting* 31(1), 144–154.
- Dovern, J., U. Fritsche, and J. Slacalek (2012). Disagreement among forecasters in G7 countries. *Review of Economics and Statistics* 94(4), 1081–1096.
- Dovern, J. and N. Jannsen (2017). Systematic errors in growth expectations over the business cycle. *International Journal of Forecasting* 33(4), 760–769.
- Dovern, J. and J. Weisser (2011). Accuracy, unbiasedness and efficiency of professional macroeconomic forecasts: An empirical comparison for the G7. *International Journal of Forecasting* 27(2), 452–465.
- Dräger, L. and M. J. Lamla (2012). Updating inflation expectations: Evidence from micro-data. *Economics Letters* 117(3), 807–810.
- Duca, J. V. (1999). What credit market indicators tell us. *Federal Reserve Bank of Dallas Economic & Financial Review*, 2–13.
- El-Shagi, M., S. Giesen, and A. Jung (2016). Revisiting the relative forecast performances of Fed staff and private forecasters: A dynamic approach. *International Journal of Forecasting* 32(2), 313–323.
- Emery, K. M. (1996). The information content of the paper-bill spread. *Journal of Economics and Business* 48(1), 1–10.
- Estrella, A. and G. A. Hardouvelis (1991). The term structure as a predictor

- of real economic activity. *The Journal of Finance* 46(2), 555–576.
- Ewing, B. T., G. J. Lynch, and J. E. Payne (2003). The paper-bill spread and real output: What matters more, a change in the paper rate or a change in the bill rate? *Review of Financial Economics* 12(3), 233–246.
- Faust, J., S. Gilchrist, J. H. Wright, and E. Zakrajšek (2013). Credit spreads as predictors of real-time economic activity: A Bayesian model-averaging approach. *Review of Economics and Statistics* 95(5), 1501–1519.
- Foroni, C. and M. Marcellino (2014). A comparison of mixed frequency approaches for nowcasting Euro area macroeconomic aggregates. *International Journal of Forecasting* 30(3), 554–568.
- Foroni, C., M. Marcellino, and C. Schumacher (2015). Unrestricted mixed data sampling (MIDAS): MIDAS regressions with unrestricted lag polynomials. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 178(1), 57–82.
- Foroni, C. and M. G. Marcellino (2013). A survey of econometric methods for mixed-frequency data. *Norges Bank Working Paper*.
- Friedman, B. M. and K. Kuttner (1993). Why does the paper-bill spread predict real economic activity? In *Business Cycles, Indicators and Forecasting*, pp. 213–254. University of Chicago Press.
- Gallo, G. M., C. W. Granger, and Y. Jeon (2002). Copycats and common swings: The impact of the use of forecasts in information sets. *IMF Staff Papers*, 4–21.
- Galvão, A. B. (2013). Changes in predictive ability with mixed frequency data. *International Journal of Forecasting* 29(3), 395–410.
- Gertler, M. and C. S. Lown (1999). The information in the high-yield bond spread for the business cycle: Evidence and some implications. *Oxford Review of Economic Policy* 15(3), 132–150.

- Ghysels, E., P. Santa-Clara, and R. Valkanov (2004). The MIDAS touch: Mixed data sampling regression models. *Unpublished Manuscript*.
- Ghysels, E., A. Sinko, and R. Valkanov (2007). MIDAS regressions: Further results and new directions. *Econometric Reviews* 26(1), 53–90.
- Ghysels, E. and J. H. Wright (2009). Forecasting professional forecasters. *Journal of Business & Economic Statistics* 27(4), 504–516.
- Gilchrist, S., V. Yankov, and E. Zakrajšek (2009). Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets. *Journal of Monetary Economics* 56(4), 471–493.
- Gilchrist, S. and E. Zakrajšek (2012). Credit spreads and business cycle fluctuations. *The American Economic Review* 102(4), 1692–1720.
- Gorodnichenko, Y. (2008). Endogenous information, menu costs and inflation persistence. Technical report, National Bureau of Economic Research.
- Guha, D. and L. Hiris (2002). The aggregate credit spread and the business cycle. *International Review of Financial Analysis* 11(2), 219–227.
- Hamilton, J. D. (2008). Daily monetary policy shocks and new home sales. *Journal of Monetary Economics* 55(7), 1171–1190.
- Harvey, C. R. (1989). Forecasts of economic growth from the bond and stock markets. *Financial Analysts Journal* 45(5), 38–45.
- Hur, J. and I. Kim (2016). Information rigidities in survey data: Evidence from dispersions in forecasts and forecast revisions. *Economics Letters* 142, 10–14.
- Isiklar, G., K. Lahiri, and P. Loungani (2006). How quickly do forecasters incorporate news? Evidence from cross-country surveys. *Journal of Applied Econometrics* 21(6), 703–725.
- Krishnamurthy, A. and T. Muir (2015). Credit spreads and the severity of

financial crises. *Unpublished Manuscript*.

- Kuzin, V., M. Marcellino, and C. Schumacher (2011). MIDAS vs. mixed-frequency VAR: Nowcasting GDP in the Euro area. *International Journal of Forecasting* 27(2), 529–542.
- Lahiri, K. and X. Sheng (2010). Measuring forecast uncertainty by disagreement: The missing link. *Journal of Applied Econometrics* 25(4), 514–538.
- Loungani, P., H. Stekler, and N. Tamirisa (2013). Information rigidity in growth forecasts: Some cross-country evidence. *International Journal of Forecasting* 29(4), 605–621.
- Mankiw, N. G. and R. Reis (2002). Sticky information versus sticky prices: A proposal to replace the new Keynesian Phillips curve. *The Quarterly Journal of Economics* 117(4), 1295–1328.
- Manzan, S. (2011). Differential interpretation in the survey of professional forecasters. *Journal of money, Credit and Banking* 43(5), 993–1017.
- Marcellino, M. and C. Schumacher (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.
- Messina, J. D., T. M. Sinclair, and H. Stekler (2015). What can we learn from revisions to the Greenbook forecasts? *Journal of Macroeconomics* 45, 54–62.
- Modugno, M. (2013). Now-casting inflation using high frequency data. *International Journal of Forecasting* 29(4), 664–675.
- Mody, A. and M. P. Taylor (2004). Financial predictors of real activity and the financial accelerator. *Economics Letters* 82(2), 167–172.
- Monteforte, L. and G. Moretti (2013). Real-time forecasts of inflation: The

- role of financial variables. *Journal of Forecasting* 32(1), 51–61.
- Mueller, P. (2009). Credit spreads and real activity. *Unpublished Manuscript*.
- Nordhaus, W. D. (1987). Forecasting efficiency: Concepts and applications. *The Review of Economics and Statistics*, 667–674.
- Ribeiro, R. and P. Veronesi (2002). The excess comovement of international stock markets in bad times: A rational expectations equilibrium model. *Unpublished Manuscript*.
- Rudebusch, G. D. and J. C. Williams (2009). Forecasting recessions: The puzzle of the enduring power of the yield curve. *Journal of Business & Economic Statistics* 27(4), 492–503.
- Schumacher, C. (2014). MIDAS regressions with time-varying parameters: An application to corporate bond spreads and GDP in the euro area. *Annual Conference 2014 (Hamburg): Evidence based Economic Policy 100289*, German Economic Association.
- Schumacher, C. and J. Breitung (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.
- Sheng, X. and J. Wallen (2014). Information rigidity in macroeconomic forecasts: An international empirical investigation. *Unpublished Manuscript*, American University Washington, DC.
- Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics* 50(3), 665–690.
- Sinclair, T. M., F. Joutz, and H. O. Stekler (2010). Can the Fed predict the state of the economy? *Economics Letters* 108(1), 28–32.
- Stock, J. H. and M. W. Watson (1989). New indexes of coincident and leading economic indicators. *NBER Macroeconomics Annual* 4, 351–394.

- Stock, J. H. and M. W. Watson (2003). Forecasting output and inflation: The role of asset prices. *Journal of Economic Literature* 41(3), 788–829.
- Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of Money, Credit and Banking* 1(1), 15–29.
- Wheelock, D. C., M. E. Wohar, et al. (2009). Can the term spread predict output growth and recessions? A survey of the literature. *Federal Reserve Bank of St. Louis Review* 91(5 Part 1), 419–440.
- Woodford, M. (2001). Imperfect common knowledge and the effects of monetary policy. Technical report, National Bureau of Economic Research.
- Wright, J. H. (2006). The yield curve and predicting recessions. *Finance and Economics Discussion Series, Federal Reserve Board*.
- Xie, Z. and S.-H. Hsu (2016). Time varying biases and the state of the economy. *International Journal of Forecasting* 32(3), 716–725.

<Abstract in Korean>

고빈도 신용스프레드 변화가 경제전망 수정에 미치는 영향

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본 논문에서는 금융시장의 고빈도(high-frequency) 가격 정보중 하나인 일별 신용스프레드가 시장참가자의 경제전망 수정에 미치는 영향에 대해 분석하였다. 혼합자료 샘플링(Mixed Data Sampling, MIDAS) 모형을 이용하여 추정한 결과, 일별 신용스프레드 증가 시 GDP성장률에 대한 월별 컨센서스 전망이 하향 조정되는 것으로 나타났다. 실물경제 상황에 따라 예측기관들의 금융정보 활용 정도가 달라지는지를 평가한 결과, 경기가 부진한 것으로 인식되는 시기에 일별 신용스프레드의 변화가 GDP성장률 전망 컨센서스에 더 큰 영향을 주는 것으로 분석되었다. 이와 같은 금융시장 정보 활용에도 불구하고 경제전망 수정은 상당 수준의 자기상관을 보여 예측기관들의 전망 수정에 경직성(stickiness)이 있음이 확인되었다.

핵심 주제어: 전망 수정, GDP 전망, 신용스프레드, 고빈도 데이터, 혼합자료 샘플링

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3	직간접 무역연계성을 통한 해외충격의 우리나라 수출입 파급효과 분석	최문정 · 김근영
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10	인구 고령화와 정년연장 연구 (세대 간 중첩모형(OLG)을 이용한 정량 분석)	홍재화 · 강태수
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14	Global Liquidity and Commodity Prices	Hyunju Kang · Bok-Keun Yu · Jongmin Yu

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10	유가가 손익분기인플레이션에 미치는 영향	김진용 · 김준철 · 임형준
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10	Upgrading Product Quality: The Impact of Tariffs and Standards	Jihyun Eum
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3	Taking a Bigger Slice of the Global Value Chain Pie: An Industry-level Analysis	Chong-Sup Kim · Seungho Lee · Jihyun Eum
4	Trend Growth Shocks and Asset Prices	Nam Gang Lee
5	Uncertainty, Attention Allocation and Monetary Policy Asymmetry	Kwangyong Park
6	Central Bank Digital Currency and Financial Stability	Ohik Kwon
7	은행의 수익 및 자산구조를 반영한 통화정책 위험선호경로	김익진 · 정호성
8	혁신기업에 대한 산업금융 지원: 이론모형 분석	강경훈 · 양준구
9	가계부채 제약하의 통화정책: 2주체 거시 모형(TANK)에서의 정량적 분석	정용승 · 송승주
10	Alchemy of Financial Innovation: Securitization, Liquidity and Optimal Monetary Policy	Jungu Yang
11	Measuring Monetary Policy Surprises Using Text Mining: The Case of Korea	Youngjoon Lee · Soohyon Kim · Ki Young Park
12	Tracking Uncertainty through the Relative Sentiment Shift Series	Seohyun Lee · Rickard Nyman
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