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Mixed Frequency Machine Learning Forecasting of the Growth of Real Gross Fixed Capital Formation in the United States: The Role of Extreme Weather Conditions

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Abstract

We forecast quarterly growth rate of real gross fixed capital formation of the United States using the information content of a monthly metric of extreme weather conditions, while controlling for a set of principal components derived from a large data set of economic and financial indicators. In this regard, we utilize a Mixed Frequency Machine Learning framework over the period of 1974:Q1 to 2022:Q1. Our results show that incorporating monthly data on severe climatic conditions, especially information contained in relatively higher (above the mean) extreme weather values, significantly outperforms not only the benchmark autoregressive model, but also the econometric framework that includes the macro-finance factors when forecasting the growth rate of quarterly real gross fixed capital formation.

Keywords: Gross fixed capital formation; Extreme weather conditions; Mixed frequency; Machine learning; Forecasting

JEL Codes: C22, C53, E22, Q54

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1. Introduction

Gross fixed capital formation (GFCF) is both the most cyclically sensitive and the most forward-looking component of private domestic investment in the United States (US): its expansions finance new structures, equipment and intellectual property, while its contractions often presage broader slowdowns. A fast-growing strand of macro-climate research shows that extreme temperatures, storms and precipitation shocks already depress firm-level capital spending by tightening credit constraints, raising replacement costs and increasing the option value of waiting when climatic and regulatory conditions are uncertain (Giglio et al., 2021; Kahn et al., 2021). Long-run simulations further suggest that a 4 °C rise in global temperatures could reduce average global income by roughly 40 percent, mainly through delayed or foregone investment (World Bank, 2012). Despite this evidence, short-horizon macro-forecasting models have remained largely climate-agnostic. Policymakers and investors therefore lack a real-time, data-driven lens through which to gauge how the growing incidence of climate extremes will feed through the investment channel into near-term output and potential growth.

Existing literature has increasingly focused on quantifying the economic consequences of climate change. Early studies highlighted the immediate negative impacts of natural disasters on economic growth (Barro, 2006; Noy, 2009), while later research broadened to explore longer-term effects on productivity, labor supply, and innovation (Dell et al., 2012; Dasgupta et al., 2021; Matos et al., 2022). Within the realm of investment, studies have shown that heightened climate risk can lead to lower investment levels and increased cost of capital for exposed firms (Cepni et al., 2024; Lai et al., 2025) via deterioration of the quality of capital (Donadelli et al., 2021), with investors also beginning to price in climate-related risks in asset markets (Faccini et al., 2023, Bua et al., 2024). This growing body of evidence underscores the potential for climate information to significantly influence GFCF dynamics.

This paper investigates the importance of climate variables in forecasting the quarterly growth of real GFCF in the US. Recognizing the complex and dynamic relationship between climate and economic activity, we employ a sophisticated methodological framework that leverages the strengths of both mixed-frequency data analysis and machine learning techniques. Specifically, we adopt the Mixed Frequency Machine Learning (MFML) approach proposed by Borup et al. (2023). This innovative methodology allows us to incorporate high-frequency monthly data on climate conditions, as captured by the Actuaries Climate Index (ACI), alongside additional monthly macroeconomic and financial indicators to generate more accurate and timely forecasts of GFCF. Furthermore, the integration of machine learning, specifically the Least Absolute Shrinkage and Selection Operator (LASSO), enables us to effectively handle a potentially high-dimensional set of predictors, including lagged values of GFCF and 8 factors (principal components) extracted from a large dataset (FRED-MD) of 134 macroeconomic and financial indicators, and to identify the most relevant variables for prediction. The control variables, over and above the indicator of extreme weather condition, is important, as they allow us to accommodate for the various theories (such as, accelerator, neoclassical, Tobin's *Q*, cash-flow, stock price models, among others) via which macroeconomic and financial variables impact investment decisions (Rapach and Wohar, 2007; Aye et al., 2016). Our findings demonstrate that incorporating ACI data improves forecasting performance in a statistically significant manner compared to benchmark autoregressive models and MFML models without climate variables. This highlights the critical role of climate risks in shaping investment behavior and provides a novel framework for climate-informed economic forecasting, for the first time.

The remainder of the paper is organized as follows: Section 2 outlines the data, while Section 3 presents the methodology, with Section 4 devoted to the empirical findings, and Section 5 concluding the paper.

2. Data

Our empirical analysis combines three publicly available data sets: (i) quarterly real Gross Fixed Capital Formation (GFCF) for the US, (ii) monthly observations of the ACI, and; (iii) 8 monthly macro-finance factors extracted from the FRED-MD database of McCracken and Ng (2016).

The quarterly series for US real GFCF is obtained from the FRED database, maintained by the Federal Reserve Bank of St. Louis.[1] The level data is then transformed into quarterly growth rates, calculated as the percentage change from the previous quarter, to align with the specification of our forecasting model.

To incorporate climate-related variables, we use monthly data of the ACI.[2] The ACI is a composite index of the frequency of severe weather (high and low temperatures, heavy rainfall, drought (consecutive dry days), and high wind, with all based on gridded data at the resolution of 2.5 by 2.5 degrees latitude and longitude), and the extent of sea level rise (using tidal gauge station data).

As control variables, we include a set of macroeconomic and financial factors derived from the FRED-MD database.[3] The 8 factors are constructed using principal component analysis on 134 US macroeconomic and financial time series, and capture broad economic conditions relevant for a forecasting exercise. These factors are included to account for traditional macroeconomic drivers of GFCF and to isolate the marginal impact of the ACI on forecasting accuracy.

Our sample period covers 1974:Q1 to 2022:Q1, with an in-sample involving the first 100 quarterly observations, i.e., 1974:Q1 to 1998:Q4, and 1999:Q1 to 2022:Q1 as the out-of-sample.

3. Methodology

Following the MFML approach of Borup et al. (2023), we generate simulated out-of-sample predictions of the US quarterly growth of real GFCF based on monthly data of ACI and the macro-financial factors of McCracken and Ng (2016). The method of Borup et al. (2023) combines the unrestricted mixed-data sampling (U-MIDAS) model of Foroni et al. (2015) with machine learning techniques. The mixed frequency data help us to examine how the flow of information on monthly predictors affect the out-of-

[1] https://fred.stlouisfed.org/series/NFIRSAXDCUSQ.
[2] https://actuariesclimateindex.org/data/.
[3] https://www.stlouisfed.org/research/economists/mccracken/fred-databases.

sample results of quarterly GFCF growth, with the machine learning being useful in exploring the simultaneous role of the high-dimensional predictors.

Following the approach of Borup et al. (2023), the prediction model is specified as

$$Y_t = \alpha^{(j)} + \beta_{AR1}^{(j)} Y_{t-1} + \beta_X^{(j)\prime} X_t^{(j)} + \beta_{X1}^{(j)\prime} X_{t-1}^{(j)} + \beta_Z^{(j)\prime} Z_t^{(j)} + \beta_Z^{(j)\prime} Z_{t-1}^{(j)} + \epsilon_t^{(j)} \qquad (1)$$

where Y_t is the quarterly-*t* target variable (i.e., real GFCF growth), an AR(1) term is included in the equation to account for possible serial correlation in Y_t. $X_t^{(j)}$ is a vector of the ACI-based predictors. $X_t^{(j)} = [X_{t+j/3}^{m}{}' \, X_{t+(j-1)/3}^{m}{}' \, X_{t+(j-2)/3}^{m}{}']$, and $X_{t+i/3}^{m} = [X_{1+i/3}^{m} \ldots X_{K_m+i/3}^{m}]'$ is a vector of predictors for the $(i+1)$-th month of quarter *t* for $i = 0,1,2.$[4] $j = 0, 1, 2$ aligns with prediction of Y_t formed at the 1st, 2nd, and 3rd month in quarter *t*. $\beta_X^{(j)}$ and $\beta_{X1}^{(j)}$ is a vector of slope coefficients for monthly ACI in quarter *t* and quarter *t*-1. The model allows for each of the higher-frequency predictors to have its own coefficient, which can be viewed as an unrestricted MIDAS model. We also use the macro factors of Ludvigson and Ng (2009) in quarter *t* and *t*-1 as control variables (represented by $Z_t^{(j)}$and $Z_{t-1}^{(j)}$).

The mixed frequency nature arises because Y_t is quarterly while $Z_t^{(j)}$ and ACI ($X_t^{(j)}$) are monthly. This formulation essentially treats the monthly data as leading indicators within the quarter, useful for nowcasting the quarter's end outcome. The above regression specification yields a potentially large number of coefficients relative to the number of quarterly observations. Specifically, with 8 factors plus the ACI, we have 9 predictors, each with 3 monthly contemporaneous and one lagged values, besides an intercept, and one lag of the growth in real GFCF, giving us a total of 56 coefficients. Therefore, we use the machine-learning approach of LASSO (Tibshirani, 1996) to perform variable selections and improve the out-of-sample performance of high-dimensional models.[5]

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[4] The vectors of predictors for the month of quarter t are as follows: the1st month X_t^m, the 2nd month $X_{t+1/3}^m$, and the 3rd month $X_{t+2/3}^m$.

[5] We employ the LASSO to estimate the models, enabling simultaneous shrinkage and selection of coefficients in a data-driven manner. The LASSO is a popular machine-learning device that improves

4. Empirical Results

We produce the out-of-sample predictions of US quarterly growth of real GFCF for the first quarter of 1999 through the first quarter of 2022 using a rolling-window approach associated with 100 observations. Our prediction models relate quarterly GFCF with its last lag and the last three months of ACI data. We also include the eight macro-finance factors of McCracken and Ng (2016) as control variables. Table 1 reports the Root Mean Square Error (RMSE) ratio for the MFML models without and with including ACI versus an AR(1) benchmark model for predictions.[6]

Table 1 summarizes the out-of-sample forecasting results for one-quarter-ahead GFCF growth across various models. Focusing on the two key models: the MFML model with ACI (our proposed model) and the MFML model without ACI (macro-finance factors only).

We find that the RMSE ratios for MFML models (without and with ACI) decrease gradually, and are generally (barring the case of the 1st month forecast without ACI) all below one, as we move from the predictions formed in the first month of each quarter to the ones formed in the second and third month of each quarter, which use more recent information contained in monthly frequency data to form the predictions. In the second row of Table 1, the RMSE ratios for the MFML model with ACI are all below one, suggesting that based on the LASSO-reliant MFML approach,[7] incorporating the information of monthly ACI data is always able to outperform the AR(1) benchmark in terms of the RMSE, ranging from 7% to 21%, depending on when within the quarter

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forecast accuracy in complex models with many predictors by performing automatic variable selection. See Borup et al. (2023) for further details on the estimation procedure.

[6] The root mean squared error (RMSE) is defined as $RMSE = [\frac{1}{T_{OS}}\sum_{t=1}^{T_{OS}}(Y_t - \widehat{Y}_t)^2]^{1/2}$, where Y_t and $\widehat{Y}_t$ represent the realized and predicted values of quarterly GFCF growth, respectively, and T_{OS} is the number of out-of-sample observations available for analyzing the predictions.

[7] The ACI-included MFML models estimated using Elastic Net and Artificial Neural Network (with one hidden layer) produced RMSE ratios greater than one (see, Table A1 in the Appendix), suggesting the relative superiority of the LASSO estimator, and hence, justifying our reliance on it.

the prediction is generated.[8, 9] More importantly, the results also show that incorporating monthly ACI data to forecast quarterly real GFCF growth can further reduce RMSEs and improve accuracy in all cases compared to its counterpart for the MFML model without the ACI. From an intuitive perspective, this suggests that extreme weather conditions—such as droughts, heatwaves, or severe storms—carry relevant information that helps anticipate fluctuations in investment activity.

The reason behind this improved accuracy is straightforward: extreme weather events often disrupt economic operations, affecting business confidence, capital allocation, and investment decisions. Capturing these disruptions early through the monthly ACI data provides an edge in forecasting future investment activity, as firms might delay or accelerate investments depending on perceived risks and uncertainties linked to climatic conditions.

Table 1. RMSE ratios (relative to AR(1)) for predictions without and with ACI for the US

without ACI	1st month	2nd month	3rd month
RMSE	1.028	0.915	0.873
with ACI	1st month	2nd month	3rd month
RMSE	0.934	0.866	0.825

Furthermore, we employ the Clark and West (2007) test to examine whether the forecast performance of model without and with the ACI is statistically significant relative to the nested AR(1), and the same holds for the comparison across the two MFML models. The test statistics reported in the first two rows of Table 2 indicate that

[8] We also find evidence that MFML models incorporating information of US regional ACI data, covering Alaska, Central East Atlantic (CT, DC, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT, WV), Central West Pacific (WA, OR, ID), Midwest (IA, IL, IN, MI, MN, MO, OH, WI), Southeast Atlantic (AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA), Southern Plains (KS, MT, ND, NE, OK, SD, TX, WY), and Southwest Pacific (AZ, CA, CO, NM, NV, UT), can outperform the AR(1) benchmark (see, Table A2 in the appendix).
[9] We also report RMSE ratios for MFML models (without and with ACI) using Canadian data from the 1983:Q1 to the 2022:Q1 (see, Table A3 in the Appendix). Using an out-of-sample period of 2008:Q1 to 2022:Q1, we find that MFML models outperform the AR(1) benchmark, but, we could not find evidence that monthly ACI data can be useful for predicting quarterly real GFCF growth in Canada, over and above 8 macro-financial predictors, derived from the CAN-MD-QD or LCDMA database of Fortin-Gagnon et al. (2022), available at: https://www.stevanovic.uqam.ca/DS_LCMD.html. This finding could be an indication of relatively better adaptation measures to climate change in Canada when compared to those in the US, with the latter subject to heightened climate policy related uncertainties (Sheng et al., 2024).

both the MFML models significantly outperform the AR(1) benchmark model. Specifically, the MFML model without ACI yields test statistics of 2.939, 2.232, and 2.425 for the predictions formed in the first, second and third month of each quarter respectively, with corresponding *p*-values indicating significance at the 1% and 5% levels. Similarly, the MFML model incorporating ACI also shows statistically significant results at least at the 5% level, with test statistics of 2.739, 2.112, and 2.367. These findings suggest that while MFML models add significant predictive value beyond the benchmark, but, more importantly, the inclusion of ACI enhances further the statistical strength of the forecast improvement derived from the factors, as depicted by the Clark and West (2007) test statistics in the last row of Table 2. Specifically speaking, test statistics are 1.405, 1.755, and 1.982 for the forecasts in the first, second and third month of each quarter respectively, which, in turn, are statistically significant at the 10%, 5%, and 5% levels.

Table 2. Clark and West (2007) test results for predictions of MFML models with ACI for the US

Models	1st month	2nd month	3rd month
MFML without ACI versus AR(1)	2.939*** (0.002)	2.232** (0.014)	2.425*** (0.009)
MFML with ACI versus AR(1)	2.739*** (0.004)	2.112** (0.019)	2.367*** (0.010)
MFML with ACI versus MFML without ACI	1.405 * (0.082)	1.755** (0.041)	1.982** (0.025)

Note: ***, **, * indicate the 1%, 5%, and 10% significance levels.

Having confirmed the importance of the ACI in forecasting GFCF, an interesting follow-up question to ask would be whether higher values of the extreme weather conditions matter more in this context than its corresponding lower values. In other words, we such an exercise would allow us test for possible predictive asymmetry, which we believe would be value to policymakers in determining the strength of appropriate policy responses. The hypothesis that we make in this regard is that higher ACI values reflecting greater disaster risks should carry more information than lower values of the same in forecasting GFCF. Given this, we decompose the ACI into ACI_High or ACI_Low, by creating a dummy which takes a value of 1 if the ACI is greater or less than the average of the previous 100 observations of the ACI, and zero otherwise, and then multiplying these two dummies with the ACI series.

The forecasting results using the MFML model with ACI_High or ACI_Low along with the factors, relative to the AR(1) model and the MFML model without the ACIs are presented in Table 3. In line with our hypothesis, ACI_High produces stronger forecasting gains compared to ACI_Low compared to both the benchmark and the MFML model including on the macro-finance factors. More importantly, the Clark and West (2007) test statistics in Table 4 confirm that the forecasting gains, especially under ACI_High are consistently statistically significant relative to the AR(1) and the MFML with factors.

Table 3. RMSE ratios for predictions of MFML Models with ACI_High and ACI_Low for the US

Models	1st month	2nd month	3rd month
MFML Models with ACI_High (relative to an AR (1) model)	0.911	0.819	0.813
MFML Models with ACI_Low (relative to an AR (1) model)	0.985	0.927	0.859
MFML Models with ACI_High (relative to MFML Models without ACI)	0.886	0.895	0.931
MFML Models with ACI_Low (relative to MFML Models without ACI)	0.958	1.013	0.984

Table 4. Clark and West (2007) test results for predictions of MFML models with ACI_High and ACI_Low for the US

Models	1st month	2nd month	3rd month
MFML Models with ACI_High (relative to an AR (1) model)	2.854*** (0.003)	2.420*** (0.003)	2.553*** (0.006)
MFML Models with ACI_Low (relative to an AR (1) model)	3.186*** (0.001)	2.710*** (0.004)	2.910*** (0.002)
MFML Models with ACI_High (relative to MFML Models without ACI)	1.503* (0.068)	1.825** (0.036)	1.897** (0.031)
MFML Models with ACI_Low (relative to MFML Models without ACI)	1.839** (0.035)	0.579 (0.282)	1.395* (0.083)

In sum, we find that the information in the high-dimensional monthly ACI data, especially those emanating from its relatively higher values, are useful in a statistically significant fashion for predicting quarterly real GFCF growth, over and above one of its lag and macroeconomic and financial predictors.

5. Conclusion

This study demonstrates the statistically significant predictive power of the ACI, capturing extreme weather conditions, for forecasting quarterly US real GFCF growth. Using a MFML framework, we find that incorporating high-frequency monthly ACI data, and in particular associated above the mean values, not only outperforms an autoregressive benchmark, but also information contained in macroeconomic and financial indicators. This highlights the growing influence of climate conditions on investment decisions, a dynamic often missed by climate-agnostic forecasting. The ACI's ability to enhance accuracy of GFCF forecasts, especially with intra-quarterly (monthly) data, underscores climate change as an increasingly relevant near-term factor in economic activity through investment.

The implications of these findings for policymakers and investors are manifold. Firstly, our results highlight the need for integrating climate-related data into mainstream macroeconomic forecasting and risk assessment frameworks, especially information on above the historical mean of weather conditions. Central banks and government agencies could leverage climate indexes like the ACI to gain a more nuanced understanding of the factors driving investment and to potentially improve their economic projections. This enhanced foresight can inform more effective policy responses to both cyclical fluctuations and climate-related economic disruptions. Secondly, investors can utilize climate-augmented forecasting models to better anticipate future investment trends and to assess the potential impact of evolving climate conditions on asset valuations and portfolio risk.

Incorporating climate intelligence into investment strategies can lead to more informed capital allocation decisions and potentially identify both risks and opportunities associated with the transition to a more sustainable economy. Finally, the demonstrated link between climate variables and real GFCF growth suggests that policies aimed at mitigating climate change and enhancing climate resilience are not only crucial for environmental sustainability, but also for fostering a stable and predictable investment environment, thereby supporting long-term economic growth and stability.

As part of future research, a similar analysis can be performed for emerging economies, contingent on data availability, to allow us to generalize our findings.

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APPENDIX

Table A1. RMSE ratios for predictions with ACI for the US using elastic net and neural networks

Elastic net	1st month	2nd month	3rd month
	1.050	1.120	0.962
Neural networks	1st month	2nd month	3rd month
	1.136	1.120	1.127

Table A2. RMSE ratios for predictions with regional ACI data for the US

with ACI	1st month	2nd month	3rd month
RMSE	0.946	0.875	0.950

Table A3. RMSE ratios for predictions with and without ACI for Canada

without ACI	1st month	2nd month	3rd month
RMSE	0.927	0.846	0.937
with ACI	1st month	2nd month	3rd month
RMSE	0.937	0.867	1.005