Research Statement

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1. Research Interests

My research interests span the fields of econometrics, applied macroeconomics and machine learning. I am particularly interested in macroeconomic forecasting and how machine learning methods can be brought to bear on these questions. Modeling and forecasting macroeconomic risk is another subject of my attention, as are structural vector autoregressions (SVAR) for studying how different shocks propagate. Below I describe my research and outline a few potential lines of future inquiry.

2. Machine Learning in Macroeconomics

The first set of contributions focuses on the use of machine learning methods for macroeconomic forecasting. It has been known for some time that machine learning methods would frequently offer substantial improvements in point forecasting accuracy over standard econometric models such autoregressive moving average (ARMA) models or the autoregressive diffusion index (ARDI) model of Stock and Watson (2002a,b).

Yet, these methods introduce deviations from common tools in a variety of dimensions. Some can provide flexible approximations to nonlinear conditional means and many will involve some form of regularization or shrinkage. All will require selecting some hyperparameters and this introduces a choice between different forms of cross-validation. Finally, methods such as support vector regressions work by changing the standard square loss function.

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In "How is Machine Learning Useful for Macroeconomic Forecasting?", we sought to quantify how choices made in each of these dimensions influence the accuracy of point forecasts. We selected a handful of well-studied target variables and performed a pseudo-out-of-sample forecasting experiment featuring a large cross-section of models so that the variation in forecasting accuracy could then be used in regressions to answer our question.

We found that enabling nonlinearities was the biggest driver of improvements in forecasting accuracy from using machine learning models. It's especially useful when measures of macroeconomic uncertainty or of financial stress are high. Comparing LASSO, ridge, elastic net and latent factors estimated by principal components (PCA), we found factors to be the best choice and that it worked especially well in conjunction with nonlinear algorithm such as random forest, a result which anticipates a key finding from "Macroeconomic Data Transformation Matters." This result is interesting in its own right as it is consistent with standard macroeconomic theory which assigns the bulk of business cycle fluctuations to a small set of structural shocks.

We applied a similar forecasting experiment in "Macroeconomic Data Transformation Matters," but this time we focused on inputs, on how to best transform predictors to help machine learning algorithms forecast better. We considered some standard options such as leaving variables in levels to perhaps avoid overdifferencing or to let algorithms uncover cointegration on its own, as well as PCA factor estimates. We also considered less common choices. The moving average factors (MAF) transformation takes every predictor we have and forms a matrix of its lags before extracting a few principal components. The moving average rotation of X (MARX) involves introducing several moving averages for each predictor. It can be shown that this transformation in a ridge setting leads to shrinking coefficients in an autoregressive distributed lag model toward the previous coefficient rather than toward zero. All of those options thereof implicitly encode some macroeconomics-specific intuitions or priors into machine learning algorithms.

We compared standard autoregressive (AR) and ARDI benchmarks with adaptative LASSO, elastic net, linear boosting, random forests and boosted trees with these different predictors in an out-of-sample forecasting experiment. The nonstandard transformations (MAF and MARX) are almost always part of the best model, as well as PCA factors. And just as in "How is Machine Learning Useful for Macroeconomic Forecasting?" it works best when used in conjunction with nonlinear models like random forest and boosted trees.

The last element of this research agenda was the introduction of a Canadian equivalent to FRED-MD in "A Large Canadian Database for Macroeconomic Analysis." I programmed the first version to be easy to update with most of the work being automated. Besides saving time, having such a large panel of macroeconomic variables allows to standardize macroeconomic research and facilitates making it reproducible. This is especially interesting considering the value of latent factors discussed above.

3. Macroeconomic Risk

In "Quantile VARs and Macroeconomic Risk Forecasting" I provide an extensive evaluation of the capacity of quantile VAR (QVAR) models to forecast measures of risks defined as density or quantiles in the tails of the distribution. Just as in the previous papers, I leveraged an out-of-sample forecasting experiment to perform this evaluation and generated ample variation in considering 112 target variables over a span of over 40 years at monthly frequency. The benchmark models are three parametric alternatives: a Gaussian VAR (VAR-N), a VAR-GARCH and a VAR-SV.

The results in this paper suggests QVAR models provide adequate approximations to conditional distributions. It's especially true for the labor markets at horizons of between 1 and 12 months, as well as interest and exchange rates at shorter horizons. The improvements over the VAR-N can range between 10 and 30%, it also does significantly better than the two other models in many cases and almost never does significantly worse suggesting it is a robust modeling choice. Adding PCA factors or the quantile factor estimates of Chen, Dolado, and Gonzalo (2021) does not significantly improve risk forecasting accuracy, except in a few cases at longer horizons.

We also studied density and quantile forecasts in the last section of "How is Machine Learning Useful for Macroeconomic Forecasting?" by comparing single equation linear quantile models with quantile random forest models. The quantile random forests provided substantial improvements.

4. Structural VARs

News shocks have often been identified by maximizing their contribution to the forecast error variance decomposition (FEVD) of some measure of productivity at a distant, but finite horizon. Some versions use a range of horizons (Barsky and Sims 2011) or apply it to a frequency band in the frequency domains (Angeletos, Collard, and Dellas 2020).

Researchers usually apply this method to a VAR estimated by OLS in levels in an effort to obviate the need to take a stance on cointegration. We know that Fernald (2014)'s TFP in levels has a unit root because it is obtained by adding growth rate estimates. Hours worked are frequently included and they are very persistent.

In "Max Share Approach With Persistent Series," we study the asymptotic properties of this method when some of the time series are driven by stochastic trends or near stochastic trends. The key result in the paper shows this approach generally fails. The max share weighting matrix is built from reduced-form impulse response estimates which are only consistent at short horizons for persistent series (Phillips 1998), so it has a random limit. Intuitively, if more than one shock has permanent effects, we end up conflating them and the problem gets worse as use more distant horizons. Monte Carlo simulations illustrate the problem in cases that are relevant in practice. In other words, the paper says there is no free lunch: we have to take a stance on the long-run behavior of our VAR system to accurately estimate what happens in the medium to long-run.

5. Future Directions

In the next several months, I plan to extend some of my existing lines of research in particular regarding the modeling of macroeconomic risk, the importance of long-run behavior for macroeconomic modeling and the use of SVARs to understand macroeconomic events and I expect to continue working with my coauthors on these topics.

The results in my job market paper "Quantile VARs and Macroeconomic Risk Forecasting" indicate QVAR models are reasonable models of macroeconomic risks. As Chavleishvili et al. (2021) proposed to use this model to generate forecasts scenarios as part of a risk management approach to macroprudential policy, it would be a natural complement to explore the properties of QVAR models within the context of data simulated by DSGE models, especially those featuring financial frictions. Some exploration I have already carried out on other data generating processes suggest QVARs may have more difficulty approximating conditional skewness and conditional volatility in some cases.

Similarly, I have not considered using information about the long-run behavior of time series in this paper. Many cointegrating vectors can be justified on the basis of standard macroeconomic theory[1] and studies such as Xiao (2009), Kuriyama (2016) and

[1]As noted by King et al. (1991), a standard RBC model implies two cointegrating vectors between output, consumption and investment because the great ratios should be stationary. A stable money demand would imply real money balances, the corresponding short term nominal rate and output should

Cho, Kim, and Shin (2015) proposed methods for handling cointegration in a single equation quantile regression setting. Quantile regression offers the possibility that cointegration may hold only for some portion of the distribution of the dependent variable and allows for conditional volatilities to depend on cointegrating vectors. For instance, Tsong and Lee (2013) tested the Fisher hypothesis[2] on specific quantiles, as well as across intervals of quantiles. They found it holds for the upper quantiles of the distribution of nominal interest rates, but not for the lower quantiles. This suggests some theoretical restrictions may be useful for forecasting risk even if they do not hold exactly at the conditional mean.

It would be particularly interesting to approach this problem vis-à-vis the question of money demand stability. Money demand equations imply real money balances, income and the relevant short term nominal interest rate should be cointegrated. Results in paper such as Friedman and Kuttner (1992) called this prediction into question leading to a widespread belief that money demand is unstable. However, as noted by Belongia (1996), they relied on simple sum monetary aggregates rather than Divisia monetary aggregates which rests on a sound theoretical footing. Recent studies such as Hendrickson (2013), Serletis and Gogas (2014) and Belongia and Ireland (2019) reappraised the role of money using Divisia aggregates showing how some conclusions change when using adequately measured aggregates.

To my knowledge, no work has been done exploring the usefulness of such information for forecasting macroeconomic risk and, in particular, inflation risk. The two most recent periods of higher volatility in the growth rates of Divisia monetary aggregates in the US are the Great Recession where they turned negative in spite of quantitative easing and the pandemic period where they increased above 20% on a year-over-year basis for several months before falling rapidly and turning negative again as the federal funds rate increased. The aggregates moved in ways that suggest it may act as a meaningful leading indicator of inflation in both cases.

Of course, all of this would work on the basis of linear quantile regression. By noting that the integral of the quantile function on the unit interval is the expected value, we can see that the implied model of the conditional mean when using quantile regression is also linear in parameters. My papers "How is Machine Learning Useful for Macroeconomic Forecasting?" and "Macroeconomic Data Transformations Matter"

be cointegrated. If the real interest rate is stationary, then the Fisher equation would imply inflation and the nominal interest rate are also cointegrated.

[2]The nominal interest rates should respond one-for-one to changes in expected inflation in the long-run.

suggest this is an important limitation. Moreover, in the first of those two papers, we considered quantile random forests and have shown using a nonlinear function for conditional quantiles may prove useful. Hence, it stands to reason that there might be important benefits to considering machine learning models in conjunction with theory-implied long-run restrictions to address the problem of forecasting macroeconomic risk. This would also be a natural extension of my work, sitting at the intersection of "Macroeconomic Data Transformations Matter" and my job market paper "Quantile VARs and Macroeconomic Risk Forecasting."

A related project I intend to pursue with Alain Paquet (UQÀM) will explore the use of these aggregates in understanding the recent rise in inflation in the United States. In a textbook New Keynesian model, the supply side of the economy is summarized by a Phillips curve. It is well known that it has a shallow slope (Hazell et al. 2022) and this poses a particular problem for the current rise and subsequent fall in inflation. A shallow slope would require much larger movements in output growth or unemployment. Benigno and Eggertsson (2023) proposed a particular search and matching mechanism justifying a kink in the Phillips curve: when the labor market is tight, the slope is steeper. In that world, supply and demand shocks can produce large responses in inflation while having moderate real effects. Belongia and Ireland (2015) proposed a SVAR model of monetary policy which includes prices, output, commodity prices, the federal funds rate, Divisia money and the user cost specific to the Divisia index being used which offers an interesting way to approach this question. We plan to explore the use of a threshold SVAR or a smooth transition SVAR using observed market tension as thresholding variable to see how well stories along the lines of Benigno and Eggertsson (2023) which points to unusual conditions on the supply side works for recent events.

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