Real-time Forecasts of State and Local Government Budgets with an Application to COVID-19*

Eric Ghysels Fotis Grigoris Nazire Özkan

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Abstract

Using a sample of the 48 contiguous United States, we consider the problem of forecasting state and local governments' revenues and expenditures in real time using models that feature mixed-frequency data. We find that single-equation mixed-data sampling (MIDAS) regressions that predict low-frequency fiscal outcomes using high-frequency economic data historically outperform both traditional fiscal forecasting models and theoretically motivated multi-equation models. We also consider an application of forecasting fiscal outcomes in the face of the economic uncertainty induced by the 2019–2020 coronavirus pandemic. Overall, we show that MIDAS regressions provide a simple tool for predicting fiscal outcomes in real time.

Keywords: Fiscal Policy, Forecasting, Mixed-Frequency Bayesian VAR, MIDAS Regressions.

JEL codes: C22, C32, C50, C53, E62.

*Eric Ghysels is the Edward M. Bernstein Distinguished Professor of Economics at the University of North Carolina at Chapel Hill and Professor of Finance at the Kenan-Flagler Business School, Chapel Hill, NC 27599, and is affiliated with the Centre for Economic Policy Research (CEPR) (e-mail: eghysels@gmail.com); Fotis Grigoris is a Ph.D. candidate at the Kenan-Flagler Business School, Chapel Hill, NC 27599 (e-mail: foti@fotig.com); Nazire Özkan is an Economist at Amazon Web Services, Seattle, WA, 98109 (e-mail: nazireozkan@gmail.com) and completed work on this paper prior to joining Amazon. This paper has benefited from comments from Greg Brown, Christian Lundblad, and seminar participants at the University of North Carolina at Chapel Hill. We thank Kaiji Motegi for providing code related to the simulation exercise. All errors are our own.

1 Introduction

In 2017 the total spending by the state and local governments comprising the 48 contiguous United States exceeded three trillion dollars. Of this aggregate amount approximately $1 trillion was spent on education, $1 trillion was spent on public welfare and health care, and $1.1 trillion was spent on services ranging from public safety to the retirement benefits of public employees. Given the quantity of essential services that subnational governments provide their constituents, this paper proposes procedures to forecast state and local governments' revenues and expenditures on a state-by-state basis in real time. We also show how our proposed procedures can assist policy makers to evaluate the economic impacts of the 2019-2020 coronavirus pandemic on their state budgets for fiscal years 2020 and 2021.

Obtaining accurate forecasts of state and local government budgets is economically important because, unlike the Federal government, most subnational governments are expected to run balanced budgets in which estimated revenues exceed expenditures. This requirement restricts the flexibility of policy makers facing fiscal deficits who need to make difficult choices regarding tax increases and spending cuts to ensure that their government's budget is balanced. The flexibility of policy makers is further impeded by the fact that, unlike the Federal government, subnational governments are unable to run prolonged budget deficits.

To illustrate the real effects of these balanced budget requirements, consider how states responded to the shocks caused by the Great Recession. NASBO (2013) reports that states collectively enacted $39.7 billion worth of revenue (e.g., tax) increases and reduced spending by $64 billion, a large portion of which was cut from higher education and public assistance programs at the same time that unemployment was rising and the demand for these services was increasing. With the aim of limiting the public service disruptions caused by future recessions, a key recommendation by NASBO (2013) is to improve a state's preparedness for fiscal shocks by providing policy makers with more frequent updates of their state's fiscal health. With this recommendation and the real consequences of fiscal shocks in mind, we evaluate the performance of forecast models able to produce fiscal projections in real time.

A major drawback of many existing fiscal forecasting models is their inability to update budget projections within a fiscal year. This is because many of these models rely exclusively on low-frequency, henceforth LF, annual data and can only produce updated forecasts annually. Additionally, since the finances of subnational governments are closely tied to prevailing economic conditions, on which data are readily available at high frequencies, traditional models that only include annual macroeconomic indicators may not promptly detect deteriorating (or improving) economic conditions. In contrast, two of the forecasting models we consider not only take advantage of this high-frequency, henceforth HF, data directly, but can also produce updated forecasts of fiscal outcomes within a fiscal year.

To highlight the usefulness of forecasting fiscal outcomes in real time, consider a policy maker who is standing at the end of March 2020 and is trying to evaluate how the economic effects induced by the 2019-2020 coronavirus pandemic are likely to affect her state's budget in fiscal year 2020. If the policy maker were to rely on a traditional LF fiscal forecasting model, then it would be *impossible* for her to update her expectations of fiscal outcomes for fiscal year 2020. This is because the most recent data that can be included in a LF model is related to fiscal year 2019 (i.e., before the coronavirus pandemic). In contrast, the models we consider allow the policy maker to predict fiscal outcomes for fiscal year 2020 using both LF fiscal data from 2019 *and* HF economic data (e.g., stock returns, GDP growth, etc) from the first quarter of 2020. This allows the policy maker to predict the LF fiscal outcomes for fiscal year 2020 *conditional* on financial market and economic data in 2020.

Specifically, we propose that policy makers use mixed-data sampling (MIDAS) models developed by Ghysels, Santa-Clara and Valkanov (2006, 2005) and Ghysels, Sinko and Valkanov (2007) to meet the challenges of producing real-time forecasts of states' revenues and expenditures. Each of the two mixed-frequency, henceforth MF, models we consider – single-equation augmented distributed lag MIDAS (ADL-MIDAS) regressions and multi-equation MF Bayesian vector autoregressions (MF-BVARs) – relate HF data to LF fiscal outcomes in a parsimonious fashion. We focus our attention on these two particular MF time-series methods because they often produce accurate forecasts in a variety of settings.

Our empirical results show that ADL-MIDAS models typically produce more accurate forecasts of state-level revenues and expenditures than either MF-BVARs or traditional LF models. While forecast performance varies across states, the implication of this results is that policy makers may become more informed about their state's current fiscal situation by using ADL-MIDAS models to forecast fiscal outcomes in real time. Consequently, this can improve the government's preparedness for fiscal crises, such as those induced by the Great Recession, and avoid the need to increase taxes and cut spending when crises occur. Similarly, when fiscal shocks do materialize, such as those initiated by the 2019-2019 coronavirus pandemic, then these models allow policy makers to update their expectations of LF fiscal outcomes using the most recent HF financial and economic data available.

Beyond showing that ADL-MIDAS models have historically produced accurate forecasts of state-level fiscal outcomes, we also consider three additional analyses. First, we consider an application of our proposed methodology, and show how the ADL-MIDAS model can help predict states' revenue growth rates in fiscal years 2020 and 2021. This allows us to gauge how the economic impact of the coronavirus pandemic is likely to affect state budgets. Second, in the spirit of Feenberg, Gentry, Gilroy and Rosen (1989) and Gentry (1989), we conduct Mincer and Zarnowitz (1969) tests to examine whether the forecasts produced by ADL-MIDAS models are rational. Compared to the other models we consider, the ADL-MIDAS regressions produce rational forecasts of revenues and expenditures for the greatest number of states. Finally, motivated by Mattoon and McGranahan (2012), we examine the economic drivers of heterogeneity in forecast performance across states. We show that states that tend to rely on income taxes have revenue streams that are more difficult to forecast.

We also conduct a simulation-based experiment to understand whether the superior forecast performance of ADL-MIDAS models extends to settings beyond fiscal forecasting. The results of our Monte Carlo analysis show that ADL-MIDAS models often outperform both LF- and MF-VARs unless (i) the sample period underlying the analysis is (unrealistically) large, reducing the estimation errors that often plague the more highly parameterized multi-equation models, or (ii) there are a large number of HF observations per LF period (e.g., Foroni, Marcellino and Schumacher (2015)). The main takeaway from this simulation exercise is that the improved forecast performance of the ADL-MIDAS model relative to LF and other MF forecasting models generalize beyond our particular empirical setting.

While parts of our analysis are similar to Onorante, Pedregal, Pérez and Signorini (2010), Pedregal and Pérez (2010), Ghysels and Ozkan (2015), Asimakopoulos, Paredes and Warmedinger (forthcoming), and Lahiri, Yang, Bugdayci and Delaney (2018), who also consider fiscal forecasting with MF models, our study can be distinguished from these works in three key ways. First, while these other studies focus exclusively on a single class of MF model, ours is the only study to examine two distinct classes of MF models that are theoretically and empirically motivated. We do so because there are no a priori reasons to believe that single-equation MIDAS regressions, which restrict the joint dynamics of fiscal and macroeconomic variables, necessarily outperform unrestricted MF-BVARs, or vice versa. Second, ours is the only study to evaluate MF fiscal forecasting models within a comprehensive panel comprising the 48 contiguous United States. In contrast, the samples in other studies cover only a single U.S. state, a single country, or 14 eurozone countries at most. Third, unlike these existing studies that only evaluate a model's performance *within* each cross-sectional unit, we also formally assess each MF model's performance *across* our comprehensive panel of 48 states. While our present focus is on fiscal forecasting, the methods we consider and the results we obtain are also of interest to researchers in other settings, such as forecasting economic or financial outcomes across multiple countries or firms using MF panel data.

The paper proceeds as follows. Section 2 describes our models and methodology while Section 3 describes the data. Section 4 presents our main empirical results, and shows how ADL-MIDAS models can predict state-level fiscal outcomes in real time in the midst of the 2019-2020 coronavirus pandemic. Finally, Section 5 provides concluding remarks.

2 Models

Agencies involved in fiscal forecasting have a duty to provide policy makers with prompt warnings when a government's finances are diverging from the assumptions on which the government's official budgets are based. In practice, these agencies typically implement forecast procedures that are based on judgment, econometric models, or both. For example, a survey by The Pew Center on the States and The Nelson A. Rockefeller Institute of Government (2011) on the revenue projection methods used within each of the 50 United States finds that 27 states employ time-series forecasting models, 27 states use simple trend analyses, and 32 states use linear regressions. Additionally, 25 states require the legislative and executive branches of the state's government to agree on a single forecast revenue forecast, often in consultation with academic and economic advisers.

In contrast to the relatively simple approaches mentioned above, some fiscal agencies also estimate large-scale macroeconomic models to forecast fiscal outcomes. For example, the Congressional Budget Office (CBO) employs a macroeconomic model that features over 900 variables and 600 equations, including both fiscal and macroeconomic components. This model is described by Arnold (2018) and accounts for feedback between fiscal policies and general economic activity to ensure that fiscal forecasts from the model are internally consistent with macroeconomic dynamics. This feature of the model is appealing because economic fluctuations can affect both a government's revenues, such as income taxes, and expenditures, such as social security, as discussed, for example, by Pike and Savage (1998) and Sentance, Hall and O'Sullivan (1998) in relation to the public finances of the United Kingdom.

The models we consider also rely on economic data, albeit in a reduced-form setting. Section 2.1 describes single-equation forecasting models that allow for unidirectional links between current economic conditions and future fiscal outcomes, while Section 2.2 suggests multi-equation models that allow for feedback between fiscal and economic variables in the spirit of the CBO's model. Notably, two of the models we propose use MF intra-annual fiscal year data and stand in contrast to traditional fiscal forecasting models that rely exclusively on annual data. While traditional models preclude policy makers from updating budget forecasts within a fiscal year, our MF models can be updated in real time. This is particularly relevant given the recent reports recommending that policy makers produce more frequent forecasts of fiscal outcomes to reduce budget related uncertainty (see, e.g., The Pew Center on the States and The Nelson A. Rockefeller Institute of Government (2011, 2015)).

Related literature. Our focus on forecasting the finances of subnational governments with MF data is partly motivated by the few studies that show the benefits of using intra-fiscal year data to produce fiscal projections in various settings. For example, Onorante *et al.* (2010) and Pedregal and Pérez (2010) use a combination of monthly and quarterly data to forecast the finances of eurozone countries using MF state-space models and show that using intra-annual data improves the accuracy of budget projections. Asimakopoulos *et al.* (forthcoming) also forecast fiscal outcomes in the eurozone in real-time using MIDAS regressions. However, unlike our study, their study neither evaluates the forecast performance of theoretically motivated multi-equation MF models nor considers the United States.

Similar to our focus on fiscal forecasting within the United States, Ghysels and Ozkan (2015) use single-equation MIDAS regressions to predict U.S. federal government revenues and expenditures. The authors show that their MIDAS models provide more accurate forecasts of the Federal government's fiscal health than traditional LF models. Our study expands upon Ghysels and Ozkan (2015) along two main dimensions. First, we focus on the subnational governments comprising the 48 mainland United States instead of the Federal government. Given the total expenditures by these subnational governments exceeded \$3.26 trillion in 2014, almost matching the Federal government's \$3.96 trillion worth of spending in the same year, state and local governments collectively represent a large proportion of the U.S. economy. Second, we also evaluate economically motivated multi-equation forecast models that Ghysels and Ozkan (2015) do not consider. Finally, Lahiri *et al.* (2018) also use a MF model to forecast the revenues of New York state. The authors find that their factor MIDAS model often produces more accurate revenue forecasts than those produced by the Division of the Budget of New York at horizons of one year or longer. However, unlike our study, their study focus exclusively on one specific state.

Notation. The annual growth rate of real revenues (REV) and expenditures (EXP) per capita in each of the 48 contiguous United States are denote by $Y^{(A)}_{s,t+h}$, where Y represents the budget series of interest (REV or EXP), h denotes the forecast horizon in years, and

s refers to a particular state. To produce forecasts of $Y_{s,t+h}^{(A)}$, denoted by $\hat{Y}_{s,t+h}^{(A)}$, we use a combination of the lagged values of $Y_{s,t+h}^{(A)}$ and other predictors that are referred to as $X_{s,t}^{(HF)}$, but are not necessarily state specific. All forecasts are conditional on information available at time t, unless otherwise noted. Superscripts in parentheses denote the frequency at which each variable is included in a given model. State-level fiscal data is reported at the annual frequency (A), whereas the other data we employ are available at either the quarterly (Q) or monthly (M) frequency. Consequently, we typically refer to annual fiscal data as LF data, and all other data as HF data. We often omit this superscript to economize on notation.

2.1 Single-equation models

There is considerable interest in developing forecast models based on MF data. MIDAS regressions have been show to provide numerous advantages for different forecasting purposes compared to single-frequency models. MIDAS models were first employed by Ghysels *et al.* (2006, 2005) to forecast volatility in the US stock market and have subsequently been applied in a number of different settings, from forecasting GDP growth (Andreou, Ghysels and Kourtellos, 2013; Kuzin, Marcellino and Schumacher, 2011) to the predictions of professional forecasters (Ghysels and Wright, 2009). Motivated by the results of these studies, we begin our analysis by forecasting state-level fiscal outcomes using MIDAS regressions. While studies such as Onorante *et al.* (2010) propose MF fiscal forecasting models based on state-space methods, Bai, Ghysels and Wright (2013) show that MIDAS regressions provide a computationally simple, albeit inefficient, way to approximate these state-space approaches. The augmented distributed lag mixed data sampling (ADL-MIDAS) model we employ is:

$$Y_{s,t+h}^{(A)} = c + \sum_{j=0}^{P_Y^A - 1} \alpha_{j+1} Y_{s,t-j}^{(A)} + \beta \sum_{j=0}^{Q_X^{HF}-1} \sum_{i=0}^{N_{HF}-1} \omega_{i+j \cdot N_{HF}} (\theta) \, X_{s,N_{HF}-i,t-j}^{(HF)} + u_{s,t+h}. \tag{1}$$

Here, N_{HF} denotes the number of times the HF predictor is observed within each year and $\omega(\theta)$ is a weight function that involves a low-dimensional vector of unknown parameters, θ. This weight function, or MIDAS polynomial, determines the extent to which the value of the HF predictor observed in period i of year $t-j$ is associated with $Y^{(A)}_{s,t+h}$. Different weight functions can be used to estimate equation (1), each of which results in a different model specification. In our forecast combination scheme, described shortly, we treat models using the same predictor but a *different* one of the six MIDAS polynomials described by Ghysels (2016b) as *separate* models. The model is estimated using nonlinear least squares (see, e.g., Ghysels, Santa-Clara and Valkanov (2004), Ghysels *et al.* (2006), and Andreou, Ghysels and Kourtellos (2010) for technical details regarding estimation), and the Akaike information criterion (AIC) is used to select the lag lengths P^A_Y and Q^{HF}_X.[1]

Benchmark models. Forecasts obtained from the ADL-MIDAS model are compared to those obtained from three models that rely exclusively on LF data. These models are selected as benchmarks because they are the workhorse models of the single-equation forecasting literature, especially in the context of fiscal forecasting. The benchmarks are the:

1. Random walk (RW) model, $Y^{(A)}_{s,t+h} = Y^{(A)}_{s,t} + u_{s,t+h}$,
2. Autoregressive (AR) model, $Y^{(A)}_{s,t+h} = c + \sum_{j=0}^{P_Y-1} \alpha_{j+1} Y^{(A)}_{s,t-j} + u_{s,t+h}$,
3. AR distributed lag (ADL) model, $Y^{(A)}_{s,t+h} = c + \sum_{j=0}^{P_Y-1} \alpha_{j+1} Y^{(A)}_{s,t-j} + \sum_{j=0}^{P_X-1} \beta_{j+1} X^{(A)}_{s,t-j} + u_{s,t+h}$.

Predictors in the ADL model are aggregated to the annual frequency, and a maximum of four years worth of data are used to estimate all models, including ADL-MIDAS regressions.

Forecast combinations. The forecasts generated by ADL-type models depend on HF predictors, $X_{s,t}$. However, since many of the HF predictors we consider are highly colinear, and ADL-MIDAS models employ nonlinear estimation methods that may become impaired in the presence of colinearity, it is difficult to include multiple HF predictors in a single ADL-type regression. Therefore, to take advantage of the wealth of HF data at our disposal while not subjecting ourselves to estimation issues related to collinearity, we follow the approach advocated by Andreou *et al.* (2013). Specifically, we estimate multiple ADL-type models,

[1] Section OA.1.4 of the Online Appendix shows that our results are similar if the Bayesian information criterion (BIC) is used to select the lag lengths instead.

each containing a single HF predictor, and then combine these multiple predictions into a point forecast using the forecast combination scheme described below.

Forecast combinations have been employed in a variety of contexts, including forecasting output growth (Stock and Watson, 2004; Andreou *et al.*, 2013), inflation (Stock and Watson, 2008), and exchange rates (Wright, 2008). Timmermann (2006) points out that forecast combinations provide a simple way to both improve forecast accuracy by using evidence from numerous models and hedge against model uncertainty. Specifically, combining forecasts across multiple models can produce forecasts that are robust to model misspecification and measurement errors in data sets. Hendry and Clements (2002) also show that forecast combinations can mitigate the detrimental affects of structural breaks on predictive accuracy.

A forecast combination is a (time-varying) weighted average of N individual forecasts: $\hat{f}_{N,t+h} = \sum_{j=1}^{N} \hat{\omega}_{j,t} \hat{Y}_{j,t+h}$. Here, $\hat{\omega}_{j,t}$ is the weight corresponding to model j in period t, which in our case depends on the historical forecast performance of model j. We follow Stock and Watson (2004, 2008) and use the squared discounted mean squared forecast error (dMSFE) to assign weights that are inversely proportional to each model's historical dMSFE as follows:

$$\hat{\omega}_{j,t} = \left[\left(\lambda_{j,t}^{-1} \right)^{\kappa} \right] / \left[\sum\nolimits_{i=1}^{N} \left(\lambda_{i,t}^{-1} \right)^{\kappa} \right], \text{ where } \lambda_{j,t} = \sum\nolimits_{m=T_1}^{t-h} \delta^{t-h-m} \left(Y_{m+h}^{(A)} - \hat{Y}_{j,m+h|m}^{(A)} \right)^2. \quad (2)$$

Here, T_1 denotes the year the first estimation period ends and δ is a discount factor attaching more weight to the recent predictive ability of each model. We set $\delta = 0.90$ and $\kappa = 2$.[2]

Nowcasting. ADL-MIDAS regressions also provide policy makers with a simple tool to construct forecasts in real time (see, e.g., Ghysels and Ozkan (2015)) as recommended by NASBO (2013), among others. Consider a state official who is standing 2 quarters into year t and is tasked with predicting revenue growth between years t and $t+1$. The official's information set includes both the information released by the end of year t and the information released during the first two quarters of year $t+1$. However, the ADL-MIDAS

[2]Section OA.1.2 of the Online Appendix considers alternative choices of (δ, κ) and shows that while these alternatives deliver small forecast gains relative to our benchmark values, a flat weighting scheme in which $\hat{\omega}_j = 1/N$ is detrimental to forecast performance.

model considered above only accounts for the first component of the official's information set. By extending the MIDAS model to incorporate the second component of the official's information set we can examine whether this additional data yields forecast gains compared to standard models that only utilize data that is publically available at the end of year t. We refer to forecasts constructed using an extra $J_X^{HF} = 1, 2, 3$ quarters worth of intra year $t+1$ data as nowcasts (see, e.g., Nunes (2005)). An ADL-MIDAS regression that includes an extra J_X^{HF} quarters worth of year $t+1$ HF data can then be written as:

$$Y_{s,t+h}^{(A)} = c + \sum_{j=0}^{P_Y^A - 1} \alpha_{j+1} Y_{s,t-j}^{(A)} + \gamma \tilde{X}(J_X^{HF}, \theta^{HF}) + u_{s,t+h}, \quad (3)$$

where $\tilde{X}(J_X^{HF}, \theta^{HF}) = \sum_{i=0}^{J_X^{HF}-1} \omega_i \left(\theta^{HF}\right) X_{s,J_X^{HF}-i,t+1}^{(HF)} + \sum_{j=0}^{Q_X^{HF}-1} \sum_{i=0}^{N_{HF}-1} \omega_{i+j \cdot N_{HF}} \left(\theta^{HF}\right) X_{s,N_{HF}-i,t-j}^{(HF)}$.

2.2 Multi-equation models

Following Sims (1980) the vector autoregression (VAR) has become a workhorse model for forecasting and characterizing the dynamic relations among multiple macroeconomic time series. However, VARs are potentially rich in parameters and these parameter rich models often produce inaccurate out-of-sample forecasts (Giannone, Lenza and Primiceri, 2015). The literature has proposed two main solutions to the issue of improving the predictive accuracy of large-dimensional VARs: reducing the set of predictors to a few common but latent factors (see, e.g., Stock and Watson (2002)) and shrinking unrestricted parameter estimates towards a benchmark model via Bayesian techniques (see, e.g., Bańbura, Giannone and Reichlin (2010) and Koop (2013)). We employ the latter approach and use Bayesian methods to forecast state-level revenues and expenditures simultaneously since latent factor models often impede the economic interpretation of results.

We investigate the forecast performance of Bayesian VARs (BVARs) that exploit MF data by comparing the accuracy of the forecasts obtained from these models to the accuracy of the forecasts obtained from two benchmark LF-VARs. These benchmark VARs follow the traditional approach to forecasting in the presence of MF data by temporally aggregating

HF predictors and estimating the models at the lowest frequency that data on all variables are jointly available. One of these LF-VARs is estimated using frequentist methods while the other is also estimated using Bayesian techniques.

Although there are a number of ways to specify a MF-VAR, we follow the approach introduced by Foroni, Ghysels and Marcellino (2013), Ghysels (2016b), and McCracken, Owyang and Sekhposyan (2018) that treats MF data as arising from a skip-sampled process. The primary advantage of this approach is that models are specified exclusively in terms of observable data. In contrast, other approaches rely on latent processes and state-space representations to account for the mismatch in the frequencies that variables are observed. For instance, the MF-VAR of Eraker, Chiu, Foerster, Kim and Seoane (2015) treats HF observations of LF variables as missing and draws estimates of these missing values via a Gibbs sampler. Additionally, Schorfheide and Song (2015) examine a MF-VAR that is represented as a state-space model and apply data-driven Bayesian methods to forecast the dynamics of state variables. By avoiding these latent processes, and the consequent need to filter unobservable states, the approach of Ghysels (2016a) can produce impulse response functions and variance decompositions that are readily interpretable in terms of observable variables rather than unobservable shocks.

While McCracken *et al.* (2018) also evaluate the forecast performance of MF-BVARs empirically, our study differs from theirs in at least three ways. First, our focus is on fiscal forecasting whereas McCracken *et al.* (2018) focus on forecasting macroeconomic series, such as GDP. Second, unlike McCracken *et al.* (2018), we compare the forecast performance of MF-VARs, MIDAS models, and LF forecasting models both empirically and via Monte Carlo simulations. Third, unlike us, McCracken *et al.* (2018) consider nowcasting with MF-BVARs, while we refrain from nowcasting fiscal outcomes using our state-level MF-BVARs for computational simplicity. We leave this task of understanding the benefits of nowcasting fiscal outcomes using MF-VARs to future research.

In a related application Koop, McIntyre, Mitchell and Poon (2018) also examine a MF-VAR and apply Bayesian techniques to produce quarterly estimates of Gross Value Added

(GVA) for regions of the United Kingdom. A key difference between the methodologies underlying our studies is that while we focus on forecasting LF fiscal outcomes using a host of observable HF data, Koop *et al.* (2018) focus on inferring the dynamics of latent HF variables (quarterly regional GVA) using a host of annual LF observables.

Using notation consistent with Ghysels (2016a), state-specific MF Bayesian VARs (MF-BVARs) are constructed as follows. For each state, we let $\boldsymbol{x_L}\left(\tau_L\right)$ denote the vector of LF fiscal data that contains the annual growth rates of government revenues and expenditures per capita observed in year τ_L, and we let $\boldsymbol{x_H}\left(\tau_L, j\right)$ denote the vector of HF data that contains economic and financial market conditions observed in quarter j of year τ_L. In our baseline analysis we include five HF predictors in these $\boldsymbol{x_H}\left(\tau_L, j\right)$ vectors. We stack the five vectors of data related to year τ_L into $\boldsymbol{x}\left(\tau_L\right) = \left[\boldsymbol{x_H}\left(\tau_L, 1\right)', \ldots, \boldsymbol{x_H}\left(\tau_L, 4\right)', \boldsymbol{x_L}\left(\tau_L\right)'\right]'$, a $m \times 1$ vector that holds of $m = 22 \equiv 4 \times K_H + K_L$ variables. Here K_H (K_L) is the number of HF (LF) variables in the system. A MF-BVAR with one lag can then be written as $\boldsymbol{x}\left(\tau_L\right) = \boldsymbol{A_0} + \boldsymbol{A_1}\boldsymbol{x}\left(\tau_L - 1\right) + \boldsymbol{\varepsilon}\left(\tau_L\right)$. This system includes an intercept, represented by the $m \times 1$ column vector $\boldsymbol{A_0}$, and a matrix of autoregressive parameters, represented by the $m \times m$ matrix $\boldsymbol{A_1}$. Focusing on $\boldsymbol{A_1}$, the MF-BVAR can also be expressed as:

$$\boldsymbol{x}\left(\tau_L\right) = \boldsymbol{A_0} + \begin{bmatrix} \boldsymbol{A^{1,1}} & \ldots & \boldsymbol{A^{1,4}} & \boldsymbol{A^{1,5}} \\ \vdots & \ddots & \vdots & \vdots \\ \boldsymbol{A^{4,1}} & \ldots & \boldsymbol{A^{4,4}} & \boldsymbol{A^{4,5}} \\ \boldsymbol{A^{5,1}} & \ldots & \boldsymbol{A^{5,4}} & \boldsymbol{A^{5,5}} \end{bmatrix} \boldsymbol{x}\left(\tau_L - 1\right) + \boldsymbol{\varepsilon}\left(\tau_L\right), \tag{4}$$

where $\dim\left(\boldsymbol{A^{5,5}}\right) = K_L^2$, $\dim\left(\boldsymbol{A^{i,5}}\right) = K_H \times K_L$ for $i = 1, \ldots, 4$, $\dim\left(\boldsymbol{A^{5,i}}\right) = K_L \times K_H$ for $i = 1, \ldots, 4$, and $\dim\left(\boldsymbol{A^{a,b}}\right) = K_H^2$ for $a, b = 1, \ldots, 5$. We assume that this system is covariance stationary and that the error term $\boldsymbol{\varepsilon}\left(\tau_L\right)$ has a variance-covariance matrix represented by the unknown but positive definite matrix $\boldsymbol{\Sigma} = \mathbb{E}\left[\boldsymbol{\varepsilon}\left(\tau_L\right)\boldsymbol{\varepsilon}\left(\tau_L\right)'\right]$. This model contains a total of 506 free parameters in $\boldsymbol{A_0}$ and $\boldsymbol{A_1}$, motivating our need to rely on Bayesian estimation methods that shrink (noisy) parameter estimates towards the parameter values implied by the prior described below. We only consider VAR models featuring one lag due to the large number of free parameters relative to the short length of the sample period.

The priors. We utilize priors introduced by Ghysels (2016a) that follow those developed by Doan, Litterman and Sims (1984), Litterman (1986), Kadiyala and Karlsson (1997), and Sims and Zha (1998), among others. As is typical in the literature on BVARs, Ghysels (2016a) assumes that each variable in the MF-BVAR evolves according to an AR(1) process. However, to account for the MF data, these priors further assume that the expectation and variance associated with each HF predictor changes within each LF period.

Below, lags of the HF predictors within the LF periods are represented by (a, b). $\mathbb{E}[\cdot]$ and $\mathbb{V}[\cdot]$ denote matrices of expectations and variances, respectively, $\mathbf{0}$ and $\mathbf{1}$ are matrices of zeros and ones, respectively, and $\mathbf{diag}(x)$ is matrix containing x along the main diagonal. The dimensions of each of these matrices are indicated by the subscripts. The scalars $\mathbb{S}_{HL} = \left[\sigma^2_{i,H}/\sigma^2_{j,L}; i = 1, \ldots, K_H, j = 1, \ldots, K_L\right]$ and $\mathbb{S}_{LH} = \left[\sigma^2_{j,L}/\sigma^2_{i,H}; i = 1, \ldots, K_H, j = 1, \ldots, K_L\right]$ account for differences in scaling between HF and LF data. Additionally, ϑ_{HL} $\left(\vartheta_{LH}\right)$ governs the extent to which LF (HF) data affects HF (LF) data and lies in the interval $(0, 1)$. The persistence parameter associated with the evolution of the HF (LF) variables is ρ_H (ρ_L). Finally, the hyperparameter λ controls the overall tightness of the prior distributions around the univariate AR(1) model. Smaller values of λ cause posterior point estimates to be more heavily weighted towards the prior. For $a = 1, \ldots, 4$, the priors for $\boldsymbol{A_1}$ are:

$$
\begin{aligned}
&\mathbb{E}\left[\boldsymbol{A^{a,b}}\right] = \mathbf{0}_{K_H^2} && \mathbb{V}\left[\boldsymbol{A^{a,b}}\right] = \frac{\lambda^2}{(4-b+a)^2}\mathbf{1}_{K_H^2} \quad \text{for } b = 1,2,3 \\
&\mathbb{E}\left[\boldsymbol{A^{a,4}}\right] = \mathbf{diag}\left(\rho_H^a\right)_{K_H^2} && \mathbb{V}\left[\boldsymbol{A^{a,4}}\right] = \frac{\lambda^2}{a^2}\mathbf{1}_{K_H^2} \\
&\mathbb{E}\left[\boldsymbol{A^{a,5}}\right] = \mathbf{0}_{K_H \times K_L} && \mathbb{V}\left[\boldsymbol{A^{a,5}}\right] = \vartheta_{HL}\frac{\lambda^2}{a^2}\mathbb{S}_{HL}\mathbf{1}_{K_H \times K_L} \\
&\mathbb{E}\left[\boldsymbol{A^{5,b}}\right] = \mathbf{0}_{K_L \times K_H} && \mathbb{V}\left[\boldsymbol{A^{5,b}}\right] = \vartheta_{LH}\frac{\lambda^2}{(4-b+1)^2}\mathbb{S}_{LH}\mathbf{1}_{K_L \times K_H} \\
&\mathbb{E}\left[\boldsymbol{A^{5,5}}\right] = \mathbf{diag}\left(\rho_L^4\right)_{K_L^2} && \mathbb{V}\left[\boldsymbol{A^{5,5}}\right] = \frac{\lambda^2}{4^2}\mathbf{1}_{K_L^2}
\end{aligned}
$$

The priors for $\boldsymbol{\Sigma}$ follow the independent Normal-Wishart prior summarized by Koop and Korobilis (2010). Accordingly, a Markov chain Monte Carlo (MCMC) procedure based on the Gibbs sampler is required to draw from the posterior distribution of the MF-BVAR and forecast revenues and expenditures in each state. A benefit of this prior is that, unlike other priors for which the posterior distribution is available analytically, this prior does not restrict the prior covariance of the coefficients in any two equations of the MF-BVAR to differ by a multiplicative factor. Finally, the prior for $\boldsymbol{A_0}$ follows the standard Minnesota prior (e.g., Kadiyala and Karlsson (1997)), the tightness of which is governed by the hyperparameter κ.

Estimation. We estimate the Bayesian models using Monte Carlo chains of length 25,500. We discard the first 500 draws as a burn-in, and use every 5^{th} of the remaining draws to sample from the posterior distributions. For each draw of $(\boldsymbol{A_0}, \boldsymbol{A_1}, \boldsymbol{\Sigma})$ we sample from the predictive density 100 times. In our baseline analysis we set ρ_L (ρ_H) to 0.1 (0.3), and ϑ_{HL} (ϑ_{LH}) to 0.01 (0.70). Lastly, we set λ and κ equal to one.

The MF-BVAR explicitly allows MF data to impact revenue and expenditure forecasts through the last two rows of $\boldsymbol{A_1}$. The elements contained in these rows are unrestricted, meaning that each HF predictor can have a different impact on each of the LF fiscal series in $\boldsymbol{x_L}(\tau_L)$. This specification is motivated by the single-equation ADL-MIDAS regressions that employ step functions as the MIDAS polynomial, as in Ghysels *et al.* (2007) or in the unrestricted MIDAS (U-MIDAS) of Foroni *et al.* (2015). Foroni *et al.* (2015) show that U-MIDAS works particularly well when there are only a few HF observations per LF period, as is the case in our quarterly/annual frequency setting.

Benchmark models. The forecasts obtained from MF-BVARs are compared to those obtained from three benchmark forecasting models that rely exclusively on LF annual data: a frequentist VAR, a BVAR, and a RW. Both the VAR and BVAR include the same variables as the MF-BVAR, except that each of these predictors is temporally aggregated to the annual frequency and expressed as an annual change. The estimation procedure described for the MF-BVAR, including assumptions regarding the prior, are maintained for these models. Also note that with the aforementioned prior in mind, the RW model can be written as a special case of a BVAR in which the hyperparameter $\lambda = 0$ and $\rho_L = \rho_H = 1$.

2.3 Forecast evaluation

We evaluate forecast performance using three metrics: root mean squared forecast errors (RMSFEs), the panel version of the Diebold and Mariano (1995) test proposed by Pesaran, Schuermann and Smith (2009), and Mincer and Zarnowitz (1969) tests.

Root mean squared forecast errors. We first evaluate the predictive ability of each model by computing the model's RMSFE from pseudo out-of-sample forecasts of state-specific revenues or expenditures at horizons of one or two years. To aid in the interpretation of these RMSFEs, we scale each model's RSMFE by the RMSFE generated by either a RW or another benchmark model, and report relative RMSFEs. Relative RMSFEs that are less (greater) than one indicate that the model of interest produces forecasts that are more (less) accurate than those produced by the benchmark. An easy, albeit simplistic, way to compare the predictive accuracy of models is to then examine the distribution of each model's relative RMSFEs across states. Models producing lower median values of relative RMSFEs across states tend to have higher levels of predictive accuracy.

Diebold-Mariano tests. While relative RMSFEs are easy to interpret, they do not indicate whether the forecasts produced by a given model are significantly more accurate than those produced by a benchmark. To formally assess whether the accuracy of model A exceeds that of benchmark model B across all states over a pseudo out-of-sample period, we use the panel version of the Diebold and Mariano (1995) test from Pesaran *et al.* (2009).

To implement this test we first define the loss differential associated with forecasting fiscal variable y in state s at horizon h using model A relative to model B as: $z_{y,s,t}(h) = \left[e^A_{y,s,t}(h)\right]^2 - \left[e^B_{y,s,t}(h)\right]^2$. Here, $e^X_{y,s,t}(h)$ represents the h-year ahead forecast error from forecasting y in state s at time t using model X. Fixing y and h, the panel version of the Diebold-Mariano test statistic, referred to as DM, is obtained by considering $z_{s,t} = \alpha_s + \varepsilon_{s,t}$ and testing whether $\alpha_s < 0$ for any state. Under the null hypothesis that $\alpha_s = 0$ for all states, and assuming that $\varepsilon_{s,t} \overset{iid}{\sim} (0, \sigma^s_s)$, the test statistic is $DM = \bar{z}/\left[\sqrt{V(\bar{z})}\right] \sim \mathcal{N}(0,1)$. The definition $\bar{z} = \frac{1}{S}\sum_{s=1}^{S} \bar{z}_s$, where $\bar{z}_s = \frac{1}{T}\sum_{t=1}^{T} z_{s,t}$, is from Pesaran *et al.* (2009). We compute $V(\bar{z})$ per Newey and West (1987) to account for the serial correlation in $\bar{z}$.

To interpret this test statistic recall the definition of $z_{y,s,t}(h)$. Negative values of DM indicate that the squared losses of model B exceed those of model A and suggest that model A outperforms model B. Since this test is one-sided, and DM follows an asymptotically standard normal distribution, the appropriate 1% (5%) critical value is -2.326 (-1.645).

Mincer and Zarnowitz (1969) tests. Both relative RMSFEs and panel DM tests examine the predictive accuracy of one model *relative* to another model. However, neither measure indicates whether a particular model produces accurate forecasts in an absolute sense. To determine whether the forecasts produced by a given model are unbiased and optimal we estimate the following Mincer and Zarnowitz (1969) (MZ, hereafter) regressions:

$$Y_{s,t+h} = \beta_0 + \beta_1 \hat{Y}_{s,t+h|t} + \varepsilon_{s,t,t-h}, \qquad \text{for } h = 1, 2, \text{ and } s = 1, \ldots, 48. \tag{5}$$

Here, $Y_{s,t}$ ($\hat{Y}_{s,t+h|t}$) denotes the actual (model-implied) value of the revenues or expenditures of state s at time $t+h$. The null hypothesis of the MZ test is that $\beta_0 = 0$ and $\beta_1 = 1$, jointly. This is because if forecasts are unbiased (optimal), then the constant (slope) parameter should be statistically indistinguishable from zero (one). Consequently, a reliable model should not reject the null hypothesis of the MZ test. Here, standard errors are computed per Newey and West (1987) to account for serial correlation in the multi-period forecasts errors.

3 Data, summary statistics, and estimation details

Data. We obtain data on subnational government finances from the U.S. Census Bureau's annual survey of State & Local Government Finance. This survey covers the 50 state governments comprising the United States and more than 90,000 local governments, including counties, townships, and school districts. The entire universe of local governments is surveyed in years ending in either "2" or "7," while a representative subsample is surveyed in other years. Although the survey provides data as early as 1942, we start our sample period in 1958 since many state-year observations prior to 1985 are missing. We end our sample in 2014 since the results of this survey are released with a considerable lag. Both Alaska and

Hawaii are excluded from the sample due to missing fiscal data during the sample period.

This survey contains comprehensive details on the components of the revenues, such as property taxes, and the expenditures, such as spending on education, of each state and its constituent local governments. However, we focus on the sum of either total revenues or total expenditures for each state government and its constituent local governments because we are primarily interested in the overall fiscal health of the state. This choice is motivated by the fact that there are considerable transfers from state to local governments. Data from this survey shows that, on average, local governments received 36% of their funding from these transfers from the state between 2004 and 2014. We standardize total revenues and expenditures by the population of each state as recorded by the U.S. Census Bureau and deflate each variable by the consumer price index (CPI) constructed by the U.S. Bureau of Labor Statistics to account for changes in the price level over time.

The LF data on aggregate annual state and local government revenues and expenditures is combined with a range of HF economic and financial market indicators that are used to predict future fiscal outcomes. Each of the variables used in this study are listed in Table 1, along with the highest frequency at which each predictor is recorded and its source. The table also displays the mnemonic by which each predictor is referred to in the subsequent tables and figures. All predictors are seasonally adjusted, reported in real quantities, transformed to induce stationarity, if necessary, and expressed as percentage points.

[Insert Table 1 about here.]

The set of HF predictors includes one state-specific economic variable, the growth rate of personal income per capita, and five national economic variables: the growth rates of real GDP, CPI, and industrial production, the effective federal funds rate, and the ratio of the Federal government's budget deficit to total Federal government expenditures. We also include six financial variables: the spot oil price, the three-month and 10-year Treasury yields, the default spread, the level of the Bond Buyer GO 20 municipal bond index, and returns on the S&P 500. We use real-time data to mitigate the impact of data revisions on forecasts where possible. That is, at each point in time, the data used to produce forecasts are restricted to those that would have been available to a forecaster at that point in time.

Note that the variables underlying our study are only a subset of the HF financial and economic variables that are available. We choose to focus on this parsimonious subset of variables since the primary purpose of our study is to highlight the benefits of forecasting LF fiscal outcomes in real time using MF data. This means that any forecast gains we document (i) demonstrate the *quantitative* benefits of using MF data to forecast LF fiscal outcomes, and (ii) can be considered a *quantitative* lower bound on the forecast gains that are achievable with a richer set of HF predictors.

Summary statistics. Summary statistics for the transformed variable are presented in Table 2. The results show the average growth rate of real revenues per capita exceeds the average growth rate of real expenditures per capita (3.24% versus 2.69% per annum), while the volatility of expenditure growth rates is much lower than that of revenue growth rates (4.391% versus 8.763%). This latter point is important to note because expenditures are somewhat under the control of state officials who aim to keep expenses stable and below estimated revenues to avoid violating their government's balanced budget condition. Revenues, on the other hand, are typically generated through various forms of taxation that are closely tied to (volatile) economic conditions (e.g., Mattoon and McGranahan (2012)).

Real personal income grows by an average of 1.67% per annum across the 48 states in our sample, and real GDP increases by approximately 2% per annum over the sample period. The mean ratio of the Federal government's budget surplus to its total expenditures is negative, indicating that the Federal government typically runs a budget deficit. Industrial production and oil prices increase by approximately 2.6% and 5.8% per annum, respectively, whereas the average default spread is close to 1% per annum. Average returns on the S&P 500 are close to 0.65% per month and the first-order autocorrelation coefficient of these returns is 0.045. Finally, the average monthly changes in the effective federal funds rate, the three-month and 10-year Treasury yields, the municipal bond index, and the annual growth rate of CPI are all close to zero. Overall, these summary statistics show that each of the variables included in our analysis behaves in an economically plausible fashion.

[Insert Table 2 about here.]

Estimation details. In our single-equation analyses all variables are measured at the frequencies reported in Table 1, unless otherwise noted. The first estimation period for these analyses ranges from 1958 to 1998 and the pseudo out-of-sample period spans 1999 to 2014. We use a rolling window procedure to generate forecasts, and all 12 HF variables are included in these models. Forecasts in the multi-equation setting are produced using the following five HF predictors: the Federal government's budget surplus, the effective funds rate, the consumer price and industrial production indexes, and real GDP. Each variables is aggregated to the quarterly frequency, if necessary, and recorded as four-quarter change expressed in percentage points. The first estimation period for the multi-equation analyses ranges from 1958 to 2004, and the pseudo out-of-sample period spans 2005 to 2014. We use a recursive window procedure to generate forecasts in this setting. Finally, the timing associated with each state's forecasts coincides with the state's fiscal year, and all two-year ahead projections are direct rather than recursive forecasts.

4 Empirical results

4.1 Single-equation models

Forecast results. Panel A of Table 3 presents the median relative RMSFEs from one- and two-year ahead forecasts of revenues and expenditures from the ADL-MIDAS, ADL, and AR models across the 48 states in the sample. These results are obtained by following the estimation procedure outlined in Section 3, and the 5^{th} and 95^{th} percentiles of the distribution of these relative RMSFEs across states are reported in parentheses. Here, median relative RMSFEs that are smaller than one indicate that a model produces more accurate forecasts than those generated by a random walk.

[Insert Table 3 about here.]

The results show that, on the basis of the median relative RMSFE, the ADL-MIDAS model delivers the most accurate forecasts of one- and two-year ahead expenditure growth rates and one-year ahead revenue growth rates.[3] Following the discussion related to the summary statistics of the state-specific revenues and expenditures, Panel A also shows that the models perform better when forecasting revenues rather than expenditures. This is expected since most states are required to run balanced budgets, meaning that government officials endeavor to keep expenditures below estimated revenues. This policy consideration has the effect of making expenditures somewhat stable over fiscal years, and results in the random walk becoming a more difficult benchmark to outperform in these cases.

Panel B of Table 3 reports the results of panel DM tests that formally test whether ADL-MIDAS models produce significantly more accurate forecasts of fiscal outcomes than LF ADL or AR models. Each test is set up so that negative and significant DM tests indicate that the ADL-MIDAS model outperforms the alternative model. The results show that all eight DM tests return a negative test statistic, of which seven are significant at better than the 5% level. When forecasting expenditures, the predictive accuracy of the ADL-MIDAS model always significantly exceeds that of the alternative models. However, despite a negative DM test statistics, the ADL-MIDAS model does not produce two-year ahead revenue forecasts that are significantly more accurate than those generated by the ADL model.

Overall, the empirical results in Table 3 highlight the benefits of projecting LF budget data on HF variables related to both economic conditions and financial market data. Forecasting revenue and expenditure growth on a state-by-state basis using single-equation ADL-MIDAS regressions typically yields more accurate forecasts than those produced by traditional LF time-series models. In general, forecasts from ADL-MIDAS models are not only qualitatively more accurate in terms of the distribution of relative RMSFEs across states, but are also typically more accurate in a statistical sense, as determined by panel DM tests.

Nowcast results. We also consider the forecast gains that can be achieved by updating

[3] While the confidence intervals show that there is heterogeneity in forecast performance across the 48 states, Section OA.1 of the Online Appendix reports the performance of each model by state and shows that the ADL-MIDAS model is the only model that never produces a relative RMSFE greater than one across the 192 forecasts we consider (48 states $\times$ 2 budget series $\times$ 2 forecast horizons).

standard ADL-MIDAS regressions with an additional $j = 1, 2, 3$ quarters worth of year $t+1$ data on each HF predictor. State-specific nowcasts of one- and two-year ahead revenues and expenditures are obtained by using the same variables, rolling window forecasting method, and forecast combination scheme as the previous analysis. In Panel C of Table 3 we compute the forecast gains associated with incorporating this additional data by scaling the RMSFEs produced by the nowcasts by the RMSFEs produced by the standard ADL-MIDAS model that does not include any intra year $t+1$ data.

The results show that nowcasts including an extra $j = 1, 2, 3$ quarters worth of year $t+1$ data further improve the median two-year ahead revenue predictions by 9.2%, 2.4%, and 6.1%, respectively, as compared to standard ADL-MIDAS models. Nowcasts also improve the median one-year ahead revenue forecast by up to 6.8% as compared to the RMSFEs produced by regular ADL-MIDAS regressions. In contrast to the results for revenues, the nowcasts of expenditure growth rates only improve upon the median RMSFE from a standard ADL-MIDAS model by 6.4% at most.[4]

Overall, the results contained in Table 3 show that ADL-MIDAS models typically produce the most accurate forecasts of state-level revenues and expenditures compared to common LF single-equation models, and that the performance of these MIDAS models can be further improved by constructing forecasts in real time (i.e. by nowcasting). Although we do not formally test whether the predictive accuracy of the nowcasts exceeds that of forecasts, the main conclusion emanating from Panel C is that endowing forecasters with additional, publicly available, intra-year data often improves forecast performance. This directly addresses the recommendation of NASBO (2013), among others, who argue that the public service disruptions caused by fiscal shocks may be alleviated by keeping policy makers more informed about their state's fiscal health.

[4]Table OA.1.3 in the Online Appendix shows that when the RMSFEs of the nowcasts are scaled by those from LF ADL or AR models, the median relative RMSFE from the nowcasts drops by up to 20.7%. Additionally, this table also shows that although the ADL model produces the smallest median RMSFE when forecasting two-year ahead revenue growth, including an extra one quarter's worth of data into an ADL-MIDAS regression can drop its median RMSFE relative to the LF ADL model by 10.3%.

4.2 Multi-equation models

In this section we compare the forecasts of revenue and expenditure growth rates from MF-BVARs to those from BVARs and VARs using the estimation procedure described in Section 3. Panel A of Table 4 presents the median relative RMSFEs of one- and two-year ahead forecasts across states. Here, RMSFEs are reported relative to those from a RW. Panel B reports the results of panel DM tests formally assessing whether MF-BVARs produces more accurate forecasts than the alternative LF multi-equation models. The panel DM tests are constructed so that negative and significant test statistics indicate that the MF-BVAR outperforms the alternative model.

The results in Panel A show that BVARs produce the most accurate forecasts of one- and two-year ahead revenue growth. For instance, BVARs produce a median relative RMSFE of 0.551 when forecasting two-year ahead revenues, whereas MF-BVARs (VARs) produce a median relative RMSFE of 0.741 (0.753). The DM tests in Panel B show that revenue forecasts from MF-BVARs are significantly *less accurate* than those from LF BVARs at the two-year horizon, and that there is only one case in which the DM test statistic is negative. Taken together with the larger relative RMSFEs reported in Panel A, these facts suggest that MF-BVAR models are inappropriate for forecasting state-level revenue growth rates.

[Insert Table 4 about here.]

In regards to the forecasts of expenditures, there is little evidence that MF-BVARs are able to outperform the RW benchmark. Specifically, the median relative RMSFEs reported for the MF-BVARs forecasts of expenditure growth rates are approximately two. Furthermore, the panel DM tests reported in Panel B indicate that the MF-BVAR performs significantly worse than either BVARs or VARs when forecasting future expenditure growth rates. In contrast to the results related to the MF-BVAR, LF BVARs produce median relative RMSFEs for expenditures that are less than one.[5]

[5]Additional results related to each model's performance on a state-level basis are reported in Section OA.2 of the Online Appendix.

Overall, the results in Table 4 suggest that all the multi-equation models that jointly forecast future revenues and expenditures can produce forecasts of state-level revenues that are more accurate than those generated by a RW, but only the LF multi-equation models produce expenditure forecasts that are more accurate than those predicted by a RW. The results also indicate that directly incorporating HF data into MF-BVARs does not necessarily result in more accurate forecasts than those obtained from LF BVARs and VARs. This latter takeaway stands in contrast to the results obtained from the single-equation models, whereby utilizing HF data in the context of ADL-MIDAS models generally leads to sizable forecast gains relative to the LF benchmarks. However, it is difficult to draw any conclusions regarding the merits of single- and multi-equation models for fiscal forecasting because the results of theses analyses are not directly comparable. For example, the single-equation models generate rolling forecasts whereas the multi-equation models produce recursive forecasts. In the next section we turn our attention to directly comparing these two sets of models.

4.3 Comparing single- and multi-equation models

In this section we directly compare the forecast performance of the ADL-MIDAS model to that of the MF-BVAR and BVAR models. This analysis is motived by Kuzin *et al.* (2011) who examine forecasts and nowcasts of eurozone GDP growth rates produced by MIDAS regressions and MF VARs estimated via maximum likelihood techniques. The authors argue that there are no a priori reasons to believe that a single model always delivers the highest forecast gains, and find that each model's predictive ability varies depending in part on the forecast horizon. While Sections 4.3.1 and 4.3.2 compare these models in our context of fiscal forecasting, Section 4.3.3 implements a simulation exercise designed to evaluate whether the results of our model comparison can also be generalized to other empirical settings.

4.3.1 Relative out-of-sample forecast performance

To implement our empirical comparison of the ADL-MIDAS, BVAR, and MF-BVAR models, we estimate each model following the recursive forecast procedure described for the multi-equation models in Section 3. Thus, there are three key differences between the ADL-MIDAS models we estimate in this section and our results pertaining to the single-equation models reported in Section 4.1: we construct forecasts using five rather than 12 HF predictors, we estimate models using a recursive rather than a rolling procedure, and the pseudo out-of-sample period ranges from 2005 to 2014 rather than ranging from 1999 to 2014. Here, the forecasts from the multi-equation models are identical to those reported in section 4.2.

The results are presented in Table 5. Panel A shows that the median forecasts from the ADL-MIDAS models outperform those from either MF-BVARs or BVARs in all cases except for the forecasts of two-year ahead revenues. In this case the median forecast produced by the BVAR achieves the highest forecast gain relative to a RW. Differences between the relative RMSFEs of the single- and multi-equation models are especially pronounced for expenditure forecasts. While the MF-BVARs almost never outperforms a RW when forecasting expenditures, and the median BVAR forecast improves upon the median RW forecast by up to 21.3%, while the median ADL-MIDAS forecast outperforms the RW by 36.1% to 43.4%.[6]

[Insert Table 5 about here.]

Panel B of Table 5 reports the results of panel DM tests comparing the predictive accuracy of the ADL-MIDAS model to the predictive accuracies of MF-BVARs and BVARs. These DM tests are set up so that negative values of the test statistic indicate that the ADL-MIDAS model outperforms the alternative model. The results show that each of the eight DM test statistics are negative, suggesting qualitatively that the forecast errors implied by ADL-MIDAS models tend to be smaller than those implied by the alternative models. Of these eight negative DM test statistics, five are significant at better than the 1% level. Thus, of the three models under consideration, the single-equation ADL-MIDAS model typically produces the most accurate forecasts of state-level expenditure growth, and also tends to produce significantly better forecasts of two-year revenue growth rates than MF-BVARs.

While ADL-MIDAS models do not statistically outperform BVARs when forecasting state-level revenues, considering the negative values of the relevant DM tests statistics in

[6]Section OA.3.1 of the Online Appendix reports the relative RMSFEs of each model at the state level.

Panel B together with the low relative RMSFEs reported in Panel A suggests that these ADL-MIDAS regressions are still a competitive model for forecasting state-level revenue growth rates. Furthermore, given the empirical evidence in Table 3 that shows that ADL-MIDAS nowcasts are typically more accurate than ADL-MIDAS forecasts, it is likely that comparing the forecasts from BVARs to nowcasts from ADL-MIDAS may further improve the relative performance of the ADL-MIDAS regressions.

The main takeaway from Table 5 is that single-equation MF forecast models provide an accurate way to predict state-level revenues and expenditures. Although multi-equation models provide a framework that allows subnational governments' revenues and expenditures to evolve over time in conjunction with other economic variables, estimating these conceptually important joint dynamics does not appear to translate into clear forecasting gains. On the other hand, while the single-equation models only allow for unidirectional links between past economic and financial market variables, and future revenues and expenditures, these computationally simple models often produce more accurate out-of-sample forecasts.

4.3.2 Absolute out-of-sample forecast performance

While the relative RMSFEs and panel DM tests reported in the previous section indicate that ADL-MIDAS regressions typically produce forecasts that are *relatively* more accurate than those produced by the alternative models, neither of these forecast evaluation schemes provides us with an indication of each model's performance in an *absolute* sense. In the spirit of Feenberg *et al.* (1989) and Gentry (1989), we address this issue by conducting Mincer and Zarnowitz (1969) tests that assess whether a model produces unbiased and efficient forecasts of future state-level revenues and expenditures.

To conduct this analysis we use the recursive procedure described in section 4.3 and, for each combination of model, forecast horizon, and budget series, record the percentage of states for which the null hypothesis of the MZ test is rejected. A rejection of the MZ test, described in section 2.3, indicates that a particular model is not suitable for forecasting the state's future fiscal outcomes. Consequently, models producing a low rejection rate of the

MZ test across the states in our sample tend to produce forecasts that are unbiased estimates of future state-specific fiscal outcomes.

The results of this analysis are presented in Table 6. The first four columns of the table show the percentage of states for which the null hypothesis of the MZ tests is rejected for a given combination of fiscal series and forecast horizon. Focusing on the rejection rates related to revenue forecasts in the first two columns, the results show that ADL-MIDAS models tend to produce unbiased estimates of future revenues most frequently. For example, ADL-MIDAS nowcasts incorporating an extra two or three quarters worth of HF data only reject the null hypothesis of the MZ test in 20.83% of states. Looking down each of these columns, the rejection rates of the ADL-MIDAS regressions generally decrease as extra HF data is included in the forecast procedure. Thus, nowcasts not only improve upon the performance of standard ADL-MIDAS models in a relative sense, as suggested by the results in Table 3, but also improve upon the performance of standard ADL-MIDAS models in an absolute sense. These MZ tests show that while BVARs are also well suited to forecasting future revenues, BVARs fail to outperform the best model in the class of ADL-MIDAS regressions.

[Insert Table 6 about here.]

The results in columns three and four suggest that ADL-MIDAS regressions often produce accurate forecasts of state-level expenditures. While LF ADL regressions outperform ADL-MIDAS regression when predicting expenditures two-year ahead, these ADL regressions underperform ADL-MIDAS regressions when predicting expenditures one-year ahead. In contrast to the rejection rates of these models, the best performing multi-equation model rejects the MZ test in at least 30 out of 48 states when forecasting expenditures.[7]

The last column of Table 6 summarizes the preceding four columns by showing the average rejection rate of each model across both budget series and forecast horizons. This provides a useful indication of each model's performance over the entire set of forecasts we consider. The results in this column mimic the conclusion from the comparison of the single- and

[7]Section OA.4 of the Online Appendix reports these rejection rates by state rather than by model.

multi-equation models in Section 4.3. That is, forecasts and nowcasts from ADL-MIDAS models not only tend to outperform alternative models in a relative sense, as indicated by relative RMSFEs and panel DM tests (see Tables 3 and 5), but also tend to outperform these alternative models in an absolute sense when forecast performance is evaluated via MZ tests.

4.3.3 Simulation-based comparison

While Section 4.3.1 and 4.3.2 show that ADL-MIDAS models typically produce accurate forecasts in the context of fiscal forecasting, the extent to which these results generalize to other empirical settings is unclear. To address this concern we consider a simulation-based experiment that compares the forecast performance of the MIDAS model to that of a LF- and MF-VAR under three different data-generating processes (henceforth DGPs). Under each DGP we consider the forecast accuracy of each model given three different combinations of forecast horizons (h), LF sample size (T_L), and ratio of sampling frequencies (m).

We implement these simulations by following the experimental design and notation of Ghysels, Hill and Motegi (2016).[8] We consider two HF processes, $\{\{w(\tau_L,k)\}_{k=1}^{m}\}_{\tau_L}$ and $\{\{z(\tau_L,k)\}_{k=1}^{m}\}_{\tau_L}$, and one latent LF process, $\{\{y(\tau_L,k)\}_{k=1}^{m}\}_{\tau_L}$. Here, $\tau_L \in \{0,\ldots,T_L\}$ is the LF time index, $k \in \{1,\ldots,m\}$ denotes the HF time index *within* each LF period, and m is the number of HF periods per LF period. For example, with annual LF data and quarterly HF data, m is equal to four since each year has four quarters. Importantly, the econometrician observes both HF processes, only observes LF outcomes that are temporally aggregated from the latent LF process. These temporal aggregates, denoted $y(\tau_L)$, are aggregated via flow sampling.[9] Given this notation, data is generated via the HF-VAR(1)

$$\begin{bmatrix} w(\tau_L,k) & z(\tau_L,k) & y(\tau_L,k) \end{bmatrix}' = \mathbf{\Phi}_1 \begin{bmatrix} w(\tau_L,k-1) & z(\tau_L,k-1) & y(\tau_L,k-1) \end{bmatrix}' + \boldsymbol{\varepsilon(\tau_L,k)}, \tag{6}$$

where $\boldsymbol{\varepsilon_t} \overset{i.i.d.}{\sim} \mathcal{N}(\mathbf{0}_{3\times 1}, \boldsymbol{I}_3)$.[10] We generate data by specifying $\mathbf{\Phi}_1$ in three different ways,

[8] We thank Kaiji Motegi for providing us with code to implement these simulations.

[9] In particular, $y(\tau_L) = \sum_{k=1}^{m} \frac{1}{m} y(\tau_L,k)$.

[10] Note that for simplicity we do not formally define a HF lag operator. For example, this means that for $\tau_l \in \{1,\ldots,T_L\}$ and $k \in \{1,\ldots,m\}$, while the appropriate one HF period lag corresponding to $w(\tau_L,1)$ is

which we refer to as DGP one, two, and three, respectively. The values of $\mathbf{\Phi}_1$ are

$$\mathbf{\Phi}_1^{(1)} = \begin{bmatrix} 0.80 & 0.20 & 0.00 \\ 0.20 & 0.40 & 0.00 \\ 0.30 & 0.30 & 0.20 \end{bmatrix}, \ \mathbf{\Phi}_1^{(2)} = \begin{bmatrix} 0.80 & 0.20 & 0.00 \\ 0.20 & 0.40 & 0.00 \\ 0.30 & 0.01 & 0.20 \end{bmatrix}, \text{ or } \mathbf{\Phi}_1^{(3)} = \begin{bmatrix} 0.80 & 0.20 & 0.30 \\ 0.20 & 0.40 & 0.30 \\ 0.00 & 0.00 & 0.20 \end{bmatrix}.$$

The purpose of DGPs one and two, in which causality runs from the HF to the LF variables, is to evaluate the performance of each model when the MF-VAR is correctly specified. The key difference between DGPs one and two is that under DGP two the HF variable z is less important for generating LF outcomes than the HF variable w. Under DGP three causality runs from the LF to the HF variables, meaning the MF-VAR is misspecified.

With each DGP we forecast one- and two-period ahead LF outcomes using three different models: a MF-VAR(1), a LF-VAR(1) containing temporal aggregates of each variable, and a forecast combination of two ADL-MIDAS models. Each ADL-MIDAS model combines a single lag of the LF outcome and m lags of either HF variable. The forecasts implied by these models are combined based on each model's historical dMSFE, as in Section 2.1, and only the U-MIDAS weighting scheme is considered. For computational simplicity, the MF-VAR is estimated via frequentist instead of Bayesian methods. Finally, two-period ahead predictions from the multi-equation models are generated using both direct and indirect forecasts.

For each DGP, the combinations of LF periods and ratio of sampling frequencies we consider are $(T_L, m) \in \{(60, 4), (60, 12), (600, 4)\}$. The first case is motivated by our empirical exercises, and can be considered a mixture of quarterly HF data and annual LF data spanning 60 years. The second case can be thought of as combination of monthly HF data and annual LF data spanning 60 years, and allows us to assess how the forecast performance of the MF-VAR and U-MIDAS model changes as parameter proliferation increases. The third case can be thought of as a combination of quarterly HF data and annual LF data spanning 600 years, and allows us to examine how each model performs when estimation errors are small.

To match the forecasting procedure described in Section 3, we generate forecasts by

actually $w(\tau_L - 1, k)$, we write all lags as $w(\tau_L, k-1)$. HF lags of $z(\tau_L, 1)$ and $y(\tau_L, 1)$ are written similarly.

initially estimating each model using data spanning the first $T_L - 10$ LF periods. We then produce recursive forecasts over the remaining ten LF periods and evaluate the forecast performance by computing the RMSFE over these ten pseudo out-of-sample forecasts. The RMSFEs reported in Table 7 are the average RMSFEs across 1,000 simulations of each DGP.

[Insert Table 7 about here.]

The conclusions from Panels A and B of Table 7, which correspond to DGPs one and two, respectively, are similar. First, the results show that in the empirically realistic case of $(T_L, m) = (60, 4)$, the forecast combination of U-MIDAS models produces the most accurate one- and two-period ahead forecasts. This is noteworthy because the DGP underlying Panel B features one HF variable that is unimportant for predicting the LF outcome, suggesting that dMSFE-based forecast combinations implicitly downweight the forecasts associated with the less important HF regressor. In contrast, the multi-equation models are seemingly less readily able to detect less important HF regressors over short sample periods. Second, with $(T_L, m) = (60, 12)$, parameter proliferation causes the MF-VAR to produce forecasts that are significantly less accurate than those produced by either the LF-VAR or the combination of U-MIDAS models. While the U-MIDAS model still produces the most accurate one-period ahead forecasts in this case, the LF-VAR model produces more accurate two-period ahead forecasts. This takeaway is consistent with Foroni *et al.* (2015) who find that U-MIDAS works particularly well when there are few HF observations per LF period.

The final conclusion from Panels A and B of Table 7 is that when $(T_L, m) = (600, 4)$, an empirically unrealistic case corresponding to 600 years worth of LF data, the MF-VAR produces the most accurate one- and two-period ahead forecasts. This is expected as the MF-VAR model is correctly specified given the DGP outlined in equation (6), and the sample size is sufficiently large so that estimation errors are small. Although the MF-VAR model is correctly specified and the sample size is large, the fact that direct forecasts outperform indirect forecasts suggests that the magnitude of the estimation errors is still non-trivial.

The takeaways from Panel C are largely different. Under DGP three causality runs from the LF variable to the HF variables, meaning that the MF-VAR is misspecified. The results show that, as expected, the MF-VAR produces the least accurate forecasts under all combinations of (T_L, m). Similarly, the forecast performance of the U-MIDAS model deteriorates relative to that of the LF-VAR in all cases except one.

Overall, the evidence in Table 7 corroborates the main takeaways from our empirical analysis: forecast combinations of MIDAS models tend to produce the most accurate forecasts of one- and two-period ahead LF outcomes in empirically realistic situations, subject to two caveats. First, in line with Foroni *et al.* (2015), the accuracy of the U-MIDAS model deteriorates as the sampling frequency of the HF variables (m) increases. Second, the accuracy of the multi-equation models tends to improve as the number of LF periods, T_L, increases.

4.4 An application to forecasting during the COVID-19 pandemic

In this section we demonstrate a true out-of-sample application of using ADL-MIDAS models to forecast state-specific fiscal outcomes in real time. Specifically, we use the ADL-MIDAS models described in Section 2.1, and evaluated in Sections 4.1 and 4.3, to obtain data-driven predictions of how each state's revenues for fiscal years 2020 and 2021 are likely to be impacted by the economic effects of the 2019-2020 coronavirus pandemic. We restrict our attention to the forecasts implied by ADL-MIDAS models since the evidence presented in 4.3 shows that, by and large, these models produce the most accurate predictions of fiscal outcomes. We also focus on forecasting revenue growth because states' balanced budget requirements imply that revenues are the economic primitive of a state's budget. That is, when revenues are predicted to fall, a state can typically only satisfy its balanced budget requirement by increasing revenues (e.g., by enacting tax increases), a politically unsavory action during periods of economic distress, or by cutting expenditures.

We put ourselves in the position of a policy maker who is standing at various points of 2020 and is trying to evaluate the impact of the coronavirus pandemic on her state's revenue growth rate. If the policy maker were to rely exclusively on traditional LF fiscal forecasting models, such as the AR or ADL models described in Section 2.1, then she would be unable to update her expectations of revenue growth rates intra-fiscal year. This is because the LF data underlying these models is only released after the end of a fiscal year. Once she has data for fiscal year 2019, her predicted revenue growth rates for fiscal years 2020 and 2021 are the same regardless of how many months of fiscal year 2020 have elapsed. In contrast, if she were to use an ADL-MIDAS model to predict the LF fiscal outcomes, then she could update her predictions intra-fiscal year. This is because the ADL-MIDAS model allows the policy maker to make *conditional* forecasts based on (i) realizations of the HF predictors within the fiscal year and/or (ii) assumptions regarding how the HF predictors will evolve over the fiscal year. We demonstrate this application of the ADL-MIDAS model below.

To show how the ADL-MIDAS model can forecast fiscal outcomes in real time (i.e., intra-fiscal year), we stand ourselves at four different points in time and predict each state's one- and two-year ahead revenue growth rates. Specifically, we begin by using the ADL-MIDAS model to predict each state's revenue growth rates using only HF data that is available as of December 2019. We then augment the ADL-MIDAS model with either one, two, or three quarter's worth of HF data from calendar year 2020, and update the predicted growth rates. This allows us to assess how the changing macroeconomic and financial market conditions induced by the coronavrius pandemic are likely to impact states' revenue growth rates.

While the data and the methodology we use to implement this analysis is similar to that described in Section 3, there are five differences worth highlighting. First, since HF data related to the second and third quarter's of 2020 is not yet available, we need to make a number of assumptions regarding how each HF variable will evolve over 2020. We think of these assumptions as plausible as of April 2020. Of course, making more severe assumptions about economic downturns will only exacerbate the findings we report here. To that end, we assume the following. The effective Federal funds rate, three-month Treasury bill rate, the ten-year Treasury note rate, and the default spread will be 0.05%, 0.25%, 0.80%, and 1.25% per annum between April and September, respectively. Oil prices will rise by $1 per month from $25 per barrel in April to $30 per barrel in September. The consumer price (industrial production) index will fall by -0.5% (-4%) per month in April and May, and then rise by 0.25% (2%) per month between June and September. Both state personal income and real

GDP will rise by 1% in the first quarter of 2020, decline by 6% in the second quarter of 2020, and then fall by 2% in the third quarter of 2020. Finally, returns on the S&P 500 index in April to September 2020 will mimic those in April to September 2010.

Second, while the analyses in Section 4.1 also include data on the Federal government's budget surplus and the Bond Buyer GO 20 index, we drop these two predictors for the purpose of this application. We exclude the former variable because the Bureau of Economic Analysis is yet to update this data beyond 2018, and we exclude the latter variable because the Federal Reserve Board discontinued its coverage of this index in 2016. Third, while we base our core analyses on the government finance data reported by the U.S. Census Bureau's annual survey of State & Local Government Finance, this data has not been released for the 2018 and 2019 fiscal years. Consequently, we obtain data on state government revenues between 2014 and 2019 from the National Association of State Budget Officers.[11]

Fourth, we use the parameter estimates and forecast combination weights obtained by estimating equations (3) and (2), respectively, over the full sample period of 1958 to 2014 to predict each state's real revenue growth rate per capita in fiscal years 2020 and 2021. Finally, given the recent (large) changes in many macroeconomic and financial market variables, the forecasts emerging from some models are extreme.[12] To mitigate the effects of unrealistic forecasts, we limit the predicted value from each model to lie between $[-20\%, 40\%]$ per annum for predictions made in December 2019 or for fiscal year 2021, and to lie between $[-50\%, 10\%]$ per annum for predictions for fiscal year 2020 made in the first three quarter's of 2020. The former interval is chosen to reflect the historical minimum and maximum values of revenue growth rates (recall Table 2), while the latter interval (with a greater downside and smaller upside) is chosen to account for the fact that concerns regarding the detrimental fiscal effects of the coronavirus pandemic began to mount in March 2020.

[11] We thank the National Association of State Budget Officers for making this data available at `https://www.nasbo.org/mainsite/reports-data/state-expenditure-report/ser-download-data`.

[12] For instance, in light of the approximately 5.5% drop in industrial production in March 2020 – the largest monthly percentage decline in the industrial production index since the 1940s – some models that rely on the 12-month percentage change in industrial production predict that revenue growth may decline by 200% to 300% in fiscal year 2020. Rather than drop these variables from our analysis, or change the way these variables are transformed, we limit these extreme values to lie within a more plausible range.

The results of the aforementioned analyses are reported in Table 8. Panel A shows the cross-sectional distribution of predicted revenue growth rates using either zero, one, two, or three quarter's worth of HF data from 2020. The main conclusion from this panel is that revenue growth rates decline by an economically significant amount when we not only consider how the coronavirus pandemic has impacted the macroeconomy and financial markets in March 2020, but also consider how the pandemic is likely to affect the economy between April and September of 2020. For instance, a policy maker who is standing in December 2019 and is using the ADL-MIDAS model to forecast the mean real revenue growth rate per capita for fiscal year 2020 using historical data expects revenues to grow by 1.14% per annum. However, the same policy maker standing at the end of March 2020 *and* anticipating how the coronavirus pandemic is likely to impact the macroeconomy and financial markets in the second (and third) quarter of 2020 expects the mean revenue growth rate for fiscal year 2020 to decline by -4.67% (-4.97%) per annum. Thus, the coronavirus pandemic is likely to have a significant impact on states' budgets in fiscal year 2020.

In contrast to the results for fiscal year 2020, those related to fiscal year 2021 indicate that revenue growth rates are likely to recover from the effects of the coronavirus pandemic within one year. For instance, while a policy maker standing at the end of December 2019 predicts revenue growth rates to grow by an average of 2.02% per annum in fiscal year 2021, the same policy maker standing at the end of March 2020 *and* accounting for the anticipated impacts of the coronavirus over the second and third quarter's of 2020 now expects revenues to rise by an average of 8.10% per annum in fiscal year 2021.

[Insert Table 8 about here.]

In Panel B of Table 8 we show the mean forecasts and nowcasts for the five states in our sample with the largest gross state products: California, Texas, New York, Florida, and Illinois. In line with Panel A, Panel B shows that the coronavirus pandemic is likely to negatively affect states' revenues in fiscal year 2020. However, most states' revenues are expected to begin to recover the losses in fiscal year 2020 in fiscal year 2021. For example, while Table 8 predicts that New York's (California's) revenues are anticipated to decline by 4.04% (-11.56%) in 2020, its revenues are expected to increase by 13.09% (11.91%) in 2021.

While the estimated effect of the COVID-19 pandemic on New York's revenue growth relative to California's revenue growth for fiscal year 2020 runs counter to the extent to which COVID-19 has affected each state's residents, we note that our primary contribution is to propose a *methodology* for forecasting fiscal outcomes in real time. To that end, we limit our attention to only a small set of HF predictors that are unlikely to fully capture the structural differences between states.[13] Although this set of HF predictors yields large forecasting gains relative to traditional LF fiscal forecasting models (recall Tables 3 and 5), and can help quantify part of the impact the COVID-19 pandemic may have on states' budgets in real time, expanding the set of predictors is likely to deliver additional (and more accurate) insights. For example, recent studies show that HF data related to payment systems (e.g., Barnett, Chauvet, Leiva-Leon and Su (2016); Duarte, Rodrigues and Rua (2017); Galbraith and Tkacz (2018)) and the textual analysis of news (e.g. Babii, Ghysels and Striaukas (2019)) help predict macroeconomic outcomes. These are interesting extensions to explore.

Collectively, the results in Table 8 highlight the usefulness of using the ADL-MIDAS model to predict fiscal outcomes in real time. This model not only allows policy makers to produce data-driven forecasts using the most recent economic and financial market data available, but also provide policy makers with a simple tool through which to incorporate their expectations regarding how the HF predictors may evolve over the fiscal year.

4.5 Economic heterogeneity in forecast performance

Sections 4.1, 4.3, and 4.3.2 establish our central result that ADL-MIDAS regressions yield the most accurate forecasts of state and local governments' fiscal outcomes within the set of forecasting models we consider. In particular, we typically find that ADL-MIDAS models not only produce lower RMSFEs than competing models, but also produce unbiased forecasts

[13]For instance, New York's population is concentrated in New York City and its economy is highly dependent on financial services, whereas California's population is more dispersed and highly dependent on agriculture.

of future state-level fiscal outcomes. However, in the course of our analysis we have noted that the performance of each model varies across states.[14] In this section we exploit the forecast gains of the ADL-MIDAS model to examine whether the forecast errors associated with each state's revenues are related to the extent to which the state generates revenues via various forms of taxation and transfers received from the Federal Government. This analysis is motivated by studies, such as Mattoon and McGranahan (2012), that find that revenues become more sensitive to economic conditions as states rely more heavily on higher volatility personal income taxes to generate revenues rather than less volatile sales taxes.

We focus on general revenues obtained through taxation and transfers from the Federal Government because, although these two sources are not the only sources of income for states, these two components account for a mean of between 65.49% and 85.48% of each state's general revenues between 2004 and 2014.[15] Thus, tax revenues and transfers from the Federal Government are economically large and visible components of states' revenues, and the degree to which states rely upon these sources of income may impact the extent to which we can forecast states' future revenue growth rates. We conduct our analysis as follows.

Using the forecasts of one- and two-year ahead revenue growth produced by the ADL-MIDAS regressions described in Section 4.3, we project the absolute forecast error associated with each state's revenue forecast between 2005 and 2014 on the proportion of each state's general revenues derived from different types of taxes and transfers from the Federal Government. The six categories of taxes we consider are: property, sales, individual income, corporate income, motor vehicle and license, and other.[16] While we have data on six broad categories of taxes, property, sales, and individual income taxes tend to make up the greatest

[14]Table OA.4.8 and Figure OA.4.6 in Section OA.4 of the Online Appendix show that there is a great deal of heterogeneity in the extent to which forecast models produce unbiased estimates of future state-level revenues and expenditures. The table and figure highlight how in some states, such as Arizona and Montana, only a small number of models reject the null hypothesis of the MZ regressions. In other states, such as Ohio and North Carolina, the vast majority of the forecast models reject the null hypothesis of the MZ tests.

[15]In Figures OA.5.7 and OA.5.8 of Section OA.5 of the Online Appendix we detail the extent to which each state relies up taxation and transfers from the Federal Government to obtain revenues.

[16]Detailed information regarding the particular taxes included in each category of tax revenue are available at: `https://www2.census.gov/govs/pubs/classification/2006_classification_manual.pdf`. Figure OA.5.9 of Section OA.5 of the Online Appendix displays the extent to which, on average, each state relies on each category of tax to generate its total revenue from taxation between 2004 and 2014.

proportion of each state's total tax revenues. Consequently, we tend to focus on these three taxes due to their economically significant roles of driving state-level revenues.

The results of this analysis are presented in Table 9. Columns one and two (three and four) display the estimates associated with one-year (two-year) ahead forecasts of revenue growth, and even numbered columns feature only a subset of revenue sources. The estimates show that while there is no statistically significant association between forecast errors and the the extent to which the average state relies upon either property or sales taxes, the revenue growth rates of states that rely on income taxes more heavily are harder to forecast. Column one (three) shows that a one percent increase in the extent to which a state relies on income taxes results in the absolute forecast errors associated with one-year (two-year) ahead revenue forecast errors increasing by 0.353% (0.385%). These estimates are significant at the 10% level. Column two and four show that the magnitude and significance of this income tax effect increases slightly when controlling for additional sources of tax revenues. Finally, although the point estimate associated with Federal Government funding is negative, suggesting that the revenue growth rates of states that rely more heavily on transfers from the Federal Government are easier to forecast, this relation is statistically insignificant.

[Insert Table 9 about here.]

Overall, the signs of the point estimates related to personal income taxes in Table 9 suggest that forecast accuracy may increase if states adjusted their tax bases so as to rely on volatile personal incomes taxes to a lesser degree. Although Dye (2004) argues that there is little political will to institute changes to states' tax bases, it is useful for us to note that part of the heterogeneity associated with the revenue forecast errors stemming from our preferred model is related to the economic mechanism through which states generate revenues.

5 Conclusion

This paper considers the problem of forecasting state and local governments' revenues and expenditures using both single- and multiple-equation MF forecasting methods. Within a sample of the 48 mainland United States, we find that single-equation ADL-MIDAS regressions that predict LF fiscal outcomes using relatively HF macroeconomic and financial market data provide forecast performance gains over traditional models in which all data are included at the same (low) sampling frequency. Among the set of multi-equation models we consider, we find that LF Bayesian vector autoregressions (BVARs) typically produce more accurate forecasts than either LF VARs or MF Bayesian VARs (MF-BVARs).

When we directly compare the predictive accuracy of the ADL-MIDAS regressions to those of the MF-BVAR and BVAR models, we not only find that ADL-MIDAS models typically deliver forecast performance gains over these multi-equation models, but also find that ADL-MIDAS models often produce unbiased estimates of future fiscal outcomes. Simulation evidence shows that our conclusions regarding the accuracy of forecasts from ADL-MIDAS regressions are likely to extend beyond the case of fiscal forecasting to other empirical contexts. We also show that the forecast performance of the ADL-MIDAS model depends, at least partially, on the degree to which a state relies on income taxes as a source of revenues.

We demonstrate the usefulness of ADL-MIDAS models, and the importance of forecasting fiscal outcomes in real time, by showing how policy makers can use these models to evaluate the economic impacts of the 2019-2020 coronavirus pandemic on states' future budgets. Collectively, our results suggest that single-equation ADL-MIDAS regressions provide government officials, policy makers, and financial market practitioners with a useful tool for forecasting state-level revenue and expenditure growth rates in real time.

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Table 1: Data sets

The table lists the time series used in this paper, as well as the mnemonic by which each variable is referred to throughout the paper, the highest frequency at which each variable is recorded (denoted by "freq."), either annually (A), quarterly (Q), or monthly (M), and the source of each variable. The table also reports how each variable is transformed to induce stationarity in the context of the single-equation analyses. G denotes a year-over-year, four-quarter, or 12-month growth rate for the annual, quarterly, and monthly time series, respectively. FD corresponds to either a four-quarter or a monthly first difference, depending on whether a variable is sampled quarterly or monthly. Finally, FDG denotes the first difference of 12-month growth rates. All nominal series, except the Spot Oil Price, are converted into real, per capita, quantities. Census and BEA refer to data from the U.S. Census Bureau or the Bureau of Economic Analysis (BEA), respectively.

Time-series	Mnemonic	Freq.	Source	Start year	Trans.
State-specific					
State and Local Government Rev.	REV	A	Census	1958	G
State and Local Government Exp.	EXP	A	Census	1958	G
State Personal Income	INC	Q	BEA	1948	G
National					
Real GDP	GDP	Q	ALFRED	1947	G
Federal Government Budget Surplus	BUD	Q	ALFRED	1959	-
Effective Federal Funds Rate	EFF	M	FRED	1954	FD
CPI for all Urban Consumers	CPI	M	ALFRED	1947	FDG
Industrial Production Index	IND	M	ALFRED	1919	G
Spot Oil Price: WTI	OIL	M	ALFRED	1946	G
3-Month Treasury Rate	3MO	M	FRED	1934	FD
10-Year Treasury Rate	10Y	M	FRED	1953	FD
Default Spread (Moody's BAA - AAA)	DEF	M	FRED	1919	-
Bond Buyer GO 20-Bond Index	MSL	M	FRED	1953	FD
S&P500 Index Returns	S&P	M	CRSP	1926	-

Table 2: Summary statistics of transformed variables

The table reports the summary statistics for each variable used in this paper. Variables are transformed to induce stationarity and are denoted by the mnemonic reported in Table 1. For the state-specific time-series, each statistic is calculated on a state-by-state basis and the reported result is the average across all states. The summary statistics are computed using data that ranges from 1955 to 2014.

Time-series	Mean	Std.	Median	Min.	Max.	Skew.	Kurt.	ACF(1)
State-specific								
REV	3.240	8.763	3.223	-21.234	42.354	0.831	10.108	-0.124
EXP	2.692	4.391	2.366	-6.486	14.721	0.400	3.370	0.095
INC	1.669	1.443	1.595	-3.885	7.157	0.001	5.833	0.256
National								
GDP	1.945	2.472	2.189	-4.925	7.598	-0.431	3.174	0.850
BUD	-0.002	0.013	-0.000	-0.095	0.038	-3.224	22.343	0.431
EFF	-0.002	0.519	0.010	-6.630	3.060	-2.285	48.753	0.382
CPI	0.001	0.362	-0.008	-2.569	2.121	-0.311	9.233	0.351
IND	2.877	5.141	3.270	-16.488	19.612	-0.827	4.856	0.967
OIL	0.423	7.116	0.000	-39.601	85.259	1.998	34.653	0.233
3MO	-0.002	0.429	0.010	-4.620	2.610	-1.790	30.360	0.338
10Y	-0.000	0.276	0.000	-1.760	1.610	-0.469	9.454	0.306
DEF	0.989	0.448	0.870	0.320	3.380	1.779	7.408	0.969
MSL	0.002	0.222	-0.010	-1.050	1.120	0.176	7.710	0.206
S&P	0.653	4.208	0.938	-21.763	16.305	-0.436	4.781	0.045

Table 3: Single-equation forecast results

Panel A reports the median value of the root mean squared forecast error (RMSFE) of an ADL-MIDAS model estimated without using any additional quarters worth of high-frequency data (j=0), and ADL and AR models relative to the RMSFE of a RW for one- and two-year ahead forecasts of state and local government revenues and expenditures. Panel B compares the forecast performance of the ADL-MIDAS model to the forecast performance of each of the ADL and AR models using the panel Diebold-Mariano test proposed by Pesaran *et al.* (2009). The panel reports the test statistic, as well as the p-value associated with this test statistic in parentheses. Panel C reports the median value of the RMSFEs from one-, two-, and three-quarter ahead nowcasts of subnational government revenues and expenditures from three ADL-MIDAS models relative to the RMSFEs of an ADL-MIDAS model estimated without using any additional quarters worth of high-frequency data. Depending on the value of j, an additional 0, 1, 2, or 3 quarters worth of intra-year high-frequency data are used to produce each forecast. Each model is estimated following the procedure described in Section 3, and in Panels A and C the 5^{th} and 95^{th} percentiles of the distribution of relative RMSFEs across states are reported in parentheses.

	Revenues		Expenditures	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
Panel A: RMSFEs relative to RW				
ADL-MIDAS	0.630	0.617	0.662	0.662
	(0.546, 0.900)	(0.557, 0.701)	(0.492, 0.812)	(0.563, 0.864)
ADL	0.648	0.594	0.723	0.742
	(0.546, 0.934)	(0.447, 0.795)	(0.574, 0.845)	(0.592, 0.902)
AR	0.699	0.697	0.761	0.764
	(0.592, 0.946)	(0.612, 0.887)	(0.609, 0.930)	(0.647, 1.007)
Panel B: Panel DM tests relative to ADL-MIDAS				
ADL	-1.702	-0.763	-7.953	-3.349
	(0.044)	(0.223)	(0.000)	(0.000)
AR	-2.707	-2.185	-7.466	-4.024
	(0.003)	(0.014)	(0.000)	(0.000)
Panel B: RMSFEs Relative to ADL-MIDAS (j=0)				
j=1	0.986	0.908	0.985	0.936
	(0.932, 1.031)	(0.810, 1.035)	(0.826, 1.105)	(0.812, 1.148)
j=2	0.947	0.986	0.965	0.996
	(0.877, 1.037)	(0.924, 1.022)	(0.808, 1.149)	(0.928, 1.143)
j=3	0.932	0.939	0.976	0.958
	(0.862, 1.005)	(0.893, 1.000)	(0.780, 1.099)	(0.809, 1.059)

Table 4: Multi-equation forecasts results

Panel A reports the median value of the root mean squared forecast error (RMSFE) of the MF-BVAR, BVAR, and VAR models relative to the RMSFE of a RW for one- and two-year ahead forecasts of state and local government revenues and expenditures. Each model is estimated following the procedure described in Section 3, and the 5^{th} and 95^{th} percentiles of the distribution of relative RMSFEs across states are reported in parentheses. Panel B compares the forecast performance of the MF-BVAR model to the forecast performance of each of the ADL and AR models using the panel Diebold-Mariano test proposed by Pesaran *et al.* (2009). The panel reports the test statistic, as well as the p-value associated with this test statistic in parentheses.

	Revenues		Expenditures	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
Panel A: RMSFEs relative to RW				
MF-BVAR	0.696	0.741	1.921	2.058
	(0.536, 1.392)	(0.557, 1.455)	(0.972, 4.290)	(1.040, 4.468)
BVAR	0.683	0.551	0.926	0.787
	(0.590, 0.732)	(0.482, 0.701)	(0.621, 1.240)	(0.632, 1.453)
VAR	0.696	0.753	1.034	0.850
	(0.604, 0.777)	(0.621, 1.050)	(0.682, 1.472)	(0.619, 1.478)
Panel B: Panel DM tests relative to MF-BVAR				
BVAR	0.762	3.679	5.487	3.696
	(0.777)	(1.000)	(1.000)	(1.000)
VAR	0.312	-0.505	5.181	3.614
	(0.623)	(0.307)	(1.000)	(1.000)

Table 5: Comparing single- and multi-equation forecasts

Panel A reports the median value of the root mean squared forecast error (RMSFE) of the MF-BVAR, BVAR, and ADL-MIDAS models relative to the RMSFE of a RW for one- and two-year ahead forecasts of state and local government revenues and expenditures. Each model is estimated following the procedure for multi-equation models described in Section 3, and the 5^{th} and 95^{th} percentiles of the distribution of relative RMSFEs across states are reported in parentheses. Panel B compares the forecast performance of the ADL-MIDAS model to the forecast performance of each of the ADL and AR models using the panel Diebold and Mariano test proposed by Pesaran *et al.* (2009). The panel reports the test statistic, as well as the p-value associated with this test statistic in parentheses.

	Revenues		Expenditures	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
Panel A: RMSFEs relative to RW				
MF-BVAR	0.696	0.741	1.921	2.058
	(0.536, 1.766)	(0.557, 2.183)	(0.972, 8.757)	(1.040, 5.738)
BVAR	0.683	0.551	0.926	0.787
	(0.590, 0.782)	(0.482, 0.733)	(0.621, 1.994)	(0.632, 1.688)
ADL-MIDAS	0.537	0.572	0.639	0.566
	(0.370, 0.777)	(0.497, 0.702)	(0.464, 1.105)	(0.373, 0.978)
Panel B: Panel DM tests relative to ADL-MIDAS				
MF-BVAR	-1.175	-2.973	-6.032	-3.887
	(0.120)	(0.001)	(0.000)	(0.000)
BVAR	-0.570	-0.675	-8.786	-4.572
	(0.284)	(0.250)	(0.000)	(0.000)

Table 6: Mincer and Zarnowitz (1969) tests of forecast performance by model

The table reports the out-of-sample forecast performance of nine models as determined by the Mincer and Zarnowitz (1969) (MZ) regressions outlined in Section 2.3. For a given model, budget series, forecast horizon, and state, we test and null hypothesis of the MZ test, and report the proportion of states for which the null hypothesis of this test is rejected. Each of the first four columns of the table report the percentage of states for which a particular model rejects the MZ test for a given combination of budget series and forecast horizon. The final column, labeled "Overall," displays the combined rejection rate across both budget series and forecast horizons. The labels ADL-MIDAS(j=x) refer to forecasts obtained from the ADL-MIDAS model estimated using an extra x quarters worth of HF data. Models are estimated following the procedures described in Section 3.

	Revenues		Expenditures		Overall
	$h=1$	$h=2$	$h=1$	$h=2$	
AR	56.25	87.50	43.75	45.83	58.33
ADL	35.42	43.75	27.08	20.83	31.77
ADL-MIDAS(j=0)	31.25	60.42	18.75	25.00	33.85
ADL-MIDAS(j=1)	31.25	43.75	20.83	25.00	30.21
ADL-MIDAS(j=2)	16.67	16.67	25.00	35.42	23.44
ADL-MIDAS(j=3)	20.83	22.92	22.92	31.25	24.48
VAR	39.58	93.75	77.08	79.17	72.40
BVAR	31.25	29.17	62.50	70.83	48.44
MF-BVAR	64.58	81.25	100.00	100.00	86.46

Table 7: Simulation evidence

The table reports the results of Monte Carlo simulations that assess the forecast performance of MF-VAR(1), LF-VAR(1), and forecast combinations of two U-MIDAS models under three data-generating processes (DGPs). For each DGP, the table considers three different combinations of LF sample size (T_L), and ratio of sampling frequencies (m). These combinations are $(T_L, m) \in \{(60, 4), (60, 12), (600, 4)\}$. We generate forecasts from each model by initially estimating the model using data spanning the first $T_L - 10$ LF periods. We then produce recursive forecasts over the remaining ten LF periods and evaluate the forecast performance of these models by computing the RMSFE over these ten pseudo out-of-sample forecasts. The reported RMSFEs are the average RMSFE across $J = 1000$ simulations of each DGP. Within each panel of the table, and for each combination of (T_L, m), the RMSFE associated with the best performing model is denoted in bold.

		$T_L = 60$ and $m = 4$		$T_L = 60$ and $m = 12$		$T_L = 600$ and $m = 4$	
Model	Details	$h=1$	$h=2$	$h=1$	$h=2$	$h=1$	$h=2$
				Panel A: DGP # 1			
MF-VAR	Direct	0.759	1.038	0.975	1.143	**0.699**	**0.971**
MF-VAR	Indirect	-	1.080	-	1.252	-	0.975
LF-VAR	Direct	0.799	1.020	0.823	**0.896**	0.778	0.993
LF-VAR	Indirect	-	1.040	-	0.916	-	0.992
U-MIDAS	Comb.	**0.744**	**1.013**	**0.775**	0.963	0.727	0.978
				Panel B: DGP # 2			
MF-VAR	Direct	0.709	0.851	0.761	0.868	**0.645**	**0.814**
MF-VAR	Indirect	-	0.893	-	0.956	-	0.817
LF-VAR	Direct	0.717	0.834	0.638	0**.693**	0.692	0.828
LF-VAR	Indirect	-	0.850	-	0.708	-	0.827
U-MIDAS	Comb.	**0.679**	**0.834**	**0.609**	0.738	0.659	0.820
				Panel C: DGP # 3			
MF-VAR	Direct	0.638	0.594	0.485	0.421	0.583	0.575
MF-VAR	Indirect	-	0.639	-	0.491	-	0.578
LF-VAR	Direct	0.595	**0.585**	**0.359**	**0.349**	**0.579**	**0.575**
LF-VAR	Indirect	-	0.598	-	0.357	-	0.576
U-MIDAS	Comb.	**0.594**	0.595	0.379	0.379	0.580	0.575

Table 8: Real-time forecasts of fiscal outcomes for fiscal years 2020 and 2021

The table reports the results of out-of-sample forecasts of state-level real revenue growth per capita for fiscal years 2020 (FY20) and 2021 (FY21). All forecasts are produced in two steps. First, we estimate an ADL-MIDAS model for one- and two-year ahead revenue growth in each state using data spanning 1958 to 2014. This provides us with the squared discounted mean squared forecast error (dMSFE) underlying equation (2), and the parameter estimates underlying equation (3), for ADL-MIDAS models featuring an extra $j \in \{0, ..., 3\}$ quarter's worth of intra-fiscal year high-frequency data. Next, using the parameter estimates and forecast combination weights from the first step, we estimate the one- and two-year ahead revenue growth rates for each state. In the column denoted "19Q4" ("20Q1") we construct these out-of-sample forecasts by only using data that is available as of December 2019 (March 2020). In the columns denoted "20Q2" and "20Q3" we estimate each revenue growth rate by making assumptions regarding the evolutions of the high-frequency variables underlying our analysis between April 2020 and September 2020. We outline these assumptions in detail in the Section 4.4. In Panel A we report the cross-sectional mean, median, and standard deviation of the revenue growth rates. In Panel B we report the estimated revenue growth rate of the five largest states in our sample: California (CA), Texas (TX), New York (NY), Florida (FL), and Illinois (IL).

	FY20				FY21			
	19Q4	20Q1	20Q2	20Q3	19Q4	20Q1	20Q2	20Q3
Panel A: Summary statistics								
Mean	1.14	-0.13	-4.67	-4.97	2.92	3.97	7.58	8.10
Median	0.83	0.07	-4.77	-5.49	2.36	3.41	7.38	7.54
Std.	3.48	3.22	3.24	4.29	3.92	4.22	3.00	4.01
Panel B: State-level forecasts								
CA	-1.32	-5.10	-8.89	-11.56	1.63	4.00	6.75	11.91
TX	-2.07	-3.63	-5.56	-4.16	4.56	7.28	7.55	8.61
NY	2.09	1.09	-0.76	-4.04	6.79	7.52	9.12	13.09
FL	-0.55	-0.94	-5.15	-6.04	-0.32	-0.29	4.69	6.17
IL	-1.97	-4.21	-12.08	-14.62	8.34	9.97	12.68	15.94

Table 9: Heterogeneity in absolute forecast errors

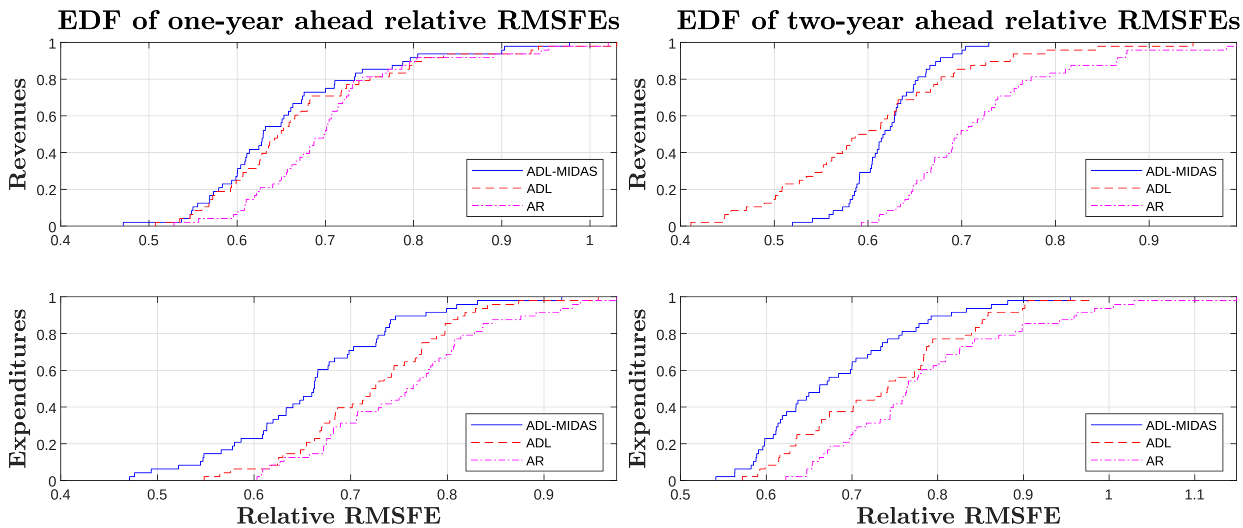
The table reports the results of pooled OLS regressions that project each state's absolute forecast errors related to forecasts of one- and two-year ahead revenue growth on the lagged proportions of the state's tax revenues derived from different sources. All forecasts are obtained from ADL-MIDAS models that are estimated following the procedure described in Section 4.3. Parentheses report t-statistics that are computed using standard errors clustered at the state level.

	(1)	(2)	(3)	(4)
	$h=1$		$h=2$	
Property	0.123	0.161	0.119	0.155
	(0.598)	(0.795)	(0.544)	(0.722)
Sales	-0.032	-0.064	-0.051	-0.076
	(-0.156)	(-0.350)	(-0.237)	(-0.389)
Income	0.353	0.389	0.385	0.422
	(1.824)	(2.038)	(1.832)	(2.029)
Corporate		-0.915		-0.838
		(-1.038)		(-0.885)
Motor		1.465		1.525
		(0.717)		(0.697)
Federal transfers	-0.034	-0.041	-0.062	-0.067
	(-0.215)	(-0.268)	(-0.362)	(-0.416)
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted-R^2	0.313	0.315	0.282	0.284

A Online Appendix

OA.1 Additional single-equation results

OA.1.1 State-by-state forecast results



(a) One-year ahead relative RMSFEs **(b)** Two-year ahead relative RMSFEs

Figure OA.1.1: Empirical distribution function of relative RMSFEs from single-equation forecasts

The figure displays the empirical distribution function (EDF) of the root mean squared forecast error (RMSFE) of the ADL-MIDAS, ADL, and AR models relative to the RMSFE of a RW for one- and two-year ahead forecasts of state and local government revenues and expenditures. Here, each model is estimated following the procedure for single-equation models described in Section 3. Panel A of the figure reports the results for one-year ahead forecasts while Panel B reports the results for two-year ahead forecasts. Points in each figure denote the state-specific relative RMSFEs associated with each model (ordered from the smallest relative RMSFE to the largest relative RMSFE) and the horizontal axis in each figure presents the percentiles of each empirical distribution function.

Table OA.1.1: Single-equation forecasts by state

Panel A reports the root mean squared forecast error (RMSFE) of the ADL-MIDAS, ADL, and AR models relative to the RMSFE of a RW for one- and two-year ahead forecasts of state and local government revenues and expenditures at the state level. In Panel B $p5$, $p10$, $p25$, $p75$, $p90$, and $p95$ refer to the 5^{th}, 10^{th}, 25^{th}, 75^{th}, 90^{th}, and 95^{th} percentiles of the distribution of relative RMSFEs across states, respectively. Here, each model is estimated following the procedure for single-equation models described in Section 3.

	Revenues						Expenditures					
	ADL-MIDAS		ADL		AR		ADL-MIDAS		ADL		AR	
$h =$	1	2	1	2	1	2	1	2	1	2	1	2
Alabama	0.547	0.677	0.569	0.678	0.596	0.794	0.831	0.833	0.874	0.902	0.917	0.899
Arizona	0.471	0.618	0.507	0.411	0.528	0.667	0.647	0.650	0.654	0.636	0.707	0.701
Arkansas	0.632	0.591	0.623	0.501	0.657	0.695	0.633	0.635	0.818	0.742	0.778	0.777
California	0.776	0.612	0.791	0.693	0.771	0.866	0.566	0.789	0.630	0.859	0.682	1.029
Colorado	0.625	0.602	0.636	0.652	0.688	0.736	0.522	0.589	0.618	0.628	0.631	0.667
Connecticut	0.550	0.635	0.576	0.509	0.622	0.752	0.548	0.598	0.782	0.702	0.785	0.690
Delaware	0.628	0.624	0.642	0.527	0.698	0.639	0.580	0.742	0.702	0.855	0.603	0.745
Florida	0.658	0.608	0.672	0.577	0.707	0.660	0.778	0.611	0.798	0.734	0.876	0.801
Georgia	0.555	0.563	0.606	0.614	0.610	0.717	0.810	0.700	0.829	0.784	0.837	0.744
Idaho	0.548	0.573	0.547	0.454	0.608	0.648	0.736	0.734	0.789	0.741	0.791	0.745
Illinois	0.805	0.612	0.812	0.726	0.891	0.817	0.666	0.647	0.729	0.674	0.729	0.697
Indiana	0.734	0.641	0.751	0.649	0.742	0.593	0.741	0.816	0.797	0.833	0.892	0.962
Iowa	0.630	0.653	0.646	0.504	0.682	0.699	0.613	0.617	0.671	0.614	0.742	0.764
Kansas	0.614	0.610	0.607	0.583	0.626	0.635	0.640	0.541	0.663	0.592	0.804	0.706
Kentucky	0.676	0.637	0.680	0.508	0.687	0.619	0.735	0.863	0.804	0.905	0.828	0.871
Louisiana	0.796	0.662	0.801	0.710	0.704	0.692	0.799	0.882	0.842	0.899	0.808	0.983
Maine	0.733	0.649	0.718	0.601	0.804	0.652	0.547	0.673	0.652	0.839	0.706	0.959
Maryland	0.600	0.604	0.613	0.534	0.671	0.630	0.620	0.671	0.668	0.773	0.765	0.825
Massachusetts	0.629	0.616	0.594	0.615	0.667	0.671	0.587	0.792	0.670	0.852	0.679	0.748
Michigan	0.573	0.587	0.572	0.565	0.601	0.668	0.610	0.736	0.678	0.787	0.675	0.764
Minnesota	0.663	0.588	0.659	0.581	0.724	0.765	0.545	0.634	0.712	0.665	0.780	0.758
Mississippi	0.537	0.519	0.551	0.470	0.556	0.690	0.728	0.775	0.743	0.780	0.706	0.782
Missouri	0.710	0.700	0.724	0.630	0.700	0.875	0.746	0.705	0.755	0.726	0.814	0.763
Montana	0.569	0.581	0.560	0.552	0.609	0.711	0.651	0.614	0.714	0.635	0.750	0.654
Nebraska	0.653	0.604	0.650	0.573	0.707	0.690	0.633	0.758	0.668	0.794	0.672	0.826
Nevada	0.599	0.626	0.660	0.561	0.714	0.732	0.678	0.608	0.684	0.773	0.672	0.699
New Hampshire	0.609	0.591	0.568	0.543	0.662	0.671	0.666	0.563	0.798	0.662	0.929	0.672
New Jersey	0.610	0.580	0.626	0.586	0.702	0.684	0.698	0.619	0.735	0.701	0.769	0.733
New Mecixo	0.674	0.628	0.665	0.551	0.732	0.756	0.703	0.698	0.745	0.751	0.806	0.766
New York	0.788	0.605	0.795	0.752	0.795	0.866	0.726	0.684	0.811	0.743	0.836	0.942
North Carolina	0.661	0.632	0.680	0.670	0.682	0.736	0.662	0.955	0.769	0.979	0.846	1.149
North Dakota	0.583	0.558	0.637	0.667	0.620	0.707	0.471	0.563	0.548	0.590	0.675	0.778
Ohio	0.900	0.586	0.933	0.846	0.954	0.876	0.740	0.662	0.767	0.616	0.938	0.717
Oklahoma	0.569	0.584	0.535	0.447	0.640	0.724	0.662	0.596	0.773	0.635	0.689	0.647
Oregon	0.903	0.630	0.941	0.755	0.945	0.993	0.609	0.612	0.686	0.655	0.756	0.809
Pennsylvania	0.650	0.648	0.653	0.674	0.713	0.774	0.677	0.598	0.774	0.615	0.799	0.653
Rhode Island	0.601	0.650	0.633	0.556	0.727	0.660	0.578	0.700	0.624	0.783	0.616	0.760
South Carolina	0.579	0.666	0.599	0.489	0.675	0.612	0.918	0.722	0.956	0.844	0.975	0.840
South Dakota	0.628	0.704	0.628	0.445	0.648	0.643	0.663	0.624	0.726	0.674	0.783	0.674

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Table OA.1.1 – Continued from the previous page

	Revenues						Expenditures					
	ADL-MIDAS		ADL		AR		ADL-MIDAS		ADL		AR	
$h =$	1	2	1	2	1	2	1	2	1	2	1	2
Tennessee	0.700	0.662	0.685	0.621	0.727	0.646	0.613	0.778	0.648	0.790	0.609	0.899
Texas	0.651	0.591	0.772	0.632	0.731	0.725	0.683	0.582	0.774	0.572	0.807	0.647
Utah	0.604	0.614	0.593	0.628	0.650	0.738	0.727	0.585	0.721	0.628	0.758	0.662
Vermont	0.711	0.628	0.682	0.631	0.703	0.612	0.625	0.718	0.625	0.851	0.608	0.809
Virginia	0.673	0.630	0.718	0.613	0.720	0.811	0.476	0.591	0.575	0.662	0.682	1.005
Washington	0.611	0.541	0.625	0.500	0.656	0.761	0.494	0.588	0.565	0.599	0.627	0.623
West Virginia	0.742	0.690	0.738	0.691	0.787	0.689	0.660	0.637	0.720	0.783	0.658	0.795
Wisconsin	0.977	0.672	1.030	0.947	1.021	0.982	0.663	0.662	0.684	0.705	0.732	0.891
Wyoming	0.594	0.729	0.834	0.790	0.765	0.648	0.697	0.755	0.742	0.787	0.772	0.843
Panel B: Summary Statistics of RMSFEs Relative to Random Walk Across States												
Minimum	0.471	0.519	0.507	0.411	0.528	0.593	0.471	0.541	0.548	0.572	0.603	0.623
$p5$	0.546	0.557	0.546	0.447	0.592	0.612	0.492	0.563	0.574	0.592	0.609	0.647
$p10$	0.551	0.575	0.562	0.476	0.608	0.631	0.545	0.586	0.625	0.614	0.628	0.656
$p25$	0.596	0.591	0.602	0.530	0.649	0.656	0.609	0.610	0.668	0.645	0.681	0.700
Median	0.630	0.617	0.648	0.594	0.699	0.697	0.662	0.662	0.723	0.742	0.761	0.764
$p75$	0.705	0.648	0.721	0.669	0.729	0.758	0.726	0.739	0.778	0.792	0.807	0.842
$p90$	0.794	0.676	0.809	0.744	0.801	0.866	0.768	0.809	0.816	0.858	0.887	0.961
$p95$	0.900	0.701	0.934	0.795	0.946	0.887	0.812	0.864	0.845	0.902	0.930	1.007
Maximum	0.977	0.729	1.030	0.947	1.021	0.993	0.918	0.955	0.956	0.979	0.975	1.149

OA.1.2 Forecast combination weights

Figure OA.1.2: Forecast combination weights for revenue growth

The figure shows the average weight placed on each predictor when combining one-year ahead forecasts of the annual growth rate of real state and local government revenues per capita (REV). For each state, ADL-MIDAS regressions forecasting one-year ahead revenue growth are initially estimated using data from 1958 to 1998. A rolling window forecast scheme is then used to generate forecasts that span 1999 to 2014. Forecast combination weights are based on the squared discounted mean square forecast errors (dMSFE) as per equation (2). Maps under the columns entitled "2004 - 2007" ("2008 - 2011") display the average forecast combination weight over the 2004 to 2007 (2008 to 2011) periods. For a given predictor, as the color in a particular state gets darker, more weight is placed on that particular predictor when determining the combined forecast for REV. The scale ranges from a weight of 0% for the lightest color to a weight of 15% for the darkest color. All independent variables are referred to by a mnemonic as detailed in Table 1.

Figure OA.1.3: Forecast combination weights for expenditure growth

The figure shows the average weight placed on each predictor when combining one-year ahead forecasts of the annual growth rate of real state and local government expenditures per capita (EXP). For each state, ADL-MIDAS regressions forecasting one-year ahead expenditure growth are initially estimated using data from 1958 to 1998. A rolling window forecast scheme is then used to generate forecasts that span 1999 to 2014. Forecast combination weights are based on the squared discounted mean square forecast errors (dMSFE) as per equation (2). Maps under the columns entitled "2004 - 2007" ("2008 - 2011") display the average forecast combination weight over the 2004 to 2007 (2008 to 2011) periods. For a given predictor, as the color in a particular state gets darker, more weight is placed on that particular predictor when determining the combined forecast for EXP. The scale ranges from a weight of 0% for the lightest color to a weight of 15% for the darkest color. All independent variables are referred to by a mnemonic as detailed in Table 1.

Table OA.1.2: Sensitivity of the predictive accuracy of ADL-MIDAS regressions to forecast combination weights

The table reports summary statistics of the root mean squared forecast error (RMSFE) of ADL-MIDAS models using different forecast combination weights relative to the RMSFE of a RW for one- and two-year ahead forecasts of state and local government revenues and expenditures. One of these ADL-MIDAS models, denoted by the column "Flat," employs a forecast combination scheme in which each forecast is equally-weighted in order to produce the forecast cominbation. The other two models, denoted by the columns "$\delta = 1$ and $\kappa = 2$" and "$\delta = 0.90$ and $\kappa = 2$," employ forecast combination schemes based on discounted mean square forecast errors (dMSFE), as per equation 2 of the main text, with values of δ and κ denoted by the column labels. $p5$, $p10$, $p25$, $p75$, $p90$, and $p95$ refer to the 5^{th}, 10^{th}, 25^{th}, 75^{th}, 90^{th}, and 95^{th} percentiles of the distribution of relative RMSFEs across states, respectively. Here, each model is estimated following the procedure for single-equation models described in Section 3.

Panel A: RMSFEs Relative to ADL-MIDAS with $\delta = 0.90$ and $\kappa = 2$

	Revenues						Expenditures					
	Flat		$\delta = 1$ and $\kappa = 2$		$\delta = 0.90$ and $\kappa = 1$		Flat		$\delta = 1$ and $\kappa = 2$		$\delta = 0.90$ and $\kappa = 1$	
$h =$	1	2	1	2	1	2	1	2	1	2	1	2
Minimum	0.821	0.878	0.916	0.924	0.994	0.993	1.038	1.043	0.908	0.921	1.011	1.004
$p1$	0.821	0.878	0.916	0.924	0.994	0.993	1.038	1.043	0.908	0.921	1.011	1.004
$p5$	0.913	0.912	0.946	0.972	1.003	0.997	1.094	1.111	0.934	0.932	1.018	1.013
$p25$	1.038	1.018	0.964	0.983	1.012	1.004	1.272	1.423	0.959	0.962	1.032	1.021
Median	1.127	1.087	0.972	0.987	1.020	1.009	1.442	1.761	0.967	0.972	1.044	1.031
$p75$	1.259	1.211	0.981	0.990	1.032	1.014	1.630	2.520	0.975	0.977	1.073	1.059
$p95$	1.776	1.682	0.989	0.994	1.068	1.027	3.083	4.610	0.981	0.985	1.135	1.127
$p99$	3.207	2.185	0.992	0.994	1.212	1.036	10.036	5.866	0.986	0.990	1.193	1.155
Maximum	3.207	2.185	0.992	0.994	1.212	1.036	10.036	5.866	0.986	0.990	1.193	1.155

OA.1.3 Additional nowcast results

Table OA.1.3: Single-equation nowcast results relative to alternative models

The table reports the median value of root mean squared forecast errors (RMSFEs) from one-, two-, and three-quarter ahead nowcasts of state and local government revenues and expenditures from the ADL-MIDAS models relative to the RMSFEs from two low-frequency single-equation forecast model. Depending on the value of j, an additional 0, 1, 2, or 3 quarters of intra-year high-frequency data is used to produce each forecast. Each model is estimated following the procedure described in Section 3, and the 5^{th} and 95^{th} percentiles of the distribution of relative RMSFEs across states are reported in parentheses. In Panel A, RMSFEs are scaled by the RMSFEs from ADL models, while in Panel N RMSFEs are scaled by the RMSFEs from AR models.

	Revenues		Expenditures	
	$h=1$	$h=2$	$h=1$	$h=2$
Panel B: RMSFEs Relative to ADL				
j=1	0.973	0.897	0.902	0.845
	(0.910, 1.021)	(0.817, 0.963)	(0.773, 0.980)	(0.732, 0.975)
j=2	0.930	1.009	0.880	0.939
	(0.865, 0.985)	(0.801, 1.336)	(0.726, 1.000)	(0.812, 1.009)
j=3	0.961	0.968	0.898	0.900
	(0.761, 1.304)	(0.748, 1.294)	(0.741, 0.992)	(0.727, 0.986)
Panel C: RMSFEs Relative to AR				
j=1	0.921	0.840	0.849	0.793
	(0.837, 1.005)	(0.747, 0.971)	(0.718, 1.040)	(0.656, 0.978)
j=2	0.875	0.839	0.829	0.894
	(0.803, 0.979)	(0.673, 1.060)	(0.664, 1.027)	(0.700, 1.017)
j=3	0.797	0.801	0.855	0.822
	(0.642, 1.008)	(0.643, 1.042)	(0.626, 0.976)	(0.630, 0.974)

OA.1.4 Results using the Bayesian information criterion (BIC)

Table OA.1.4: Single-equation forecasts using the BIC

Panel A reports the median value of the root mean squared forecast error (RMSFE) of ADL-MIDAS, ADL, and AR models relative to the RMSFE of a RW for one- and two-year ahead forecasts of state and local government revenues and expenditures. Each model is estimated following the procedure described in Section 3, and the 5^{th} and 95^{th} percentiles of the distribution of relative RMSFEs across states are reported in parentheses. Panel B compares the forecast performance of the ADL-MIDAS model to the forecast performance of each of the ADL and AR models using the panel Diebold-Mariano test proposed by Pesaran *et al.* (2009). The panel reports the test statistic, as well as the p-value associated with this test statistic in parentheses. The Bayesian information criterion (BIC) is used to select the optimal lag length for each model.

	Revenues		Expenditures	
	$h=1$	$h=2$	$h=1$	$h=2$
Panel A: RMSFEs relative to RW				
ADL-MIDAS	0.630	0.617	0.662	0.662
	(0.546, 0.900)	(0.557, 0.701)	(0.492, 0.812)	(0.563, 0.864)
ADL	0.653	0.596	0.726	0.730
	(0.521, 0.945)	(0.445, 0.795)	(0.604, 0.850)	(0.608, 0.886)
AR	0.683	0.686	0.743	0.754
	(0.582, 0.813)	(0.588, 0.924)	(0.607, 0.934)	(0.651, 0.937)
Panel B: Panel DM tests relative to ADL-MIDAS				
ADL	-1.892	-0.783	-8.189	-3.074
	(0.029)	(0.217)	(0.000)	(0.001)
AR	0.505	-2.007	-5.005	-3.793
	(0.693)	(0.022)	(0.000)	(0.000)

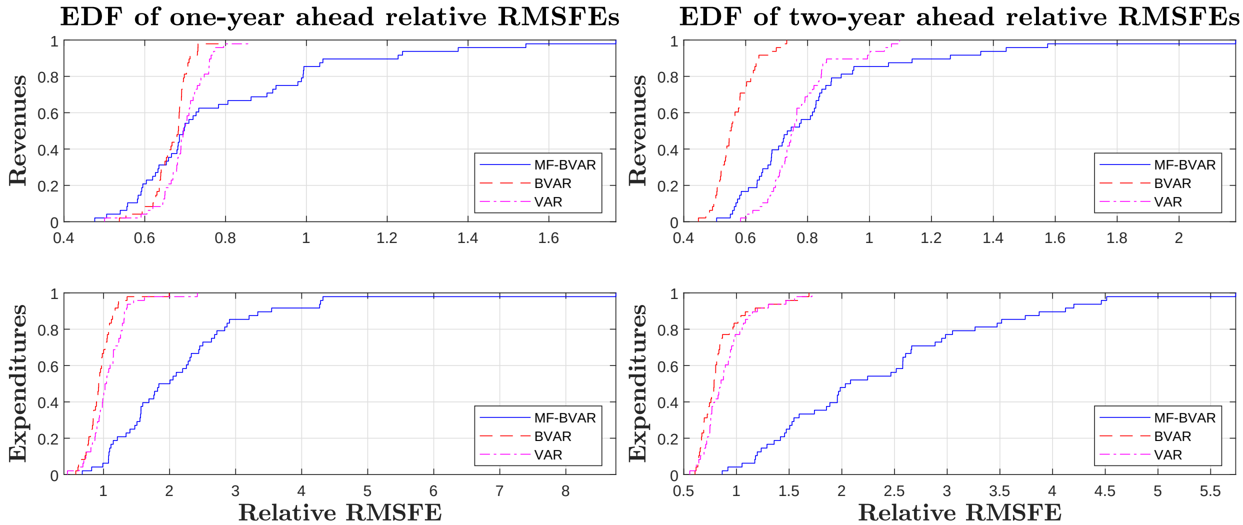
Table OA.1.5: Single-equation nowcasts using the BIC

The table reports summary statistics of relative root mean square forecast errors (relative RMSFEs) from one-, two-, and three-quarter ahead nowcasts of state and local government revenues and expenditures from the ADL-MIDAS models. Depending on the value of j, an additional 0, 1, 2, or 3 quarters of intra-year high-frequency data is used to produce each forecast. In Panel A the RMSFEs from ADL-MIDAS models estimated using an additional $j = 1$, $j = 2$ or $j = 3$ quarters of intra-year high-frequency data are compared to the RMSFEs from ADL-MIDAS models estimated without using any additional quarters of high-frequency data ($j = 0$) to obtain the relative RMSFE. In Panel B the RMSFEs from the ADL-MIDAS nowcasts are scaled by the RMSFEs from ADL models, while in Panel C the RMSFEs from the ADL-MIDAS nowcasts are scaled by the RMSFEs from AR models. Each model is estimated following the procedure described in Section 3, and the 5^{th} and 95^{th} percentiles of the distribution of relative RMSFEs across states are reported in parentheses. The Bayesian information criterion (BIC) is used to select the optimal lag length for each model.

	Revenues		Expenditures	
	$h = 1$	$h = 2$	$h = 1$	$h = 2$
Panel B: RMSFEs Relative to ADL-MIDAS (j=0)				
j=1	0.986	0.908	0.985	0.936
	(0.932, 1.031)	(0.810, 1.035)	(0.826, 1.105)	(0.812, 1.148)
j=2	0.947	0.986	0.965	0.996
	(0.877, 1.037)	(0.924, 1.022)	(0.808, 1.149)	(0.928, 1.143)
j=3	0.932	0.939	0.976	0.958
	(0.862, 1.005)	(0.893, 1.000)	(0.780, 1.099)	(0.809, 1.059)
Panel B: RMSFEs Relative to ADL				
j=1	0.972	0.894	0.898	0.841
	(0.911, 1.049)	(0.814, 0.986)	(0.783, 0.980)	(0.714, 0.950)
j=2	0.940	0.999	0.873	0.941
	(0.862, 1.002)	(0.797, 1.335)	(0.710, 1.008)	(0.799, 1.027)
j=3	0.958	0.962	0.907	0.891
	(0.757, 1.308)	(0.744, 1.298)	(0.731, 0.995)	(0.724, 0.992)
Panel C: RMSFEs Relative to AR				
j=1	0.940	0.867	0.880	0.840
	(0.815, 1.106)	(0.722, 1.047)	(0.708, 1.059)	(0.640, 1.016)
j=2	0.894	0.865	0.868	0.907
	(0.768, 1.059)	(0.700, 1.117)	(0.659, 1.072)	(0.736, 1.012)
j=3	0.825	0.823	0.860	0.843
	(0.661, 1.022)	(0.651, 1.072)	(0.625, 0.995)	(0.625, 0.998)

OA.2 Additional multi-equation results

OA.2.1 State-by-state forecast results



(a) One-year ahead relative RMSFEs **(b)** Two-year ahead relative RMSFEs

Figure OA.2.4: Empirical distribution function of relative RMSFEs from multi-equation forecasts

The figure displays the empirical distribution function (EDF) of the root mean squared forecast error (RMSFE) of the MF-BVAR, BVAR, and VAR models relative to the RMSFE of a RW for one- and two-year ahead forecasts of state and local government revenues and expenditures. Here, each model is estimated following the procedure for multi-equation models described in Section 3. Panel A of the figure reports the results for one-year ahead forecasts while Panel B reports the results for two-year ahead forecasts. Points in each figure denote the state-specific relative RMSFEs associated with each model (ordered from the smallest relative RMSFE to the largest relative RMSFE) and the horizontal axis in each figure presents the percentiles of each empirical distribution function.

Table OA.2.6: Multi-equation forecasts by state

Panel A reports the root mean squared forecast error (RMSFE) of the MF-BVAR, BVAR, and VAR models relative to the RMSFE of a RW for one- and two-year ahead forecasts of state and local government revenues and expenditures at the state level. In Panel B, $p5$, $p10$, $p25$, $p75$, $p90$, and $p95$ refer to the 5^{th}, 10^{th}, 25^{th}, 75^{th}, 90^{th}, and 95^{th} percentiles of the distribution of relative RMSFEs across states, respectively. Here, each model is estimated following the procedure for multi-equation models described in Section 3.

	Revenues						Expenditures					
	MF-BVAR		BVAR		VAR		MF-BVAR		BVAR		VAR	
$h =$	1	2	1	2	1	2	1	2	1	2	1	2
Alabama	1.238	0.724	0.601	0.602	0.658	0.816	1.687	1.235	1.052	0.792	1.179	0.619
Arizona	0.593	0.859	0.676	0.483	0.704	0.792	1.209	1.174	0.932	0.692	0.808	0.725
Arkansas	0.783	0.636	0.698	0.520	0.681	0.711	2.716	2.984	0.923	0.694	1.022	0.759
California	0.686	0.774	0.710	0.579	0.764	1.002	2.441	1.180	1.023	0.758	1.258	0.766
Colorado	0.659	0.826	0.637	0.699	0.701	0.849	1.112	2.466	0.737	0.668	0.951	0.894
Connecticut	0.709	0.822	0.650	0.536	0.713	0.765	2.681	1.457	0.843	0.642	0.908	0.557
Delaware	0.686	0.574	0.654	0.558	0.646	0.682	1.400	2.578	0.927	0.825	1.308	0.988
Florida	0.591	0.685	0.680	0.503	0.710	0.747	2.456	4.513	1.357	0.977	1.264	1.303
Georgia	0.994	0.836	0.639	0.616	0.696	0.735	1.819	2.580	0.850	0.812	0.890	0.877
Idaho	0.626	0.839	0.662	0.447	0.670	0.718	4.272	2.033	1.025	0.842	1.143	0.975
Illinois	0.604	0.809	0.706	0.634	0.709	0.835	1.506	1.053	1.137	0.656	1.315	0.745
Indiana	1.376	0.779	0.782	0.556	0.855	0.644	1.473	1.417	1.076	1.178	1.149	1.198
Iowa	0.539	0.652	0.686	0.512	0.695	0.799	1.773	1.506	0.763	0.780	0.732	1.066
Kansas	0.698	0.706	0.667	0.553	0.705	0.606	1.093	1.595	0.878	0.723	0.870	0.775
Kentucky	0.695	1.138	0.703	0.560	0.758	0.584	2.282	5.738	1.087	1.597	1.227	1.469
Louisiana	0.925	0.827	0.691	0.625	0.690	0.726	1.567	2.245	0.955	1.014	1.146	1.115
Maine	0.979	0.568	0.641	0.519	0.649	0.690	1.567	1.958	0.720	0.785	0.743	1.032
Maryland	0.727	0.718	0.636	0.528	0.679	0.709	0.820	1.740	0.772	0.815	0.453	0.936
Massachusetts	0.653	0.816	0.624	0.581	0.651	0.791	1.147	1.957	0.803	0.833	0.833	0.825
Michigan	0.666	1.261	0.656	0.500	0.775	0.752	1.552	3.474	1.058	0.607	1.456	0.969
Minnesota	0.620	0.949	0.685	0.582	0.730	0.765	2.309	1.969	0.777	0.788	0.810	0.708
Mississippi	0.700	0.722	0.691	0.493	0.679	0.623	1.075	2.663	0.915	0.803	0.982	0.692
Missouri	0.635	0.672	0.712	0.603	0.724	0.846	2.102	1.527	0.971	0.841	0.938	0.854
Montana	0.584	0.655	0.640	0.547	0.687	0.733	1.761	3.873	0.622	0.689	0.701	0.839
Nebraska	0.902	0.909	0.665	0.521	0.739	0.741	2.835	2.516	0.823	0.744	1.045	0.747
Nevada	0.993	1.061	0.730	0.547	0.747	0.764	2.871	3.741	0.894	0.690	0.988	0.767
New Hampshire	1.033	0.558	0.646	0.497	0.723	0.754	2.197	1.854	0.981	0.650	0.991	0.939
New Jersey	0.992	1.441	0.594	0.532	0.650	0.745	3.545	3.264	0.973	0.672	1.313	0.953
New Mecixo	0.680	0.644	0.732	0.539	0.711	0.733	1.076	1.545	0.735	0.661	0.876	0.793
New York	0.720	0.683	0.732	0.733	0.736	0.994	2.907	3.050	1.090	0.848	1.620	0.659
North Carolina	0.506	0.684	0.683	0.581	0.696	0.758	2.254	2.578	1.151	1.437	1.359	1.552
North Dakota	1.543	1.575	0.537	0.507	0.501	0.653	4.322	1.886	0.914	1.688	1.004	1.717
Ohio	0.556	0.734	0.691	0.643	0.770	1.048	1.560	1.198	1.119	0.668	1.348	0.717
Oklahoma	0.683	0.581	0.637	0.471	0.606	0.671	1.082	1.473	0.579	0.634	0.632	0.699
Oregon	0.734	0.846	0.688	0.637	0.720	1.071	3.204	2.083	0.926	0.787	1.285	0.643
Pennsylvania	0.682	0.586	0.684	0.617	0.682	0.837	4.286	1.290	0.942	0.731	0.932	0.923
Rhode Island	0.633	0.747	0.684	0.535	0.690	0.844	3.335	4.202	0.969	0.617	1.050	0.943
South Carolina	0.806	0.681	0.696	0.516	0.760	0.705	2.329	2.885	1.227	1.084	1.283	0.876
South Dakota	0.863	0.946	0.686	0.538	0.666	0.728	1.341	2.657	1.175	0.764	1.053	0.756

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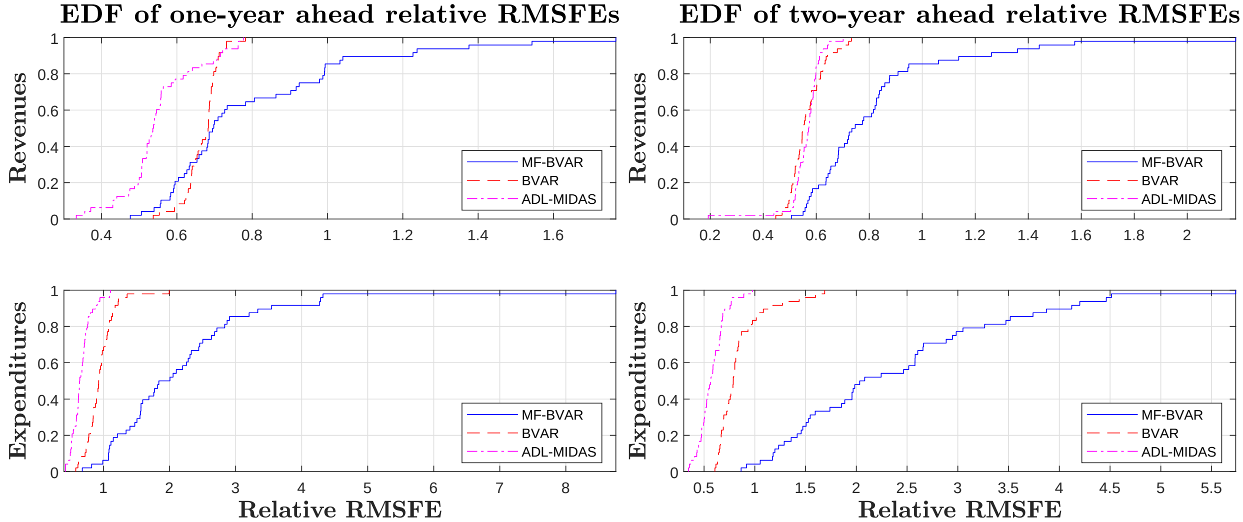
Table OA.2.6 – Continued from the previous page

	Revenues						Expenditures					
	MF-BVAR		BVAR		VAR		MF-BVAR		BVAR		VAR	
$h =$	1	2	1	2	1	2	1	2	1	2	1	2
Tennessee	0.595	0.563	0.684	0.565	0.689	0.696	0.678	0.919	0.667	1.042	0.688	1.085
Texas	1.227	0.506	0.620	0.546	0.795	0.861	2.053	0.865	0.892	0.638	0.982	0.754
Utah	0.582	1.359	0.630	0.630	0.620	0.820	2.006	3.516	1.001	0.803	1.100	0.880
Vermont	0.917	0.877	0.627	0.577	0.670	0.679	0.989	1.358	0.612	0.966	1.022	0.748
Virginia	0.558	0.550	0.685	0.549	0.759	0.780	1.593	1.985	0.846	0.867	1.078	0.846
Washington	1.766	0.609	0.707	0.508	0.759	0.765	2.503	2.605	0.841	0.738	0.900	0.619
West Virginia	1.041	0.637	0.694	0.602	0.645	0.696	8.757	4.122	1.994	1.274	2.421	1.152
Wisconsin	0.476	0.876	0.695	0.722	0.690	1.097	1.837	4.462	1.221	0.933	1.231	1.054
Wyoming	0.988	2.183	0.553	0.679	0.591	0.845	2.634	2.947	0.831	0.802	1.149	0.832
Panel B: Summary Statistics of RMSFEs Relative to Random Walk Across States												
Minimum	0.476	0.506	0.537	0.447	0.501	0.584	0.678	0.865	0.579	0.607	0.453	0.557
$p5$	0.536	0.557	0.590	0.482	0.604	0.621	0.972	1.040	0.621	0.632	0.682	0.619
$p10$	0.565	0.570	0.621	0.498	0.645	0.658	1.078	1.186	0.725	0.645	0.735	0.669
$p25$	0.623	0.648	0.639	0.519	0.670	0.707	1.436	1.489	0.827	0.690	0.895	0.748
Median	0.696	0.741	0.683	0.551	0.696	0.753	1.921	2.058	0.926	0.787	1.034	0.850
$p75$	0.952	0.867	0.695	0.602	0.733	0.828	2.658	2.966	1.055	0.858	1.245	0.981
$p90$	1.171	1.224	0.711	0.641	0.763	0.954	3.482	4.048	1.168	1.150	1.338	1.184
$p95$	1.392	1.455	0.732	0.701	0.777	1.050	4.290	4.468	1.240	1.453	1.472	1.478
Maximum	1.766	2.183	0.782	0.733	0.855	1.097	8.757	5.738	1.994	1.688	2.421	1.717

OA.3 Additional single- and multi-equation forecast comparison results

OA.3.1 State-by-state forecast results



(a) One-year ahead relative RMSFEs **(b)** Two-year ahead relative RMSFEs

Figure OA.3.5: Empirical distribution function of relative RMSFEs from single-equation and multi-equation forecasts

The figure displays the empirical distribution function (EDF) of relative root mean square forecast errors (relative RMSFEs) from one- and two-year ahead forecasts of state and local government revenues and expenditures. Here, each model is estimated following the procedure for multi-equation models described in Section 3. Panel A of the figure reports the results for one-year ahead forecasts while Panel B reports the results for two-year ahead forecasts. Panel A of the figure reports the results for one-year ahead forecasts while Panel B reports the results for two-year ahead forecasts. Points in each figure denote the state-specific relative RMSFEs associated with each model (ordered from the smallest relative RMSFE to the largest relative RMSFE) and the horizontal axis in each figure presents the percentiles of each empirical distribution function.

Table OA.3.7: Comparing single- and multi-equation forecasts by state

Panel A reports the root mean squared forecast error (RMSFE) of the MF-BVAR, BVAR, and ADL-MIDAS models relative to the RMSFE of a RW for one- and two-year ahead forecasts of state and local government revenues and expenditures at the state level. In Panel B $p5$, $p10$, $p25$, $p75$, $p90$, and $p95$ refer to the 5^{th}, 10^{th}, 25^{th}, 75^{th}, 90^{th}, and 95^{th} percentiles of the distribution of relative RMSFEs across states, respectively. Here, each model is estimated following the estimation procedures described in Section 3.

	Revenues						Expenditures					
	MF-BVAR		BVAR		ADL-MIDAS		MF-BVAR		BVAR		ADL-MIDAS	
$h =$	1	2	1	2	1	2	1	2	1	2	1	2
Alabama	1.238	0.724	0.601	0.602	0.558	0.593	1.687	1.235	1.052	0.792	0.701	0.586
Arizona	0.593	0.859	0.676	0.483	0.371	0.572	1.209	1.174	0.932	0.692	0.613	0.474
Arkansas	0.783	0.636	0.698	0.520	0.533	0.525	2.716	2.984	0.923	0.694	0.760	0.590
California	0.686	0.774	0.710	0.579	0.667	0.576	2.441	1.180	1.023	0.758	0.425	0.654
Colorado	0.659	0.826	0.637	0.699	0.558	0.562	1.112	2.466	0.737	0.668	0.491	0.447
Connecticut	0.709	0.822	0.650	0.536	0.521	0.581	2.681	1.457	0.843	0.642	0.515	0.476
Delaware	0.686	0.574	0.654	0.558	0.497	0.566	1.400	2.578	0.927	0.825	0.729	0.669
Florida	0.591	0.685	0.680	0.503	0.585	0.571	2.456	4.513	1.357	0.977	1.092	0.703
Georgia	0.994	0.836	0.639	0.616	0.544	0.532	1.819	2.580	0.850	0.812	0.684	0.663
Idaho	0.626	0.839	0.662	0.447	0.431	0.514	4.272	2.033	1.025	0.842	0.878	0.675
Illinois	0.604	0.809	0.706	0.634	0.617	0.541	1.506	1.053	1.137	0.656	0.618	0.470
Indiana	1.376	0.779	0.782	0.556	0.722	0.591	1.473	1.417	1.076	1.178	0.800	0.656
Iowa	0.539	0.652	0.686	0.512	0.500	0.530	1.773	1.506	0.763	0.780	0.673	0.600
Kansas	0.698	0.706	0.667	0.553	0.531	0.550	1.093	1.595	0.878	0.723	0.637	0.555
Kentucky	0.695	1.138	0.703	0.560	0.506	0.539	2.282	5.738	1.087	1.597	0.765	0.757
Louisiana	0.925	0.827	0.691	0.625	0.697	0.612	1.567	2.245	0.955	1.014	0.944	0.978
Maine	0.979	0.568	0.641	0.519	0.641	0.589	1.567	1.958	0.720	0.785	0.657	0.405
Maryland	0.727	0.718	0.636	0.528	0.555	0.533	0.820	1.740	0.772	0.815	0.548	0.683
Massachusetts	0.653	0.816	0.624	0.581	0.540	0.566	1.147	1.957	0.803	0.833	0.496	0.611
Michigan	0.666	1.261	0.656	0.500	0.521	0.521	1.552	3.474	1.058	0.607	0.513	0.346
Minnesota	0.620	0.949	0.685	0.582	0.475	0.552	2.309	1.969	0.777	0.788	0.524	0.431
Mississippi	0.700	0.722	0.691	0.493	0.521	0.440	1.075	2.663	0.915	0.803	0.588	0.564
Missouri	0.635	0.672	0.712	0.603	0.509	0.600	2.102	1.527	0.971	0.841	0.724	0.665
Montana	0.584	0.655	0.640	0.547	0.538	0.515	1.761	3.873	0.622	0.689	0.503	0.650
Nebraska	0.902	0.909	0.665	0.521	0.488	0.504	2.835	2.516	0.823	0.744	0.589	0.506
Nevada	0.993	1.061	0.730	0.547	0.506	0.582	2.871	3.741	0.894	0.690	0.688	0.588
New Hampshire	1.033	0.558	0.646	0.497	0.333	0.588	2.197	1.854	0.981	0.650	0.673	0.509
New Jersey	0.992	1.441	0.594	0.532	0.472	0.568	3.545	3.264	0.973	0.672	0.716	0.568
New Mecixo	0.680	0.644	0.732	0.539	0.440	0.553	1.076	1.545	0.735	0.661	0.608	0.477
New York	0.720	0.683	0.732	0.733	0.716	0.599	2.907	3.050	1.090	0.848	0.705	0.518
North Carolina	0.506	0.684	0.683	0.581	0.546	0.626	2.254	2.578	1.151	1.437	0.834	0.891
North Dakota	1.543	1.575	0.537	0.507	0.355	0.192	4.322	1.886	0.914	1.688	0.513	0.612
Ohio	0.556	0.734	0.691	0.643	0.763	0.580	1.560	1.198	1.119	0.668	0.623	0.546
Oklahoma	0.683	0.581	0.637	0.471	0.526	0.522	1.082	1.473	0.579	0.634	0.633	0.525
Oregon	0.734	0.846	0.688	0.637	0.763	0.587	3.204	2.083	0.926	0.787	0.694	0.538
Pennsylvania	0.682	0.586	0.684	0.617	0.556	0.599	4.286	1.290	0.942	0.731	0.709	0.500
Rhode Island	0.633	0.747	0.684	0.535	0.430	0.612	3.335	4.202	0.969	0.617	0.542	0.374
South Carolina	0.806	0.681	0.696	0.516	0.540	0.594	2.329	2.885	1.227	1.084	0.904	0.777
South Dakota	0.863	0.946	0.686	0.538	0.507	0.647	1.341	2.657	1.175	0.764	0.769	0.685
Tennessee	0.595	0.563	0.684	0.565	0.596	0.575	0.678	0.919	0.667	1.042	0.584	0.647

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Table OA.3.7 – Continued from the previous page

	Revenues						Expenditures					
	MF-BVAR		BVAR		ADL-MIDAS		MF-BVAR		BVAR		ADL-MIDAS	
$h =$	1	2	1	2	1	2	1	2	1	2	1	2
Texas	1.227	0.506	0.620	0.546	0.629	0.534	2.053	0.865	0.892	0.638	0.640	0.526
Utah	0.582	1.359	0.630	0.630	0.509	0.598	2.006	3.516	1.001	0.803	0.632	0.529
Vermont	0.917	0.877	0.627	0.577	0.519	0.554	0.989	1.358	0.612	0.966	0.469	0.496
Virginia	0.558	0.550	0.685	0.549	0.536	0.575	1.593	1.985	0.846	0.867	0.424	0.455
Washington	1.766	0.609	0.707	0.508	0.564	0.520	2.503	2.605	0.841	0.738	0.621	0.356
West Virginia	1.041	0.637	0.694	0.602	0.707	0.609	8.757	4.122	1.994	1.274	1.105	0.767
Wisconsin	0.476	0.876	0.695	0.722	0.777	0.642	1.837	4.462	1.221	0.933	0.617	0.428
Wyoming	0.988	2.183	0.553	0.679	0.557	0.702	2.634	2.947	0.831	0.802	0.745	0.573
Panel B: Summary Statistics of RMSFEs Relative to Random Walk Across States												
Minimum	0.476	0.506	0.537	0.447	0.333	0.192	0.678	0.865	0.579	0.607	0.424	0.346
$p5$	0.536	0.557	0.590	0.482	0.370	0.497	0.972	1.040	0.621	0.632	0.464	0.373
$p10$	0.565	0.570	0.621	0.498	0.434	0.517	1.078	1.186	0.725	0.645	0.498	0.429
$p25$	0.623	0.648	0.639	0.519	0.506	0.533	1.436	1.489	0.827	0.690	0.566	0.487
Median	0.696	0.741	0.683	0.551	0.537	0.572	1.921	2.058	0.926	0.787	0.639	0.566
$p75$	0.952	0.867	0.695	0.602	0.590	0.594	2.658	2.966	1.055	0.858	0.726	0.660
$p90$	1.171	1.224	0.711	0.641	0.713	0.612	3.482	4.048	1.168	1.150	0.865	0.741
$p95$	1.392	1.455	0.732	0.701	0.763	0.643	4.290	4.468	1.240	1.453	0.959	0.788
Maximum	1.766	2.183	0.782	0.733	0.777	0.702	8.757	5.738	1.994	1.688	1.105	0.978

OA.4 Additional out-of-sample results

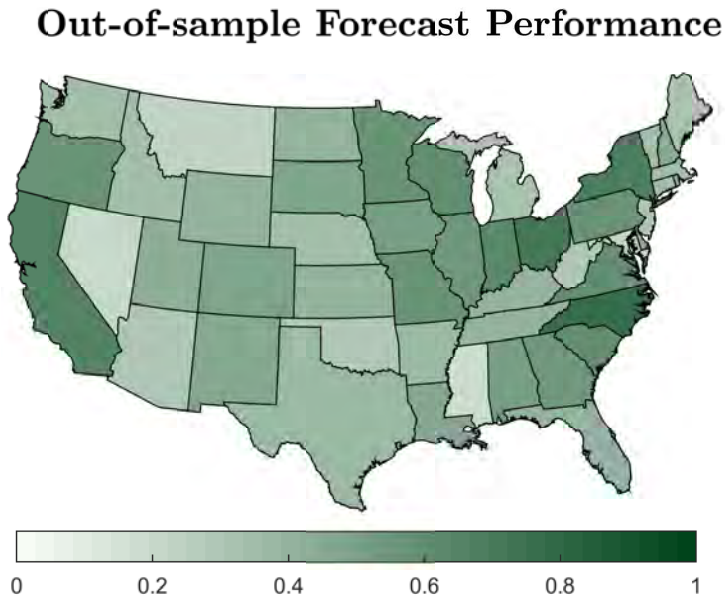

Figure OA.4.6: Out-of-sample forecast performance by state
The figure displays the average out-of-sample forecast performance associated with the nine models we consider (summarized in Table 6) at the state level. Here, out-of-sample forecast performance is determined by Mincer and Zarnowitz (1969) (MZ, hereafter) tests. For a given state, we forecast each budget series (2) at each forecast horizon (2) using each model under consideration (9) and conduct a total of $2 \times 2 \times 9 = 36$ state-specific MZ tests. The figure then displays the proportion of these MZ tests that are rejected on a state-by-state basis. The scale ranges from a rejection rate of zero percent, represented by the lightest color, to a rejection rate of 100 percent, represented by the darkest color.

Table OA.4.8: Mincer and Zarnowitz (1969) tests of forecast performance by state

The table reports state-level out-of-sample forecast performance associated with each of the nine models we consider (summarized in Table 6). Here, out-of-sample forecast performance is determined by Mincer and Zarnowitz (1969) (MZ, hereafter) tests. For a given state, we forecast each budget series (revenues or expenditures) at each forecast horizon ($h = 1$ or $h = 2$ years) using each model under consideration and conduct a total of $2 \times 2 \times 9 = 36$ state-specific MZ tests. The table then displays the number of these MZ tests that are rejected, as well as percentage of these MZ tests that are rejected, on a state-by-state basis.

	Rejections	Rejection rate (%)
Mississippi	7	19.44
Nevada	8	22.22
Maryland	9	25.00
Montana	9	25.00
Arizona	11	30.56
New Jersey	11	30.56
Oklahoma	11	30.56
West Virginia	11	30.56
Maine	12	33.33
Michigan	12	33.33
Connecticut	13	36.11
Idaho	13	36.11
Massachusetts	13	36.11
Nebraska	13	36.11
Vermont	13	36.11
Washington	13	36.11
Arkansas	14	38.89
Texas	14	38.89
Florida	15	41.67
Kansas	15	41.67
Kentucky	15	41.67
North Dakota	15	41.67
Tennessee	15	41.67
Wyoming	15	41.67
Delaware	16	44.44
Rhode Island	16	44.44
Utah	16	44.44
Louisiana	17	47.22
New Hampshire	17	47.22
New Mecixo	17	47.22
Colorado	18	50.00
South Dakota	18	50.00

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Table OA.4.8 – Continued from the previous page

	Rejections	Rejection rate (%)
Alabama	19	52.78
Iowa	19	52.78
Georgia	20	55.56
Illinois	20	55.56
Minnesota	21	58.33
Missouri	21	58.33
Oregon	21	58.33
Pennsylvania	21	58.33
South Carolina	22	61.11
Virginia	22	61.11
Wisconsin	22	61.11
Indiana	23	63.89
California	24	66.67
New York	25	69.44
Ohio	26	72.22
North Carolina	28	77.78

OA.5 Additional results on economic heterogeneity of forecasts

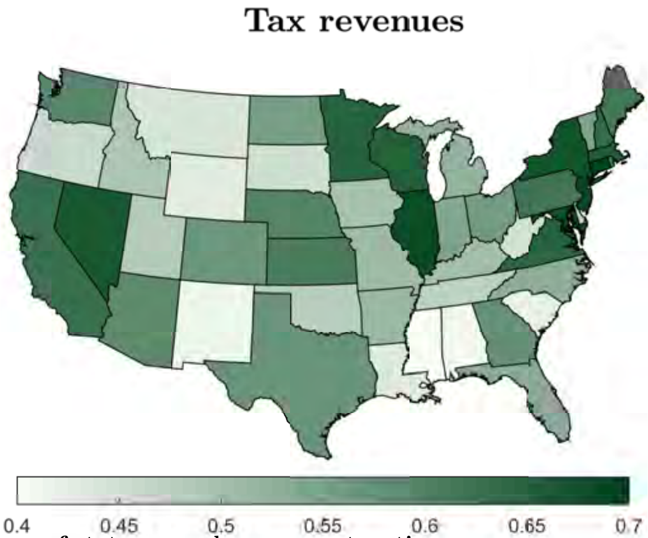

Figure OA.5.7: **Sources of state general revenues: taxation**
The figure displays the proportion of total state and local government general revenues that are collected from taxation. In each year between 2004 and 2014, data from the U.S. Census Bureau's annual survey of State & Local Government Finance is used to compute the proportion of each state's general revenues derived collectively from six different types of taxes. This annual proportion is then averaged across all years and reported in the figure. The scale ranges from a proportion of 0.40, represented by the lightest color, to a proportion of 0.70, represented by the darkest color.

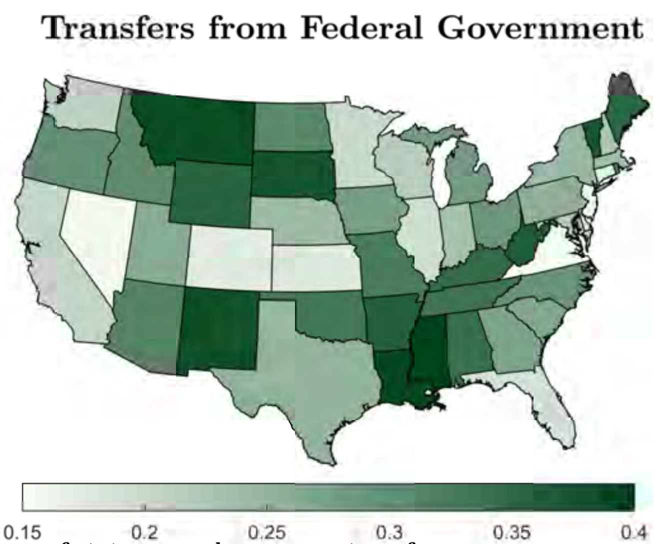

Figure OA.5.8: **Sources of state general revenues: transfers**
The figure displays the proportion of total state and local government general revenues that are obtained from transfers from the Federal Government. In each year between 2004 and 2014, data from the U.S. Census Bureau's annual survey of State & Local Government Finance is used to compute the proportion of each state's general revenues derived from transfers from the Federal Government. This annual proportion is then averaged across all years and reported in the figure. The scale ranges from a proportion of 0.15, represented by the lightest color, to a proportion of 0.40, represented by the darkest color.

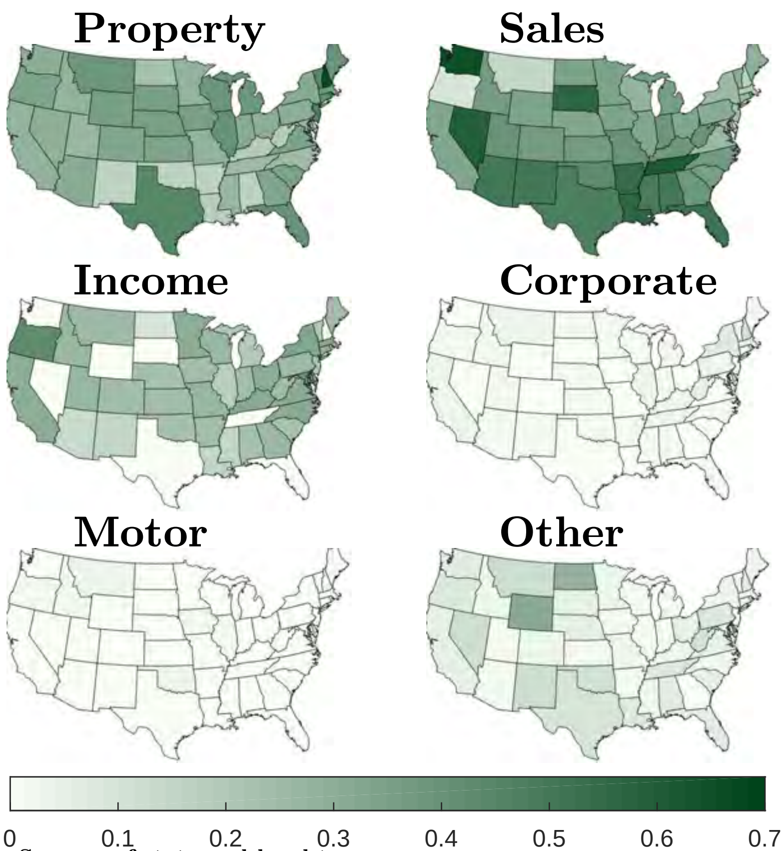

Figure OA.5.9: **Sources of state and local tax revenues**

The figure displays the proportion of total state and local government tax revenues that are collected from each of six different categories of taxes: property, sales, individual income, corporate income, motor vehicle licenses, and other. In each year between 2004 and 2014, data from the U.S. Census Bureau's annual survey of State & Local Government Finance is used to compute the proportion of each state's tax revenues derived from each of the six sources. This annual proportion is then averaged across all years and reported in the figure. The scale ranges from a proportion of zero, represented by the lightests color, to a proportion of 0.70, represented by the darkest color.