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Macroeconomic forecasting in times of crises*

Pablo Guerrón-Quintana† and Molin Zhong‡

January 31, 2017

Abstract

We propose a parsimonious semiparametric method for macroeconomic forecasting during episodes of sudden changes. Based on the notion of clustering and similarity, we partition the time series into blocks, search for the *closest* blocks to the most recent block of observations, and with the matched blocks we proceed to forecast. One possibility is to compare local means across blocks, which captures the idea of matching directional movements of a series. We show that our approach does particularly well during the Great Recession and for variables such as inflation, unemployment, and real personal income. When supplemented with information from housing prices, our method consistently outperforms parametric linear, nonlinear, univariate, and multivariate alternatives for the period 1990 - 2015.

1 Introduction

The Great Recession was a sobering experience in many dimensions. One such lesson came from the difficulties that macroeconometric models had in predicting the abrupt swings around the crisis. Figure 1 shows data for industrial production growth as well as one quarter ahead forecasts from the Survey of Professional Forecasters and the Board of Governors' Greenbook. It is not difficult to see that the forecasts were off during the recession. Both the Greenbook and SPF forecasts called for much higher industrial production growth through much of the crisis. Not surprisingly, macroeconomists were criticized for the poor performance of their forecasts (Ferrara, Marcellino, and Mogliani (2015), Del Negro and Schorfheide (2013), Potter (2011)). Given this grim backdrop, in this paper, we develop a forecasting algorithm that improves

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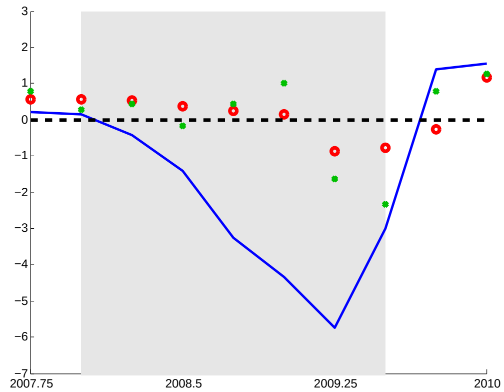
upon parametric models during rapid changes in the data such as in the 2008/2009 crisis. We borrow ideas from the machine learning (clustering/similarity/nearest neighbor) and nonparametric regression literatures.

Our approach combines the flexibility of nonparametric nearest neighbor (NN) methods (Stone (1977), Farmer and Sidorowich (1987), Yakowitz (1987), Diebold and Nason (1990), Mulhern and Caprara (1994)) with the parsimony of autoregressive integrated moving average (ARIMA) models (Hamilton (1994)). Our method is implemented in a sequence of steps. We begin by dividing the time series of interest in blocks. Next, we search for the *closest* block to the most recent block of observations. Inspired by the machine learning literature (Murphy (2012)) and the smoothing estimators literature (Lo, Mamaysky, and Wang (2000)), we propose two algorithms to cluster the data into blocks. The first method, which we call *match to levels*, compares directly two blocks of data. In contrast, the second method, *match to deviations*, compares deviations from a local mean of two sequences of a series. With the matched block, we forecast using a corrected ARMA/ARIMA prediction. The correction is based on an error term constructed with the matched block of data. This strategy of correcting a possibly misspecified parametric pilot estimate is reminiscent of the parametrically-guided nonparametric regression literature (Glad (1998), Ullah and Rahman (2002), Martins-Filho, Mishra, and Ullah (2008)). The resulting scheme excels during sudden movements in the data, but also forecasts comparably well to an ARMA/ARIMA model during more stable times.

Beyond applying and expanding semiparametric and machine learning tools to recent data, this paper makes three important contributions. First, we analyze systematically the forecasting performance of a nearest neighbor method to a wide class of macroeconomic and financial variables. In contrast, previous papers have concentrated on single variable exercises based on GDP (Ferrara, Guegan, and Rakotomarolayh (2010)), unemployment rates (Golan and Perloff (2004)), interest rates (Barkoulas, Baum, and Chakraborty (2003)), commodity prices (Agnon, Golan, and Shearer (1999)), or exchange rates (Mizrach (1992), Fernandez-Rodriguez and Sosvilla-Rivero (1998), Fernandez-Rodriguez, Sosvilla-Rivero, and Andrada-Felix (1999), Meade (2002)). Furthermore, our paper evaluates the forecasting performance of the nearest neighbor method during the Great Recession, which none of these papers do. Second, while many previous studies have concentrated on high-frequency or short-run forecasting (Lo, Mamaysky, and Wang (2000)), we explore the performance of these methods for longer horizons. Finally, we propose two extensions of the baseline model. First, we introduce a variant of our model that exploits information from financial markets (excess bond premium), housing markets (house price index), or oil markets (real oil price) that enhances substantially the forecasting ability of our method. Second, we consider a multivariate extension of the model that forecasts well when compared to a vector autoregression. We view both as novel contributions to the related literature.

Based on monthly data covering the past five decades, our main findings can be summarized as follows. First, our one-month ahead forecast is almost always at least as comparable as, and oftentimes significantly outperforms, forecasts from optimally-selected ARMA/ARIMA models. A further important point to note

Industrial production



Greenbook forecast (green dots), SPF forecast (red dots), and data (blue solid). Shaded areas are NBER recession dates.

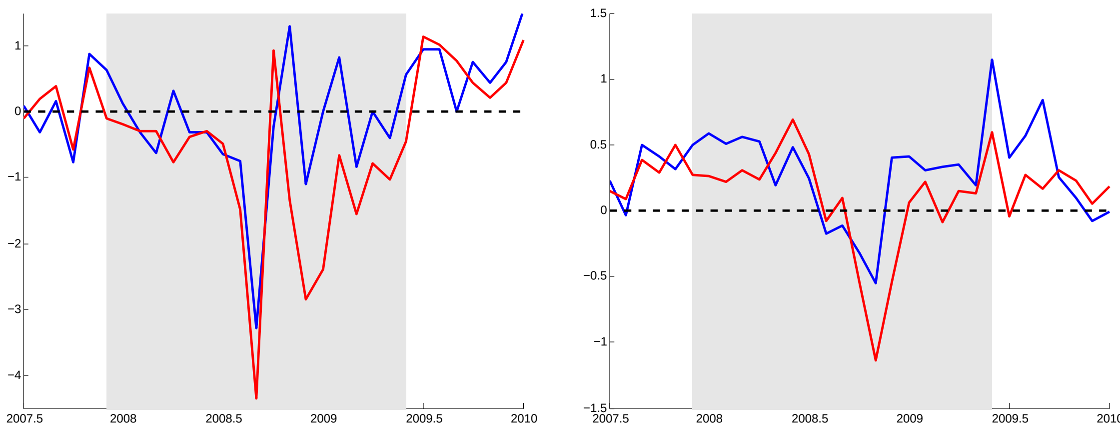
Figure 1: Industrial production forecasts during the Great Recession

is that in no instance do the ARMA/ARIMA models forecast significantly better than our model. The same cannot be said for the Markov-switching autoregression model, another popular nonlinear model, which we find often forecasts worse than the linear models. Second, our approach shows substantial gains during the Great Recession. This is vividly clear for variables such as payroll employment, industrial production, and real personal income. Third, when we supplement our NN method with house price information, we consistently forecast better than several competing linear models. Furthermore, based on the Diebold and Mariano (1995) test, our forecast is statistically significantly superior when compared to those generated from linear models for 60 percent of the series in our sample. We do a suggestive comparison between quarterly aggregates of our monthly forecasts and the Survey of Professional Forecasters and Board of Governors' Greenbook nowcasts in the Great Recession, finding that our forecasts are highly competitive. We also evaluate multi-step ahead forecasts ranging from 3 months to 12 months ahead. Our forecasts continue to perform well, beating the standard ARMA/ARIMA model for all data series considered, although the significance level of the difference drops for several series. Finally, we compare a multivariate extension of our approach to a vector autoregression, finding that our model forecasts significantly better than the linear model at the 1 month horizon for 6 out of the 13 series.

The reader might be reasonably skeptical about our enterprise given the limited/modest success enjoyed by nearest neighbor methods in the past. As we discuss at length in the main text, our approach forecasts better than linear alternatives because of a combination of conditions. First, our method does well during sharp movements in the data. These sudden changes were not present in previous studies, which were based on more stable samples (such as the late 1980s and early 1990s). Second, we perform better relative to previous studies because we have more data to characterize patterns that were nonexistent or mildly present in shorter samples. For example, we find that our approach uses information from the recessions in the 1970s and 1980s to forecast industrial production and inflation during the Great Recession. These two points are clearly seen in Figure 2, where we plot industrial production and inflation during the recent crisis (red lines) and the best match from our approach (blue lines). The matched series indeed capture the sharp declines in the variables of interest, which leads to a better forecast.[1] Finally, our approach also needs that the series under study be reasonably persistent. If the data lacks persistence or does not display consistent patterns (as is the case with hourly earnings), our methodology does not improve over alternative linear approaches.

A further advantage of our estimation approach is its ease of computation and flexibility. Although in this paper we only consider the canonical ARMA/ARIMA and VAR models as baselines, in theory any number of linear or nonlinear models can be used as the baseline model in our framework. On top of the baseline model, only two parameters of interest must be estimated: a match length parameter and a parameter that governs the number of top matches over which to average. We choose these parameters based off of previous out-of-sample forecasting performance using a mean squared error criterion.

(a) Industrial Production (b) Inflation



Red lines correspond to the actual data during the crisis. Blue lines correspond to the best matched series from our nearest neighbor approach. Shaded areas are NBER recession dates.

Figure 2: Actual Data and Matched Series in the Great Recession

Our work is closely related to recent studies that emphasize the increasing difficulties in forecasting macroeconomic variables. For example, Stock and Watson (2007) conclude that inflation "has become harder to forecast." They advocate the use of time-varying parameters or stochastic volatility to capture the dynamics of inflation. The Great Recession just reinforced the challenges that the profession faces when forecasting the change in prices (Robert Hall, 2011 AER presidential address; Del Negro, Giannoni, and Schorfheide (2014)). Our approach provides a fresh look into the inflation forecast conundrum. Importantly, similar

[1] We show in Section 5 that most of the matched series come from the 1980 recessions and a few observations from 1975.

to the findings of Del Negro, Giannoni, and Schorfheide (2014), we report that information from financial markets (in particular, house prices) tends to improve forecasts during the Great Recession. Unlike Stock and Watson (2007)'s and Del Negro, Hasegawa, and Schorfheide (2015)'s results, we find that using financial information does not worsen the predictive power of our approach outside the crisis. Broadly speaking, we view our methodology as a complementary tool to the collection of available methods to forecast macroeconomic variables.

We proceed as follows. Sections 2 and 3 outline our methodology. We discuss the data and our forecasting exercise in Section 4. We present an extension of our model that allows for exogenous data in Section 5. The last section provides some final thoughts and conclusions.

2 Nearest Neighbor Matching Algorithm

We first briefly review the nearest neighbor econometric framework to fix ideas. Our forecasting model builds on to this benchmark. Let $Y_T = \{y_1, y_2, \ldots, y_T\}$ denote a collection of observations. We suppose a general nonlinear autoregressive structure:

$$y_t = g(y_{t-1}, ...y_{t-k}) + \epsilon_t$$

with the assumption that $\mathbb{E}(\epsilon_t|Y_{t-1}) = 0$.

The goal of the nearest neighbor algorithm is to estimate the conditional expectation function:

$$\mathbb{E}(y_t|Y_{t-1}) = g(y_{t-1}, ..., y_{t-k})$$

To this end, we form the following nonparametric estimator of the function $g(y_{t-k}, ..., y_{t-1})$:

$$\widehat{g} = \frac{\sum I\left(dist(y_{j-k:j-1}, y_{t-k:t-1}) \leq dist_{m(T)}\right) y_j}{\sum I\left(dist(y_{j-k:j-1}, y_{t-k:t-1}) \leq dist_{m(T)}\right)}$$

where $y_{t-k:t-1} = \{y_{t-1}, ..., y_{t-k}\}$, $I(.)$ is the indicator function, $dist(.,.)$ is a distance function to be defined later, $dist_{m(T)}$ is a threshold level so that all matches with a distance below it are used. The summation is over the number of matches. This number in turn depends on the sample size T. Allowing the number of nearest neighbors m to grow slowly as the number of observations T increases (specifically, $\frac{m}{T} \rightarrow 0$ as $m, T \rightarrow \infty$) is a crucial condition for consistency of the nearest neighbor estimator (Yakowitz (1987)). Further detailed conditions on the convergence of the nearest neighbor estimator can be found in that paper, an important one being a sufficient degree of smoothness of the $g(.)$ function (at least twice continuously differentiable).

Operationally, our objectives are 1) to cluster data in blocks of k elements, say $\mathbb{C}_j = \{[y_{t_1}, y_{t_1+1}, \ldots, y_{t_1+k-1}],$ $[y_{t_2}, y_{t_2+1}, \ldots, y_{t_2+k-1}], \ldots, [y_{t_n}, y_{t_n+1}, \ldots, y_{t_n+k-1}]\}$; this cluster contains t_n sets/blocks of observations of size k each; and 2) assign the most recent k observations $[y_{T-k+1}, \ldots, y_T]$ to some cluster with M denoting the number of clusters; and 3) based on this assignment, forecast the next observation y_{T+1}.

We propose two main classes of matching algorithms (distance functions):

1. Match to levels

2. Match to deviations from local mean

Matching to levels makes more sense either when the level of a data series itself has important economic or forecasting value or when the series is clearly stationary. *Matching to deviations* from local mean makes more sense when the researcher would like to match the directional movements of the series as opposed to the overall level.

Match to levels The basic idea behind this alternative is to compare directly two sequences of series. This takes into account both the overall level of the series and its movements.

Let us compare two sequences of series of length k (wlog to the first sequence of length k) $[y_{t-k+1}, \ldots, y_t]$ vs. $[y_1, y_2, \ldots, y_k]$. The *similarity* between these two blocks of data is captured by the distance function:

$$dist = \sum_{i=1}^{k} weighs(i) \left(y_{t+1-i} - y_{k+1-i}\right)^2 . \tag{1}$$

Here, $weighs(i)$ is the importance (or weight) given to observation i.

Match to deviations from local mean This alternative compares deviations from a local mean of two sequences of a series. By doing so, we aim to capture the idea of matching directional movements of a series rather than the overall levels.

As before, we are interested in comparing two sequences of series of length k : $[y_{t-k+1}, ..., y_t]$ vs. $[y_1, y_2, ..., y_k]$. Denote $\overline{y}_t$ as the local mean $\overline{y}_t = \frac{1}{k}\sum_{j=1}^{k} y_{t+1-j}$, then our similarity function is:

$$dist = \sum_{i=1}^{k} weighs(i) \left((y_{t+1-i} - \overline{y}_t) - (y_{k+1-i} - \overline{y}_k)\right)^2 .$$

In our empirical exercises, we choose *weighs* to be a decreasing, linear function in i.

$$weighs(i) = \frac{1}{i}$$

We think that this weighing function provides a good compromise between simplicity and giving the highest weights to most recent observations.[2] Upon fixing the weighting function, the empirical model is completed by specifying the match length k and the number of forecasts to average over m.

3 Forecasting Model

Our approach is parsimonious. Relative to the baseline nearest neighbor algorithm, we adjust the current forecast from a baseline ARMA/ARIMA model with the model's forecast errors from previous similar time periods, where similarity is defined by the distance function. This approach is in the same spirit as the parametrically-guided nonparametric regression literature (Glad (1998), Ullah and Rahman (2002), Martins-Filho, Mishra, and Ullah (2008)), which has shown the potential finite-sample benefits of using a parametric pilot estimate to reduce the bias relative to a purely nonparametric regression without a variance penalty.

Without loss of generality, let us suppose that the first sequence is the one that is matched, i.e. the sequence that has the highest similarity (smallest distance) with the current sequence. To generate the forecast, we use the following formula:

$$\hat{y}_{t+1} = (y_{k+1} - \hat{y}_{k+1,ARMA}) + \hat{y}_{t+1,ARMA},$$

where $\hat{y}_{t+1,ARMA}$ is the forecast from an ARMA/ARIMA model. We select an ARMA/ARIMA model as the auxiliary model because our data is monthly with high variability. Hence, an autoregressive model would have a hard time capturing these movements.[3,4]

Of course, we must average the forecasts over the top m matches, which is what is done in the empirical section. Formally, the adjusted forecasting model is

$$\hat{y}_{t+1} = \frac{1}{m}\sum_{ii}^{m}\left(y_{l(ii)+1} - \hat{y}_{l(ii)+1,ARMA}\right) + \hat{y}_{t+1,ARMA}$$

where $\{y_{l(ii)-k+1}, y_{l(ii)-k+2}, \ldots, y_{l(ii)-1}, y_{l(ii)}\}$ is the iith closest match to $\{y_{t-k+1}, y_{t-k+2}, \ldots, y_{t-1}, y_t\}$.

[2] Other weighing alternatives are Del Negro, Hasegawa, and Schorfheide (2015)'s dynamic weighs scheme and exponential kernels as in Lo, Mamaysky, and Wang (2000).

[3] A baseline nonparametric version of our approach would consist of using the next observation in the matched block as the forecast. That is, suppose the first sequence gives the best match, then our forecast is $\hat{y}_{t+1} = y_{k+1}$. Alternatively, we could use a "random walk" forecast: $\hat{y}_{t+1} = y_k$

[4] To some degree, our approach is reminiscent of Frankel and Froot (1986)'s chartist-fundamentalist model of exchange rates. In their paper, a mixture of an ARIMA model (chartist) and Dornbusch's overshooting (fundamentalist) model is used to forecast exchange rates. If we take past patterns as proxies for fundamentals in the economy, we could argue that the fundamentalist component in our approach corresponds to the correction term $\hat{y}_{t+1,ARMA}$.

3.1 Discussion

Nearest neighbor methods have a decidedly local flavor, as emphasized by much of the previous literature (e.g. Farmer and Sidorowich (1987), Diebold and Nason (1990)). This fact can be seen by noticing that information contained in data related to the top m matches "close" to the current sequence at hand have full weight in the adjustment step, whereas series "far" from this sequence have no weight[5]. This local nature of the estimator is true for nonparametric estimation in general (Pagan and Ullah (1999)). We can contrast this local behavior of the nearest neighbor estimator with global methods such as linear ARMA/ARIMA models, which use all historical data with equal weight. The latter approach may be inappropriate during times of crises, where economic relationships prevailing during normal times tend to break down[6].

Furthermore, we believe that adjusting a preliminary forecast from an ARMA/ARIMA model is an important first step in the forecasting procedure. Monthly macroeconomic data is generally well-described by ARMA or ARIMA dynamics, being a popular reduced-form model for consumption growth (Schorfheide, Song, and Yaron (2014)) and unemployment (Montgomery, Zarnowitz, Tsay, and Tiao (1998)), among many other macroeconomic series. The important moving average component often found when modeling monthly data suggests the need to first remove these dynamics. Guiding the nonparametric estimator with a parametric pilot has been proposed before on cross-sectional data, the general intuition being to choose a parametric guide that is "close" to the true nonparametric function (Martins-Filho, Mishra, and Ullah (2008)).

3.2 Recursive out-of-sample forecasting exercise

To perform out-of-sample forecasting, we have a few parameters that we would like to select to determine the optimal forecasting model. We sketch an algorithm to select the match length k and how many forecasts we average over m using predictive least squares.

Suppose we have KM forecasting models: all combinations of $k = 1, 2, ..., K$ and $m = 1, 2, ..., M$. Index the forecasts made by these models for time t with $\hat{y}_{t,km}$.

$$argmin_{k,m} \quad \frac{1}{t - t_1} \sum_{\tau=t_1}^{t} (y_\tau - \hat{y}_{\tau,km})^2 \tag{2}$$

We select the optimal forecasting model by considering the out-of-sample forecasting performance as evaluated by the mean squared error using data up until the current time period t (shown in the formula above). We recursively select the optimal forecasting model at each time to forecast.[7]

[5] In the baseline nonparametric version of the approach, where we do not first estimate an ARMA/ARIMA model, sequences far from the current sequence have no bearing on the forecast.

[6] We thank Luca Guerrieri for raising our attention to this important point.

[7] Our selection mechanism shares many similarities with bandwidth selection in kernel regressions. For an application in

An important issue is the choice of t_1, which is the first time period of the model selection criterion. This may be difficult to choose if the data have structural breaks , such as a break in the optimal lag length value k^*. If so, a k^*, m^* that does well at the beginning of the sample may not do well moving forward. We could let t_1 be rolling with t to account for structural breaks, although we do not do so in our empirical application.

4 Illustrative simulation

Before we apply our methodology to the macroeconomic and financial data, we present an example of a nonlinear data generating process in which our model performs well.

Our data generating process is the following:

$$\begin{aligned} y_t = & \left(1-\Phi\left(a\left(mean\left(y_{t-10},..,y_{t-1}\right)-a_2\right)\right)\right)\left(c+\phi y_{t-1}\right)+ \\ & \Phi\left(a\left(mean\left(y_{t-10},..,y_{t-1}\right)-a_2\right)\right)\left(c_2+\phi_2 y_{t-1}\right)+\sigma\epsilon_t+\theta\sigma\epsilon_{t-1} \end{aligned} \tag{3}$$

where Φ is the normal cumulative distribution function. Importantly, this process implies a smooth function of the past data so that Yakowitz (1987)'s conditions for consistency are met.

Table 1: Parameter Values

a	40	c_2	0
a_2	−0.043	ϕ_2	0
c	−0.002	σ	0.1
ϕ	0.95	θ	−0.3

Table 1 shows the parameter values for the data generating process. The process falls in the class of smooth transition autoregression (STAR) models. Intuitively, it transitions between two different regimes via a nonlinear function of the data in the past 10 periods. The first regime has "disaster"-type characteristics. It has a lower intercept c. The data also becomes very persistent given the value of ϕ. The second regime is a normal regime with no persistence. The parameter a_2 controls the frequency of the first regime. We set it so that the first regime occurs around 30% of the time. The parameter a controls how quickly transitions occur from one regime to another.

Figure 3 gives an example of a simulated series from the data generating process. Note that for most of the time, regime 2 dominates. Occasionally, as can be seen around periods 400 and 700, a string of bad shocks can trigger the model to enter into regime 1 dynamics. Importantly, as these transitions are functions of past data, they are in theory predictable, although in a nonlinear fashion.

finance, see Lo, Mamaysky, and Wang (2000)

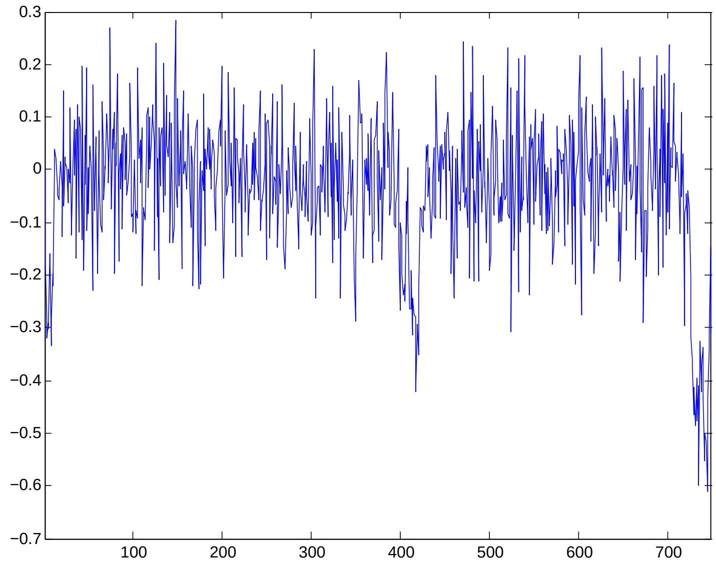


Figure 3: Simulation of data length 750.

We compare the forecasting performance of our model to a linear ARMA model on data series of length 750. We do the recursive out-of-sample forecasting exercise with the following specifications:

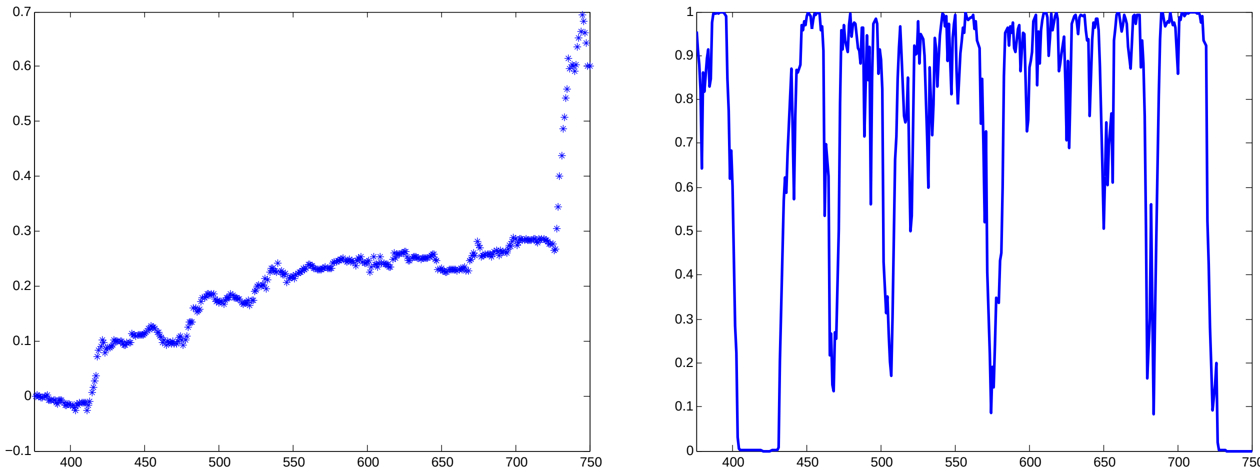
- $t_1 = 150$
- First time period for out-of-sample forecasting: 375
- Methods: Match to level
- Grid over $k : 2 - 30$ by 5, grid over $m : 2 - 70$ by 10
- To select the optimal baseline model, we use the BIC criterion with models estimated on full sample data.

We discuss in detail the relative forecasting performance of the match to level nearest neighbor method and the linear model for the example data series above. Figure 4 shows the recursive cumulative sum of squares difference between the nearest neighbor model and the linear model. Increases in this series mean that the nearest neighbor model forecasts better than the linear model. As expected, the overall trend of this sequence is upwards. The more general semiparametric model does a better job at capturing the nonlinear dynamics of the process relative to the linear model.

Looking closer at the results, we find two distinct jumps in the relative forecasting performance of the nearest neighbor model around the times with clear transitions to the "disaster regime," one around period

(a) Recursive cumulative sum of squares difference

(b) Threshold values simulated data



(a) Cumulative sum of squares difference between the match to level specification and the optimal linear selected model (ARMA(1,1)). Positive values mean that the nearest neighbor model is outperforming the linear model.
(b) Values of the threshold $\Phi(.)$

Figure 4: Forecasting results simulated data

400 and the other one at the end of our simulation.[8]. This behavior portends the large improvements in forecasting performance that our model delivers around the Great Recession when taken to the data. Our model does especially well during these times in the simulated data because 1) the dynamics within the disaster regime are quite different from those during normal times and 2) the transition between regimes is rather fast. Moreover, our model can pick up patterns in the data that signal transitions into the disaster regime, which the linear model cannot capture.

5 Forecasting exercise

5.1 Data

We consider 13 monthly U.S. macroeconomic and financial data series running from January 1959 to May 2015.[9] These variables are listed in Table 2. We use the data from FRED-MD (McCracken and Ng (2015)), the Bureau of Labor Statistics, and the Federal Reserve Board.

[8]For reference, the threshold values of the simulated data are also plotted in figure 4.
[9]The series are seasonally adjusted when needed.

5.2 Details

We do the recursive out-of-sample forecasting exercise for the data series in our sample with the following specifications:

- t_1 = Jan 1975
- First time period for out-of-sample forecasting: Jan 1990
- Methods: Match to level, match to deviations from local mean
- Grid over $k : 2 - 70$ by 10, grid over $m : 2 - 80$ by 10
- To select the optimal baseline model, we do the following. First, we perform augmented Dickey-Fuller tests of stationarity for the series. For the series in which we cannot reject the null of a unit root, we compare the BIC values of the BIC-selected ARMA model with the BIC-selected ARIMA model. For series in which we do reject the null of stationarity, we select the best ARMA model using BIC. Note that for this model-selection step only, we use full sample data.

5.3 Results

The column labeled $NN1$ in Table 2 compares the forecast from our match to level specification model versus the forecast from an optimally selected ARMA/ARIMA model. A quick look at the table reveals that our approach does better (Y) than the alternative for all variables but the federal funds rate, unemployment, and hourly earnings.[10] At the 5% level using the Diebold-Mariano test, the match to level specification forecasts better for inflation, industrial production, real personal income, and commercial and industrial loans. In addition, the match to level specification forecasts better than the linear model at the 10% level for payroll employment. When we switch to the match to deviations specification (column $NN2$), our model performs better than the linear alternative for all data series. The forecast is superior at the 5% level for unemployment, IP, real personal income, and real estate loans. It forecasts better at the 10% level for personal consumption expenditures.

[10] Relative RMSE values are in the appendix.

Table 2: Forecast comparison based on MSE (1 step ahead)

	ρ	σ	NN1	NN2	MS-AR	NNX-B	NNX-H	NNX-O	ARMAX-B	ARMAX-H	ARMAX-O
Inflation	0.72	0.27	Y^{**}	Y	N	Y^{*}	Y^{**}	Y^{**}	N	Y	Y^{**}
Federal funds rate	0.99	4.00	N	Y	–	Y	Y	N	N	Y	Y
Unemployment	0.99	1.57	N	Y^{**}	N	Y^{*}	Y^{**}	Y	Y	Y	N
Payroll employment	0.7	217.1	Y^{*}	Y	$Y(N)^{\dagger}$	Y	Y^{*}	Y	Y	N	N
Industrial production	0.35	0.73	Y^{**}	Y^{**}	Y	Y	Y^{*}	Y	Y	N	N
Personal consumption	-0.22	0.51	Y	Y^{*}	N	Y	Y^{*}	Y	N	N	N
Real personal income	-0.14	0.61	Y^{**}	Y^{**}	N	Y	Y^{**}	Y^{*}	Y	Y	Y
Average hourly earnings	0.02	0.29	N	Y	N	Y^{**}	Y	Y^{**}	Y	N	Y^{*}
Housing starts	-0.31	8.18	Y	Y	Y	Y^{*}	Y^{**}	Y	N	N	N
Capacity utilization	0.99	4.65	Y	Y	Y^{**}	Y	Y	Y	Y	N	N
S&P500	0.25	3.56	Y	Y	N	Y	N	Y	Y	N	N
Real estate loans	0.65	0.64	Y	Y^{**}	Y	Y^{**}	Y^{**}	Y^{**}	N	Y	N
Commercial and industrial loans	0.73	0.89	Y^{**}	Y	Y^{**}	Y^{**}	Y	Y	Y^{**}	N	N

Note: Comparisons relative to ARMA/ARIMA model. NN1: match to level model; NN2: match to deviation model. "Y" means that our proposed model does better than the alternative. Based on the Diebold-Mariano test, an asterisk (*) and a double asterisk (**) mean that the forecast is better at 10 % and 5 %, respectively. We use Newey-West standard errors when making these calculations.

ρ and σ correspond to the autocorrelation and standard deviation.

Note that while the comparisons NN1 and NN2 are made for models estimated on the data from 1959 until the end of the sample, the other comparisons are made for models estimated beginning in 1973 due to data limitation issues.

The MS-AR model is not estimated for the Federal funds rate because of convergence problems.

†: The MS-AR model has difficulty estimating recursively for payroll employment. The model is able to estimate using the entire sample as well as using data only up to Jan 1990 (the first time period for the forecasting exercise). Forecasting using full sample parameter estimates leads to better performance versus the linear model whereas forecasting using parameter estimates with information up to Jan 1990 leads to poorer forecasting performance.

The relative success of our method rests on a combinations of elements. First, the data under study need to be persistent and display patterns. Without these features, there is no valuable information in past data to be exploited. Second, we need several episodes of sudden movements, such as during recessions. This means that our approach benefits from longer history of data. To shed light on these issues, we discuss in some detail the results for 3 important macro series: payroll employment, industrial production, and personal consumption expenditures and one financial series: commercial and industrial loans. We find many large forecasting gains during the Great Recession time period for each of these series discussed. Indeed, for almost all of the series that exhibit significant forecasting gains, we find large improvements during the Great Recession. We also discuss the forecast of hourly earnings as a case in which our method does not improve over linear models. As will become clear momentarily, this failure results from the lack of historical patterns (especially around recessions) in the hourly earnings series.

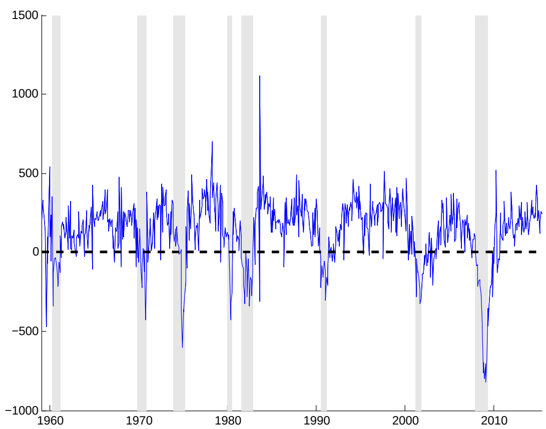
Payroll employment Nonfarm payroll employment is the change in the number of paid workers from the previous month excluding general governmental, private household, nonprofit, and farm employees. From panel (a) in Figure 5, we see that the data is mildly persistent, with a first-order autocorrelation of around 0.6. Entering recessions, payroll employment sharply declines whereas recoveries feature more gradual increases in the data series. The past 3 recessions have seen pronounced slow payroll employment rebounds. Especially notable is the decline during the recent Great Recession, which is by far the largest decline in the data sample.

In forecasting the recent time period, we look at past similar historical patterns. Crucial for our purposes, Figure 5 shows a sharp contraction in payroll employment during the 1974 recession, with employment declining by $604,000$ between October and December of that year. In terms of persistence, the 1982 episode provides some valuable information regarding the lingering effects of recessions on employment. It took roughly 18 months for payroll employment to return to positive growth. This number provides a reasonable proxy for the 2 years needed during the Great Recession

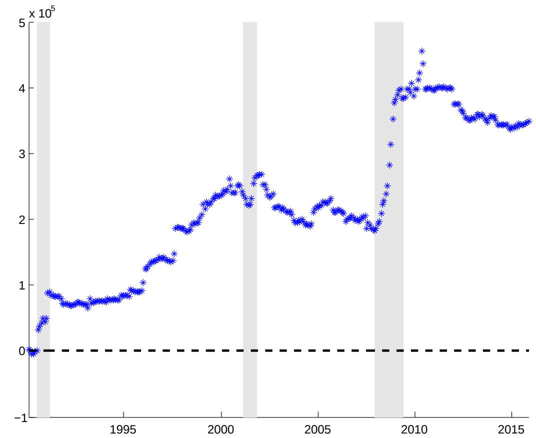
Panel (b) in Figure 5 shows the recursive cumulative sum of squares difference between the nearest neighbor method using match to level and the optimally selected linear model, which is an ARMA(2,1). Positive values mean that the nearest neighbor model is forecasting better than the linear model. The proposed methodology does especially well during recession dates, with the largest jump occurring during the Great Recession. The methodology also does especially well in the late 1990's, but otherwise the two methods appear to perform quite similarly in expansionary times.

The particularly large gain in forecasting performance motivates us to examine the Great Recession period in more depth. Panel (d) in Figure 5 presents the movements of payroll employment and the resulting linear (blue) and nearest neighbor (red) forecast errors across the Great Recession. Payroll employment change tanks in the Great Recession, reaching around $-900,000$ in late 2008 and early 2009. These declines are difficult for the linear model to forecast, as evidenced by the consistently positive forecast errors through-

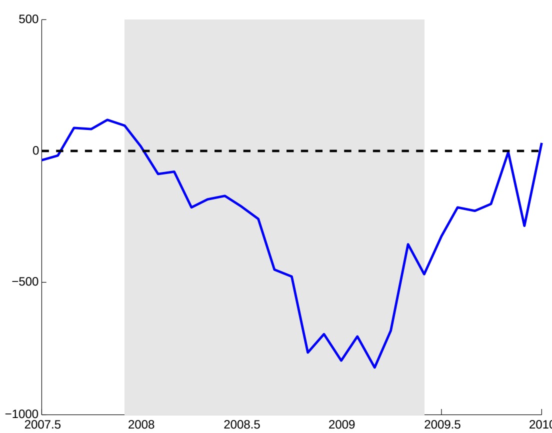
(a) Monthly nonfarm payroll employment (thousands)



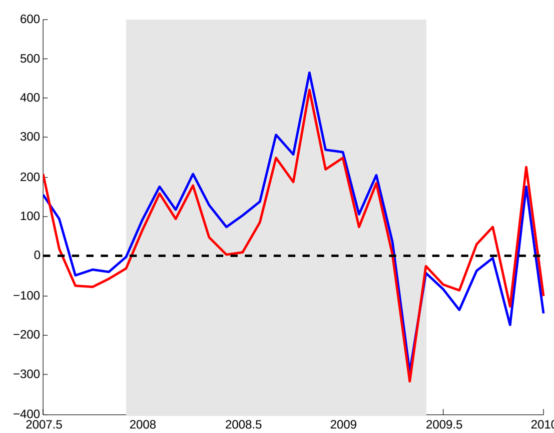
(b) Recursive cumulative sum of squares difference†



(c) Payroll in Great Recession (thousands)



(d) Forecast errors‡

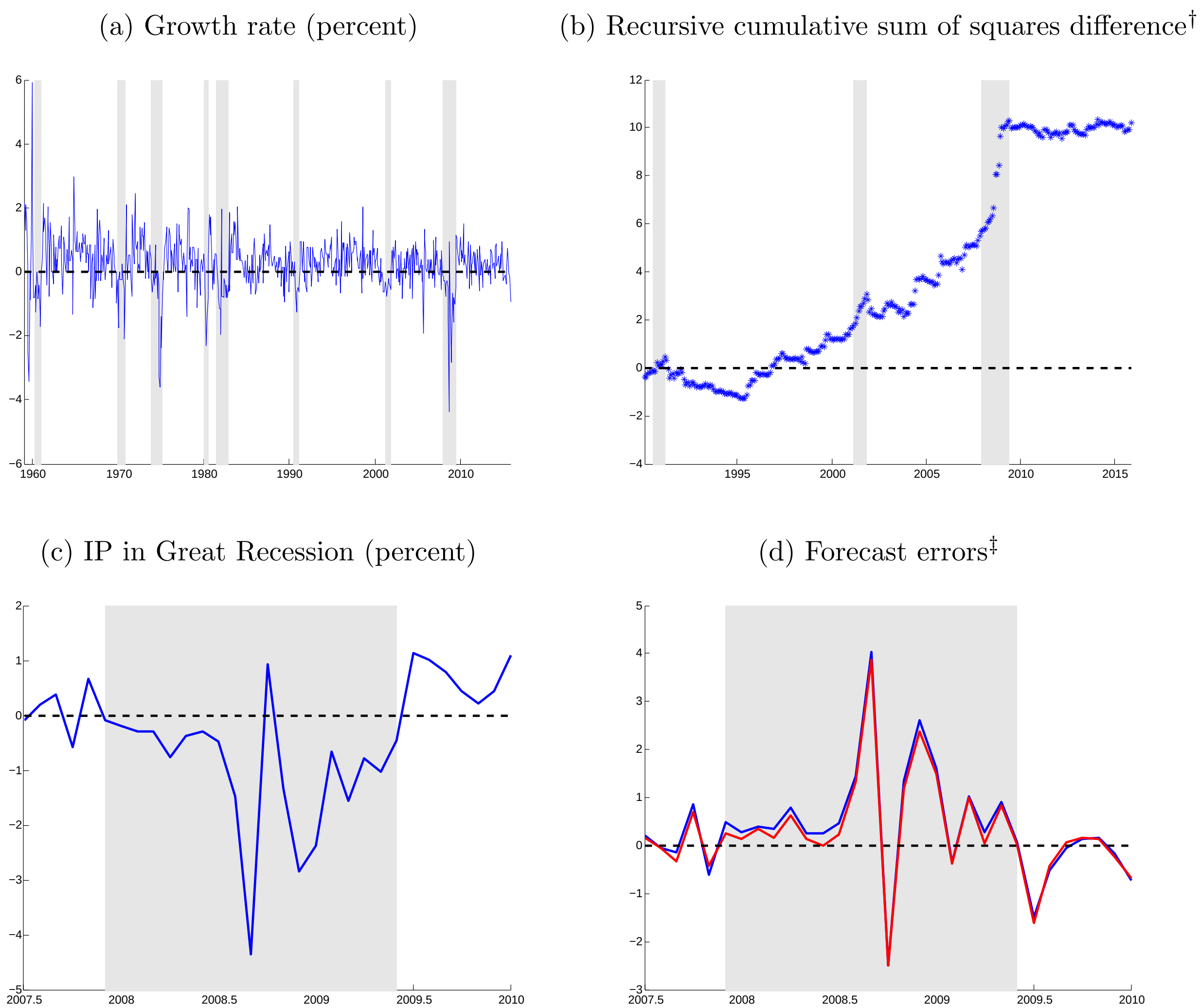


†Cumulative sum of squares difference between the match to level specification and the optimal linear selected model (ARMA(2,1)). Positive values mean that the nearest neighbor model is outperforming the linear model.

‡Forecast errors (Blue - linear model and Red - nearest neighbor model). Shaded areas are NBER recession dates.

Figure 5: Payroll Employment

out the recession. While the nearest neighbor method also generates too optimistic forecasts, its forecast errors are below those of the linear model during the Great Recession. The nearest neighbor method does especially well predicting the large decrease in payroll employment change beginning in the middle of 2008. Interestingly, our method outperforms the linear model even after the Great Recession (note the smaller forecast errors in panel (d)). However, this is not a general finding, as we will see momentarily.



†Cumulative sum of squares difference between the match to level specification and the optimal linear selected model (ARMA(4,2)). Positive values mean that the nearest neighbor model is outperforming the linear model.

‡Forecast errors (Blue - linear model and Red - nearest neighbor model). Shaded areas are NBER recession dates.

Figure 6: Industrial Production

Industrial production Industrial production growth is the monthly growth rate of the Federal Reserve Board's index of industrial production. This index covers manufacturing, mining, and electric and gas utilities. Industrial production (panel (a) in Figure 6) is much less persistent than nonfarm payroll employment changes, with a first order autocorrelation of around 0.4. Like nonfarm payroll employment, it is highly procyclical, declining during recessions. The Great Recession had declines of industrial production of over −4% per month (panel (c) in Figure 6), which was the deepest decline of any recession in the data sample. Industrial production also declined drastically during the recession in the mid−1970s.

Panel (b) in Figure 6 compares the forecasting performance of the nearest neighbor match to level specification to the linear model, which is an ARMA(4,2). The nearest neighbor specification begins to do well in 1995. Contrary to the payroll employment results, the nearest neighbor model appears to consistently outperform the linear model at approximately the same rate from 1995 to the eve of the Great Recession. The nonlinear method does especially well in the Great Recession and the two methods are comparable afterwards.

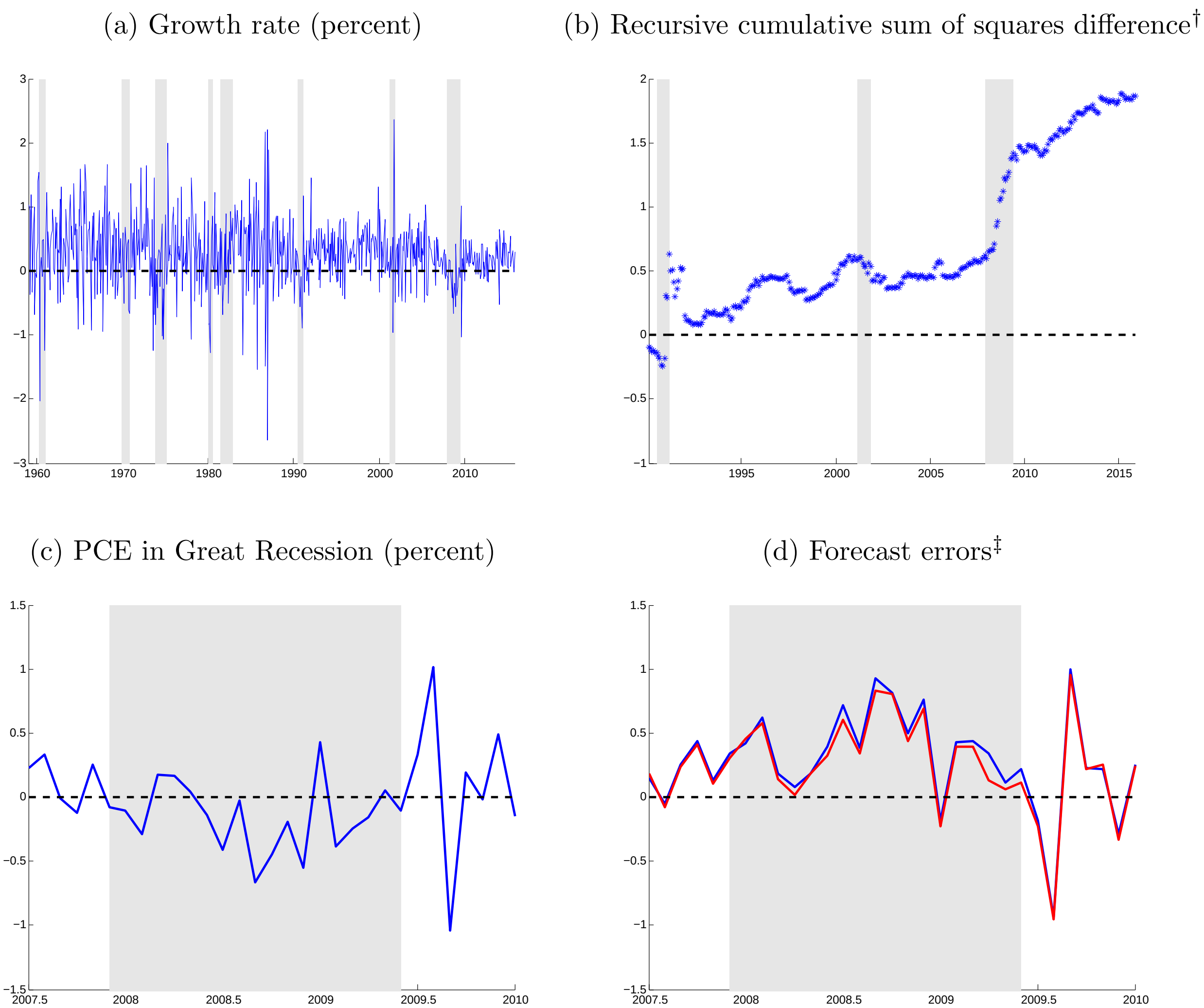
As panel (d) in Figure 6 shows, the nearest neighbor method does especially well in the initial periods of the Great Recession. The linear model overpredicts industrial production growth throughout the early part of 2008, while the nearest neighbor model has smaller positive forecast errors. It also has slight improvements relative to the linear model in forecasting the second large dip in late 2008.

Personal consumption expenditures In contrast to the other data series, PCE growth is slightly negatively autocorrelated at the monthly level (panel (a) in Figure 7). PCE growth declines in recessions, although overall the data is quite noisy. While the Great Recession did not have any especially large decreases in PCE growth, a notable feature is the particularly extended period of negative growth.

Panel (a) in Figure 7 compares the forecasting performance of the linear model (ARMA(1,2)) to that of the nearest neighbor method using the deviations from local mean specification. The nearest neighbor method does especially well at the end of the recession in the early 1990s and during the Great Recession. During periods of expansion and in the early 2000s recession, there is not too large of a forecasting difference. The nearest neighbor model also continues to forecast well after the Great Recession.

As can be seen by looking at the forecast errors in panel (d) in Figure 7, both the linear and nearest neighbor models consistently overpredict future consumption growth throughout the Great Recession. The nearest neighbor specification has the largest forecasting gains in the steep consumption growth declines in mid-2008. It also does especially well at predicting the gradual rise in consumption growth at the end of the recession. Finally, panel (d) also reveals that as the economy moved out of the recession, forecasts using our approach are comparable to those from the linear specification.

Average hourly earnings As Figure 8 shows, our approach can also underperform relative to the linear model. This is the case for real average hourly earnings growth. Across our sample period, average hourly



†Cumulative sum of squares difference between the match to deviations from local mean specification and the optimal linear selected model (ARMA(1,2)). Positive values mean that the nearest neighbor model is outperforming the linear model.

‡Forecast errors (Blue - linear model and Red - nearest neighbor model). Shaded areas are NBER recession dates.

Figure 7: Personal Consumption Expenditures

earnings growth has essentially zero autocorrelation (0.02, in Table 2). In contrast to many other macroeconomic and financial time series, its behavior during recessions has not been consistent. For example, the mid−1970s and early 1990s recessions featured particularly weak real wage growth. On the other hand, the early 1980s recession had wild fluctuations in growth. Interestingly, the Great Recession had particularly strong growth, especially after inflation collapsed in late 2008. Not surprisingly, this inconsistency in historical real wage growth behavior makes it particularly difficult for our method to forecast well. As can be seen in panel (b) in Figure 8, which compares the performance of the nearest neighbor method matched to level and the ARMA(1,1) model, the two methods generally perform similarly over time. In fact, focusing on panels (c) and (d), we see that that both methods do a poor job at capturing the large positive increases in real average hourly earnings in the latter part of 2008, with the nearest neighbor method doing worse. Unlike the other series considered, the nearest neighbor method overall does worse than the linear model during the Great Recession.

Commercial and industrial loans Finally, we show that our approach is useful for financial variables. To this end, we use commercial and industrial loans. This variable measures the total amount of lending to businesses from all commercial banks.

Panel (a) in Figure 9 shows that commercial and industrial loans growth is a lagging indicator of the business cycle. In all recessions except the first 1980 recession, commercial and industrial loans growth reaches a trough in the months after the end of the NBER-defined recession period. The aftermath of the Great Recession featured the deepest decline in commercial and industrial loan growth in the data sample. The series is fairly persistent, with a first order autocorrelation of around 0.7.

From 1990 to the early 2000 recession, the linear and nearest neighbor method matching to level forecasts comparably well. Beginning during the 2000 recession, however, the nearest neighbor method begins to do better than the linear model. There is a large jump in the relative forecasting performance for the nearest neighbor model in the latter part of the Great Recession, and continued positive gains afterwards.

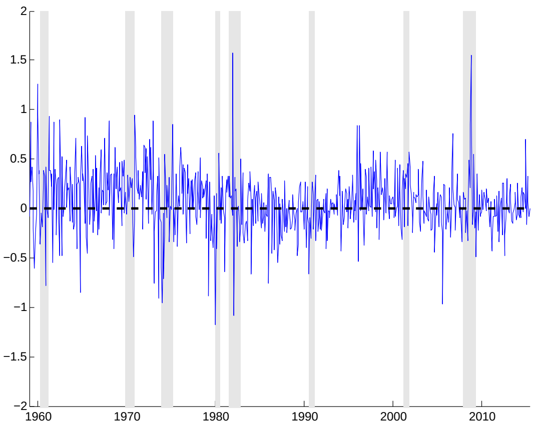
As panel (b) in Figure 9 shows, commercial and industrial loans growth largely declined throughout the Great Recession, reaching a trough in the middle of 2009. Turning to the forecast errors from the two models, we see that the nearest neighbor method does especially well relative to the linear model in predicting the accelerating declines in the data from 2009 onwards.

Comparison to Markov-switching autoregression model As a point of comparison for our nonlinear model, we also forecast using the Markov-switching autoregression model of Hamilton (1989).

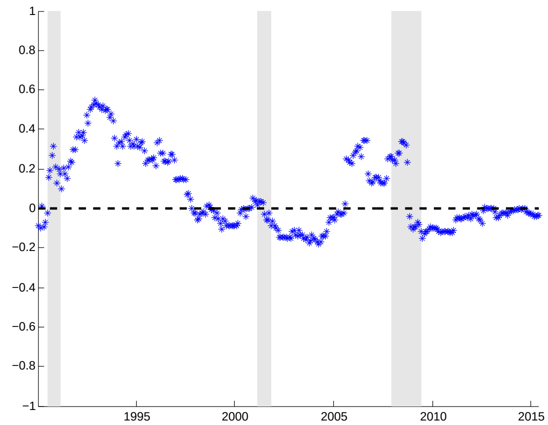
$$y_t = c_{s_t} + \phi_1 y_{t-1} + ... + \phi_p y_{t-p} + \epsilon_t, \epsilon_t \sim N(0, \sigma^2)$$

We allow $s_t \in \{1, 2\}$ to follow a first-order Markovian process $P(s_t = i|s_{t-1} = j)$. Note that we only allow the constant term in the autoregression to switch. We select the optimal lag length by using the BIC

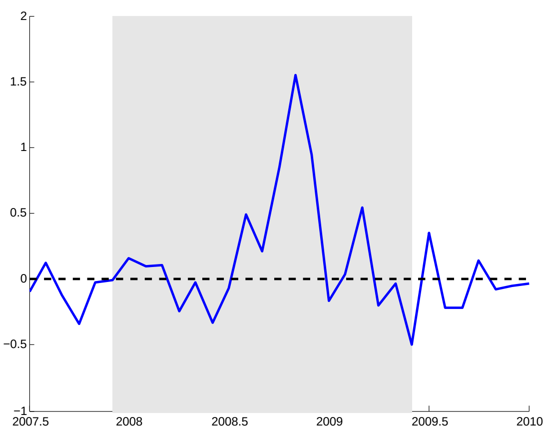
(a) Growth rate (percent)



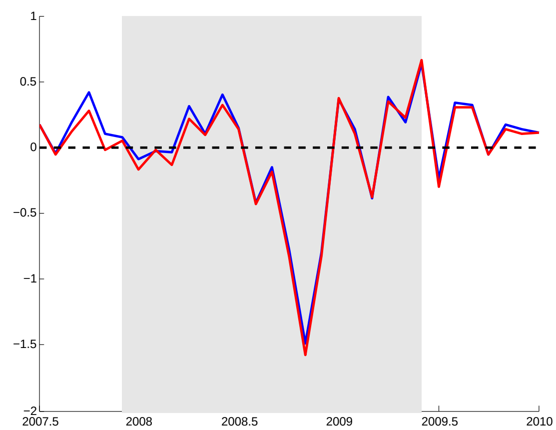
(b) Recursive cumulative sum of squares difference†



(c) AHE in Great Recession (percent)



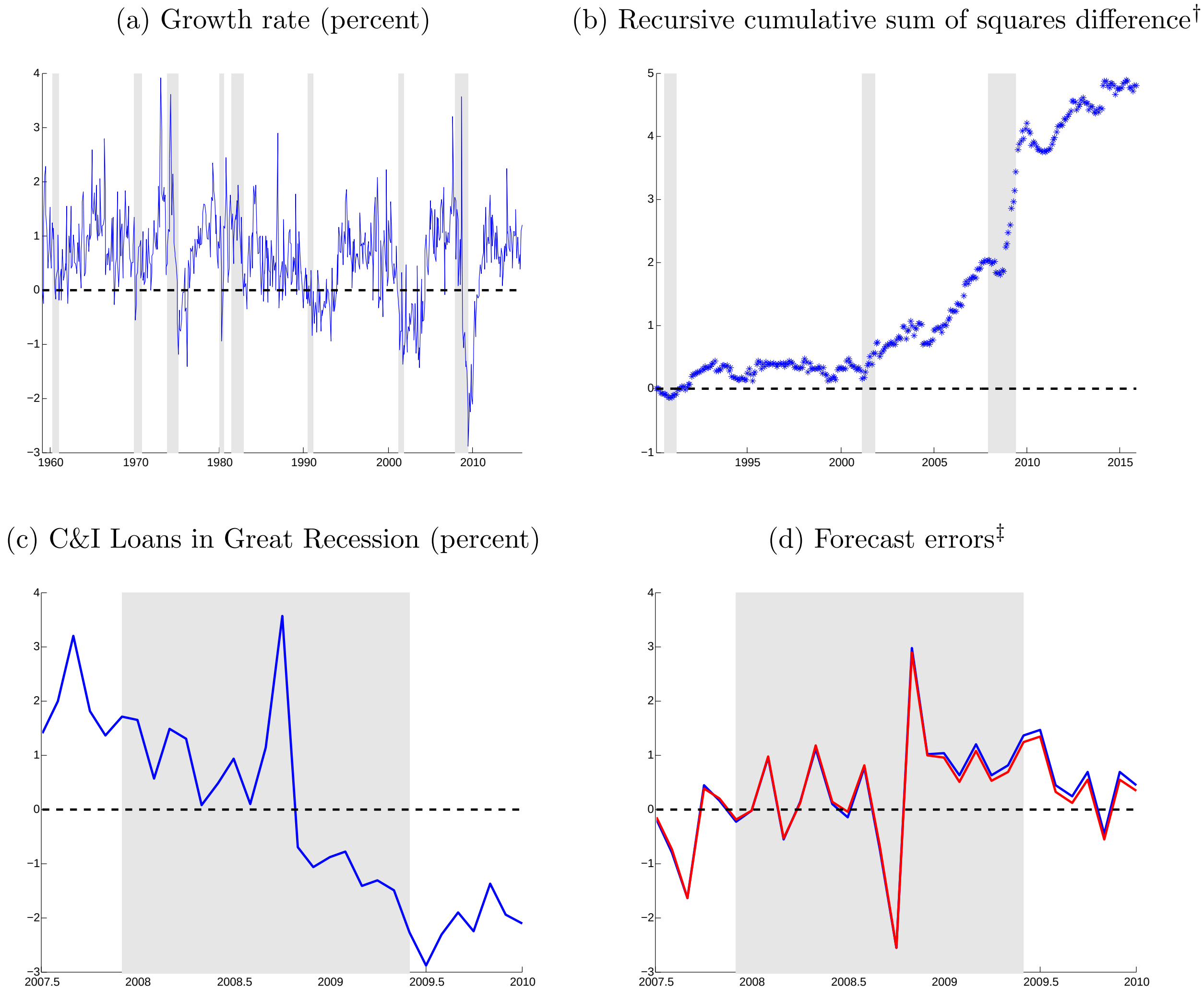
(d) Forecast errors‡



†Cumulative sum of squares difference between the match to level specification and the optimal linear selected model (ARMA(1,1)). Positive values mean that the nearest neighbor model is outperforming the linear model.

‡Forecast errors (Blue - linear model and Red - nearest neighbor model). Shaded areas are NBER recession dates.

Figure 8: Average Hourly Earnings (AHE)



†Cumulative sum of squares difference between the match to level specification and the optimal linear selected model (ARMA(1,1)). Positive values mean that the nearest neighbor model is outperforming the linear model.

‡Forecast errors (Blue - linear model and Red - nearest neighbor model). Shaded areas are NBER recession dates.

Figure 9: Commercial and industrial loans

criterion on an autoregressive model without Markov-switching. After selecting the autoregressive model, we add Markov-switching to the intercept, allowing for two states. The Markov-switching models are estimated using maximum likelihood.

We perform a recursive out-of-sample forecasting exercise and the results are shown in the column under MS-AR in Table 2. In contrast to the nearest neighbor methods, which forecast better than the linear model for most series, the Markov-switching model oftentimes forecasts worse. Of the six series in which Markov-switching model forecasts worse when compared to the linear model, the forecasting difference is significant for unemployment and personal consumption expenditures. In contrast, the linear model does not forecast significantly better than the nearest neighbor model for any of the series considered. The Markov-switching model does forecast significantly better than the linear model for capacity utilization and commercial and industrial loans.

6 Can we do better?

The results so far indicate that our approach does particularly well during the Great Recession. Researchers and policymakers alike have begun to develop theories on the drivers of the recent downturn - two of which are based on the financial sector and housing disturbances. Moreover, oil price fluctuations have also traditionally been an intriguing explanation of recessions. To exploit this potentially important information, in this section, we present a methodology to incorporate financial, housing, and oil price data into our baseline forecasting model.

To most economic commentators, the financial sector played a crucial role during the 2008/2009 crisis. For instance, Gilchrist and Zakrajsek (2012) argue that credit spreads "contain important signals regarding the evolution of the real economy and risks to the economic outlook." By the same token, the boom/bust cycle in the housing market was another key player before, during, and after the Great Recession (Farmer (2012)). Moreover, theoretical studies on the relationship between financial frictions and housing and the macroeconomy suggest that each could have a potentially important nonlinear relationship with general macroeconomic performance (Mendoza (2010); Guerrieri and Iacoviello (2013)). Likewise, recessions are also often preceded by a run-up in oil prices. For some economic observers, these sudden movements in oil prices are, at least to some degree, responsible for the subsequent crises (Hamilton (2009)). Hence, it seems natural to exploit these sources of information in our methodology.

To this end, we modify our algorithm as follows. Let x_t denote a potential driver of the Great Recession (credit spreads, housing prices, or oil prices). As before, we compare deviations from a local mean of two sequences of the driver x_t of length k $[x_{t-k+1}, ..., x_t]$ vs. $[x_1, x_2, ..., x_k]$ based on the similarity function:

$$dist = \sum_{i=1}^{k} weighs(i) \left((x_{t+1-i} - \overline{x}_t) - (x_{k+1-i} - \overline{x}_k) \right)^2 .$$

For simplicity, suppose that the first sequence is the one that is matched. Then our modified model, which we call *Nearest neighbor X* is

$$\hat{y}_{t+1} = \underbrace{(y_{k+1} - \hat{y}_{k+1,ARMA})}_{\text{Error from matched time period}} + \hat{y}_{t+1,ARMA},$$

We proceed in a similar fashion as with our benchmark model - specifically by conducting a recursive out-of-sample forecasting exercise. We use similar grid points over k and m.[11] An important point to note is that because our objective function continues to be equation 2, which changes in accordance with the changing variables to be forecast, it is possible to have different sequences of estimated k and m across the y_t series, even when using the same x_t variable. For comparison purposes, we also forecast using ARMA/ARIMA and ARMAX/ARIMAX models.

6.1 Excess Bond Premium

Our data run from January 1973 to May 2015. We begin one-step ahead forecasting at the first month of 1990. The estimation is monthly and we reestimate the model for each new month in the sample. As before, we use the recursive out-of-sample mean square error (see equation 2) to select optimal match length, k, and the number of averages, m. To this end, we set $t_1 = 1986M1$.

Figure 10 shows the difference in cumulative squared errors between our model and the best ARMA/ARIMA (blue) and between ARMAX/ARIMAX and the best ARMA/ARIMA (red). A first look shows that our method consistently outperforms the alternative. More important, significant gains from our approach happen after the 2001 recession and just before and during the Great Recession. After that, our approach does not improve upon an ARMA/ARIMA forecast (the difference stabilizes post-2010). In contrast, the performance of an ARMAX/ARIMAX model is erratic with clear gains only for commercial and industrial loans. While for many series, the ARMAX/ARIMAX model produces large forecasting gains during the Great Recession, oftentimes these gains are more than offset by poor forecasting performance during calmer times.

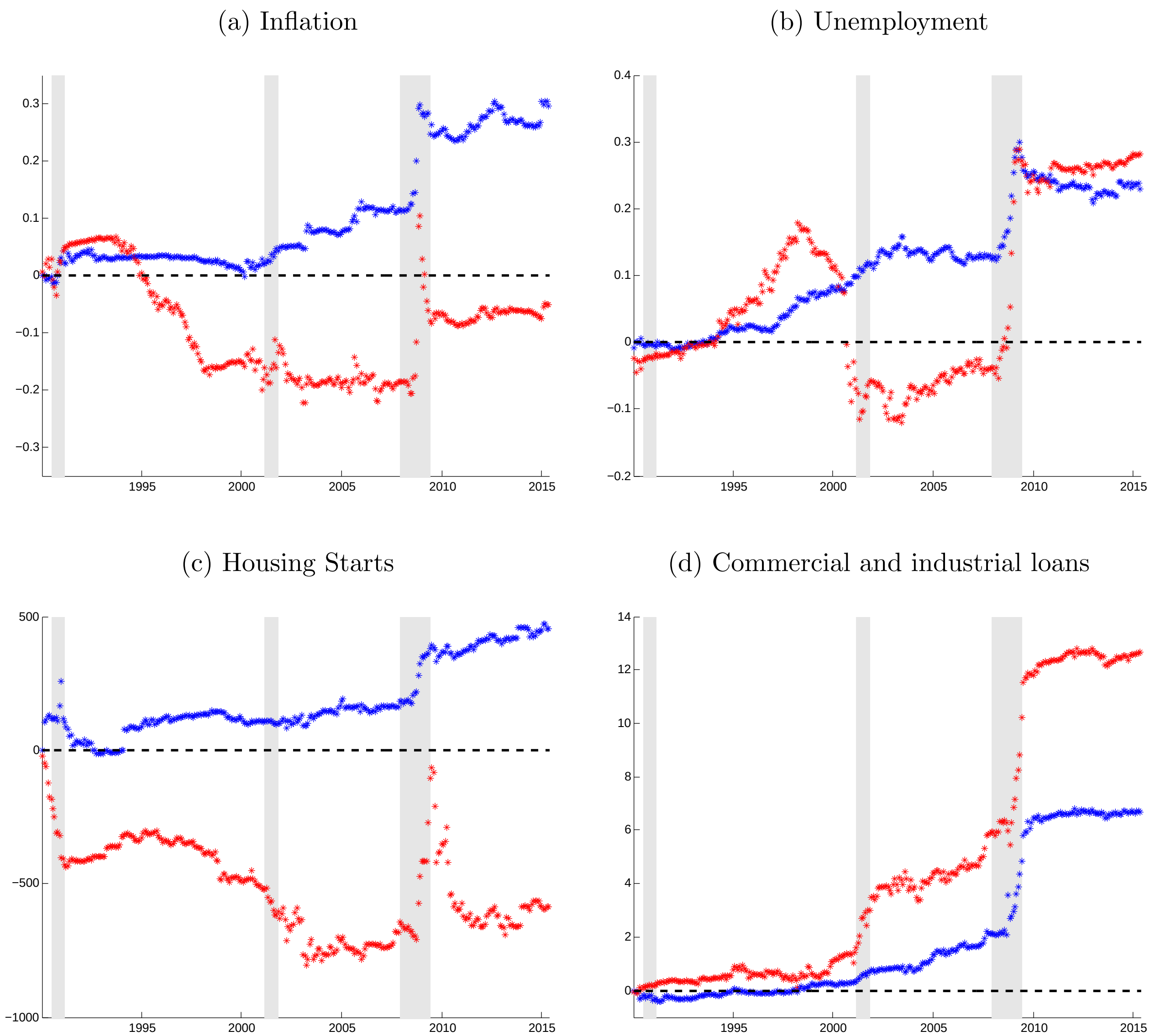
6.2 House Price Index

We also use a housing price index as another auxiliary variable. We use the Case-Shiller house price index growth.[12] Our forecasting approach follows the same specifications as those for the excess bond premium.

From this version (see column NNX-H in Table 2 and Figure 11), we draw four broad conclusions. First, our methodology continues to outperform the alternative ARMA/ARIMA. Crucially, the use of housing information boosts the forecasting ability of our model and makes the improvement statistically significant

[11] Due to data limitation issues, we only consider m up to 70. The grids for k remain the same $2 - 70$.

[12] Note that the Case-Shiller series as found on Robert Shiller's website is not seasonally adjusted. We seasonally adjust using the $X - 13$ procedure found in EViews.



The graphs show the relative performance of our model NNX versus ARMA/ARIMA in blue and ARMAX/ARIMAX versus ARMA/ARIMA in red. Increases in these series mean that the NNX/ARMAX models are doing better. Here we use the excess bond premium as the auxiliary variable. Shaded areas are NBER recession dates.

Figure 10: Forecast comparison NNX and ARMAX/ARIMAX when X = excess bond premium

for 8 out of 13 variables. Second, the forecasting performance improves dramatically for housing starts, unemployment, and real state loans (see Figure 11) during the entire forecasting window (1990 - 2015). Third, our approach improves even for those variables that display weak or no autocorrelation (personal consumption and average hourly earnings). Finally, housing information also helps forecasting for some series based on an ARMAX/ARIMAX model (last column in Table 2). However, the improvement is not statistically significant as it only gives a boost to the forecast during a small part of the sample.

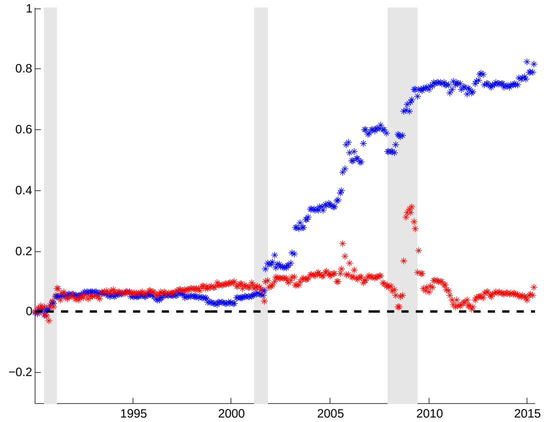
Figure 12 shows the time period of the last observation for the best matched block around the Great Recession for some variables. In our notation (see equation 1), the (x, y) coordinates correspond to y_t and y_k, respectively. For inflation (panel a), we observe that forecasting during most of the 2008/2009 crisis drew heavily on the relationship between house prices and inflation during the 1980s. Our approach also grabs some information from the 1970s. This is hardly surprising given the sharp comovements that inflation and house prices experienced during the 1975 and 1980-1982 recessions. As we move out of the crisis, we rely on more recent information to forecast inflation. The story behind industrial production (panel d) is a bit similar to that behind inflation. To forecast during the early part of the Great Recession, our approach relies on information from the 1980s. During the early part of 2009, our approach picks information from 2008 to generate the best matched block.

The unemployment (panel b) and payroll employment (panel c) series offer some important insights about our method. The best match, y_k, and the last observation, y_t, display an almost linear relation around the crisis. For example, the best matches for January 2008 and January 2010 are December 2007 and December 2009, respectively. That is, our approach is choosing recent information about the labor market as the most relevant to forecast in 2008/2009. Does this mean that the past history is irrelevant? The answer is no. To see this point, the red circles and black stars display the second and third matches picked by our method. The reader now can see that the recessions from the 1980s and 1990s provided some useful information to forecast unemployment early in the Great Recession. Yet the dire increase in unemployment at the trough of the crisis forces our method to look at the more recent available data. It is also clear that as the economy starts to heal, information from previous recoveries are handy. The payroll employment series tells us a very similar story, albeit with some small twists. For completeness, we also provide the matched series for housing starts (panel e) and commercial and industrial loans (panel f).

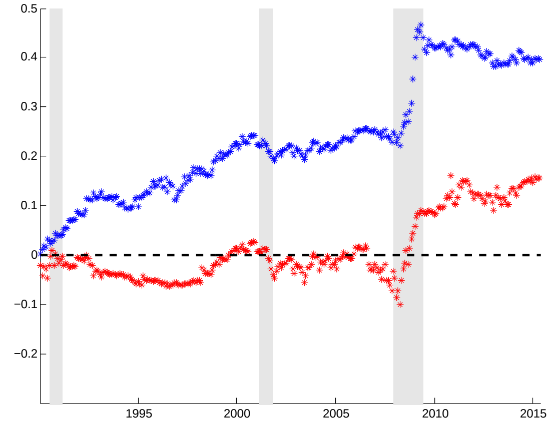
6.3 Real oil price

We also try oil prices as the auxiliary variable in our nearest neighbor method (see Table 2 and Figure 13). Overall, the NNX-O variant forecasts all series well relative to the ARMA/ARIMA model with the exception of the fed funds rate. While the NNX-O model oftentimes does better relative to the ARMA/ARIMA benchmark, the differences are significant for only inflation, average hourly earnings, and real estate loans. The ARMAX/ARIMAX model has similarly strong forecasting performance for inflation and average hourly earnings. It does poorly for real estate loans. On the other hand, we find that adding in oil price informa-

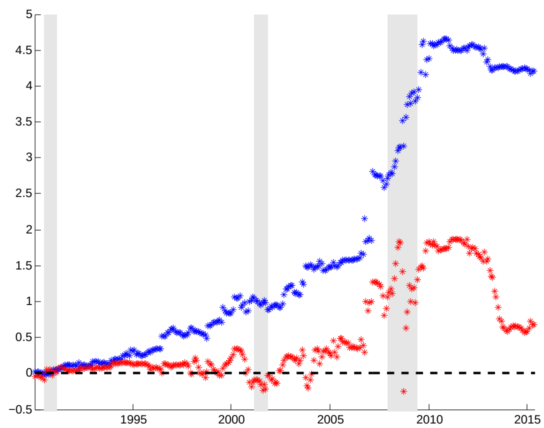
(a) Inflation



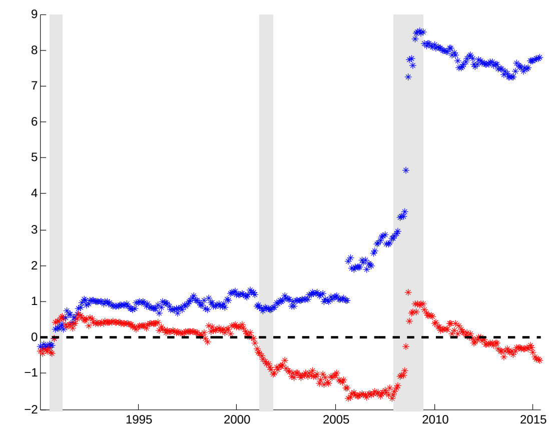
(b) Unemployment



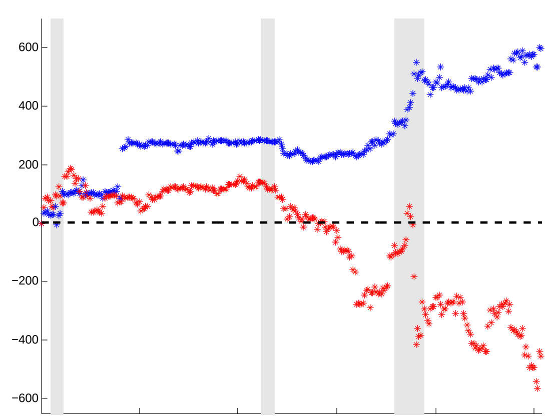
(c) Payroll Employment



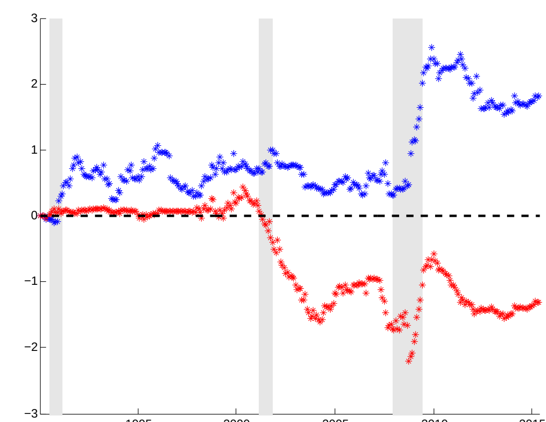
(d) Industrial Production



(e) Housing Starts

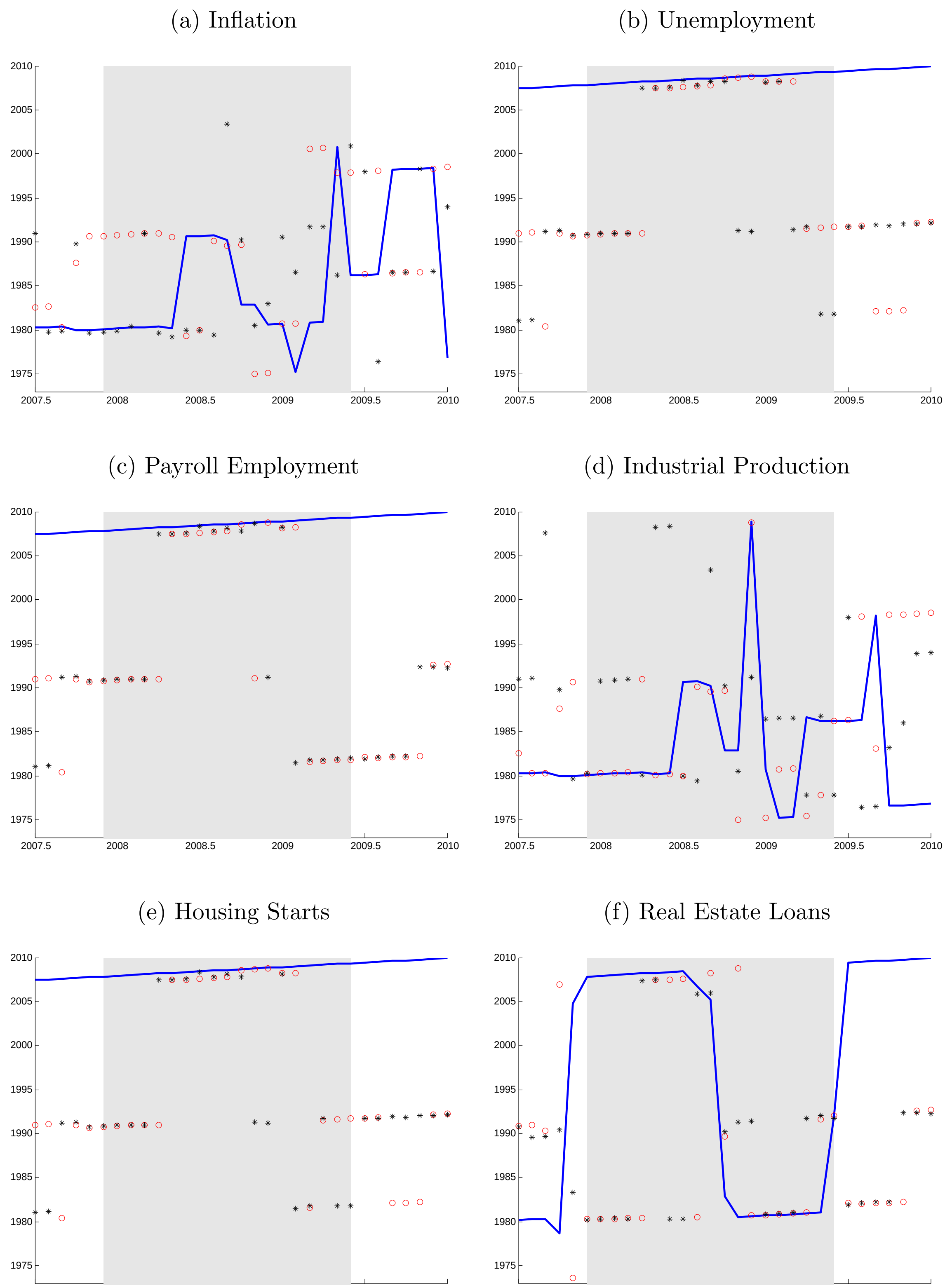


(f) Commercial and Industrial Loans



The graphs show the relative performance of our model NNX versus ARMA/ARIMA in blue and ARMAX/ARIMAX versus ARMA/ARIMA in red. Increases in these series mean that the NNX/ARMAX models are doing better. Here we use house prices as the auxiliary variable. Shaded areas are NBER recession dates.

Figure 11: Forecast comparison NNX and ARMAX/ARIMAX when X = house prices



The graphs show the matched periods during the Great Recession when we use the NNX model and house prices as the auxiliary variable. The blue line gives the corresponding best matched time period, the red circles give the second best, and the black stars give the third best. Shaded areas are NBER recession dates.

Figure 12: Matched periods during Great Recession when X = house prices

tion linearly oftentimes hurts forecasting performance relative to the ARMA/ARIMA benchmark. From a forecasting perspective, we find weaker evidence of a nonlinear relationship between oil price fluctuations and the macroeconomy compared to the other explanatory variables.

6.4 Comparison to survey-based nowcasts

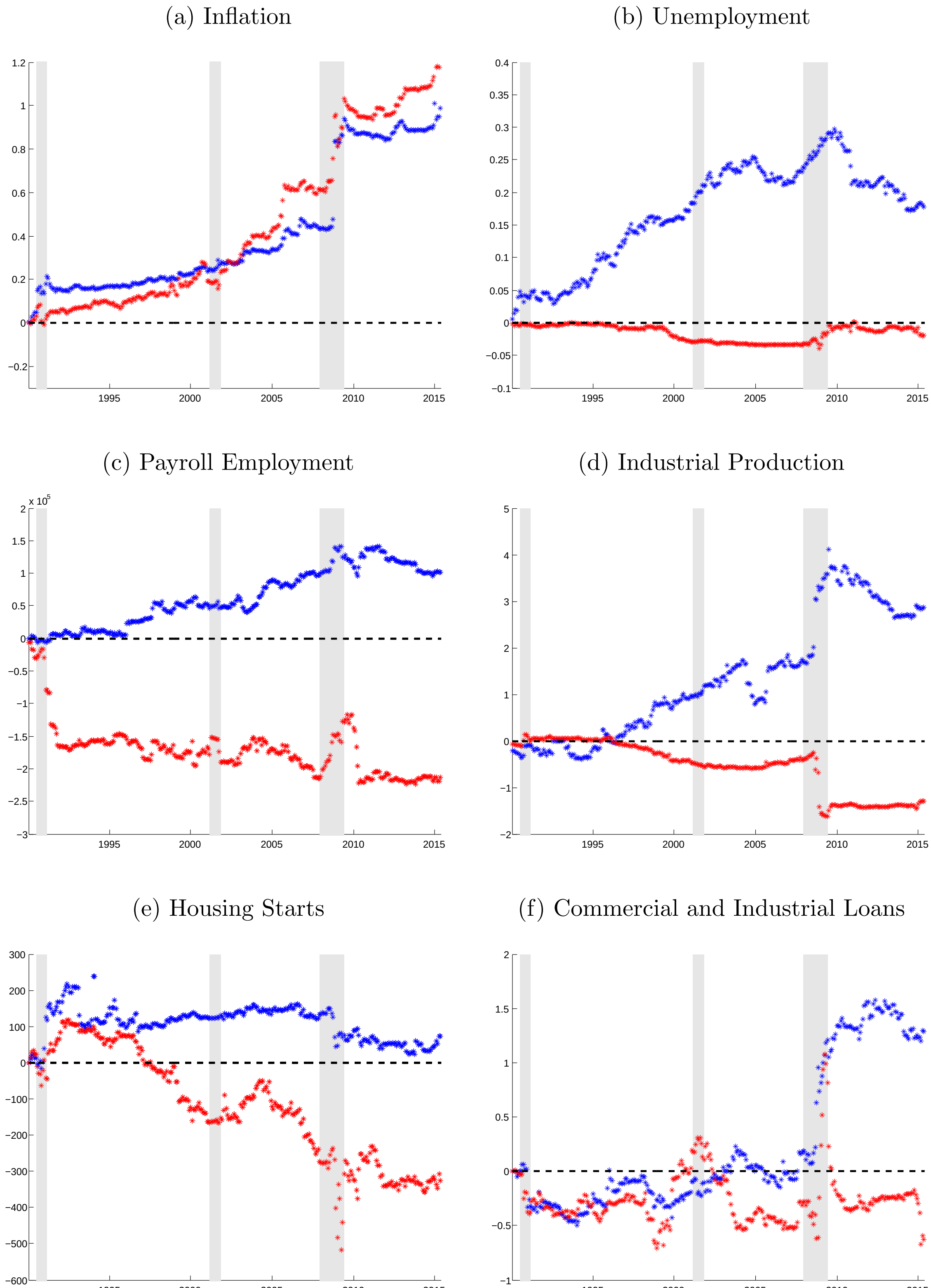
Motivated by the forecasting performance of our NN-X method that uses house prices as an explanatory variable, we find it illustrative to compare the method with alternative forecasts. Figure 14 shows the Greenbook nowcasts (green dots), the SPF nowcasts (red dots), our approach using house prices as an explanatory variable (pink diamonds), and the data (blue line) for unemployment, inflation, and industrial production. As we are time-aggregating one-period ahead monthly forecasts to form quarterly forecasts with our method, we use survey-based nowcasts in an effort to keep the information sets approximately the same. Overall, we do better than the Greenbook forecasts for unemployment and industrial production. The Greenbook survey tends to underpredict unemployment and overpredict industrial production growth. We do better than the SPF forecast for industrial production growth and are competitive for the other two data series. We do better in predicting the large drop in industrial production growth and increase in unemployment during the middle of the crisis. This comparison must be taken with some caution since we use revised data whereas the SPF and Greenbook are based on real-time data. [13] Furthermore, for inflation and industrial production data, we construct the quarterly values by summing the monthly interquarter rates. Both survey-based forecasts are instead for the growth rate of the monthly interquarter average of the level of the series. In spite of these caveats, we find it very suggestive that we compare well to more hands-on and subjective approaches.

6.5 Multi-step ahead forecasts

We also evaluate the longer-horizon predictability of our NNX - H specification. To do so, we reestimate our nearest neighbor specification, taking into account the appropriate forecast horizon when choosing our optimal k and m.

Overall, the nearest neighbor model augmented by house prices continues to forecast well at longer horizons. As Table 3 shows, the nearest neighbor model beats the ARMA/ARIMA model in forecasting for all series at all horizons considered. The significance of the differences declines, however, with unemployment, payroll employment, housing starts, and commercial and industrial loans among the data series with the strongest

[13] An interesting question concerns the extension of the model to real-time data. Considering only the baseline nearest neighbor model, two leading strategies would be to consider patterns using only the latest vintage data or using only first release data. Using the latest vintage data would exploit the most up-to-date estimates of a series, although each data point is at a different stage in the revision cycle. The patterns present in the data contain information on both actual economic fluctuations and data revisions (which may both matter for forecasting). Only considering patterns found in first release data (along the diagonal of the data matrix) would remove this revision effect, at the cost of throwing away potentially important revision information. Deciding which strategy is preferable is an empirical question. We thank Michael McCracken for raising this important point.



The graphs show the relative performance of our model NNX versus ARMA/ARIMA in blue and ARMAX/ARIMAX versus ARMA/ARIMA in red. Increases in these series mean that the NNX/ARMAX models are doing better. Here we use real oil prices as the auxiliary variable. Shaded areas are NBER recession dates.

Figure 13: Forecast comparison NNX and ARMAX/ARIMAX when X = oil prices

longer-horizon predictability. At the 1-year ahead horizon, there also appears to be a nonlinear forecasting relationship between house prices and real personal income and house prices and unemployment as hinted by the significant forecasting improvement.[14]. For payroll employment, housing starts, and commercial and industrial loans, the nearest neighbor model significantly beats the ARMAX/ARIMAX model as well, giving stronger evidence of a nonlinear forecasting relationship.

Table 3: NN - X versus ARMA/ARIMA model forecast comparison based on MSE for multiple horizons (months)

	3	6	12
Inflation	Y	Y	Y
Federal funds rate	Y	Y	Y
Unemployment	Y	Y^{*}	Y^{**}
Payroll employment	Y	Y^{*}	Y
Industrial production	Y	Y	Y
Personal consumption	Y	Y^{*}	$-$
Real personal income	Y	Y	Y^{**}
Average hourly earnings	Y	Y	Y
Housing starts	Y^{**}	Y^{**}	Y
Capacity utilization	Y	Y	Y
S&P500	Y	Y	Y
Real estate loans	Y	Y	Y
Commercial and industrial loans	Y^{*}	Y^{**}	Y^{*}

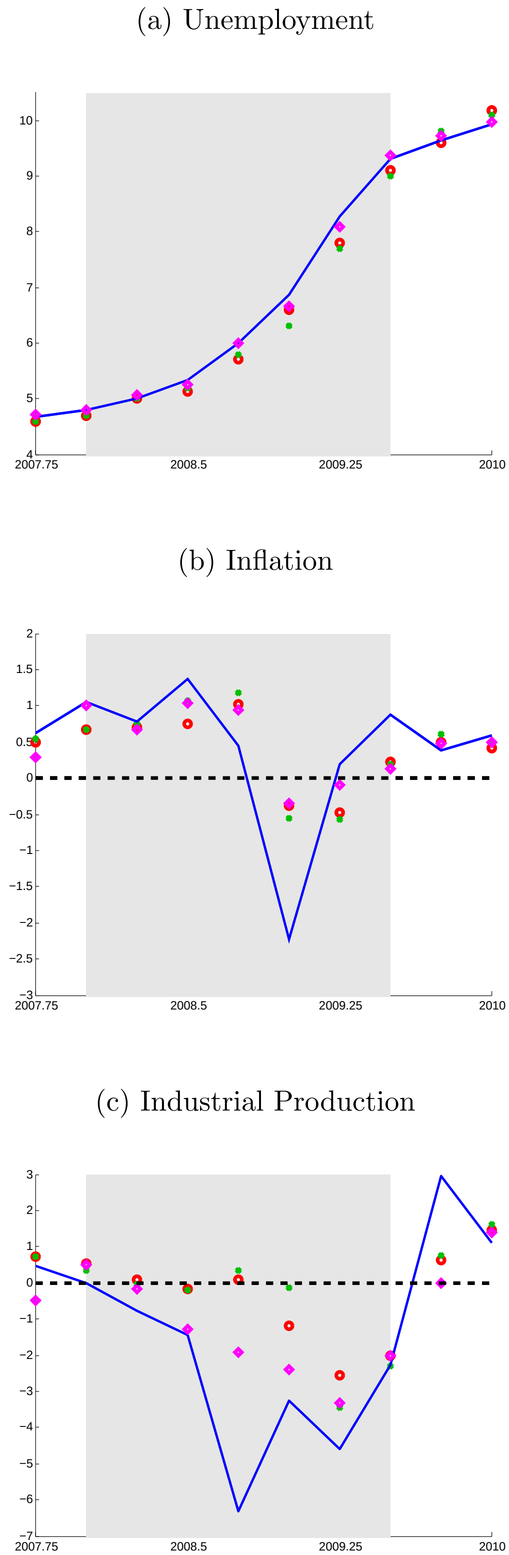
Note: Comparisons relative to the ARMA/ARIMA model for the $NNX - H$ model. "Y" means that our proposed model does better than the alternative. Based on the Diebold-Mariano test, an asterisk (*) and a double asterisk (**) mean that the forecast is better at 10 % and 5 %, respectively. We exclude results for personal consumption at horizon = 12 because the ARMAX model has difficulty estimating it.

7 Multivariate extension

Thus far, we have exclusively discussed the univariate forecasting performance of our model. It is straightforward to extend the framework to the multivariate case as well. Without loss of generality, let us consider the two variable case. Call the two variables $y_t^{(1)}$ and $y_t^{(2)}$. We first fit a vector autoregression as our baseline model to $\{y_t^{(1)}, y_t^{(2)}\}$. Call forecasts from this baseline $\{\hat{y}_{t,VAR}^{(1)}, \hat{y}_{t,VAR}^{(2)}\}$.

As before, our goal is to correct these forecasts by accounting for forecast errors made by the vector autoregression in similar previous time periods using information contained in both series. To this end, we

[14]Relative RMSE values are in the appendix.



Greenbook nowcast (green dots), SPF nowcast (red dots), NN - X forecast with the house price index (pink diamonds), and data (blue solid). Shaded areas are NBER recession dates. To construct the quarterly data for the unemployment rate, we take an interquarter average of the monthly unemployment rates. To construct the same for inflation and industrial production, we take an interquarter sum of the monthly rates.

Figure 14: Different Forecasts during the Great Recession

follow Mizrach (1992) and consider an extension of our original distance function to multiple variables. As an example, consider matching the k length series ending at time t to the same length series ending at time k [15]:

$$dist = \sum_{i=1}^{k} weighs(i) \left(\sum_{j=1}^{2} \left(\left(y_{t+1-i}^{(j)} - \overline{y}_t^{(j)} \right) - \left(y_{k+1-i}^{(j)} - \overline{y}_k^{(j)} \right) \right)^2 \right)$$

The closest match now must be close for both series $\{y_t^{(1)}, y_t^{(2)}\}$ as each is weighted equally in this calculation. We standardize both series before calculating the distance measure to remove the influence of units on the calculation.

Model selection proceeds similarly as in the univariate case. We use BIC on full sample data to select the optimal VAR lag length with a maximum lag length of 12. We continue to use the historical out-of-sample mean squared error to select the optimal k and m values. Since there are multiple series, we must specify the one on which we evaluate the model's historical forecasting performance for selection.

For our empirical exercise, we consider 2-variable VARs with each of the 13 macro and financial variables along with the house price index. Using house price as the common variable across VARs is sensible given the significant improvement in the univariate case upon controlling for house prices. Our data length is the same as in the NNX-H results and the forecasting specifications remain the same. As we are primarily interested in forecasting the 13 macro and financial variables, in each VAR, we specify that variable as the one on which we do model selection (not the house price index).

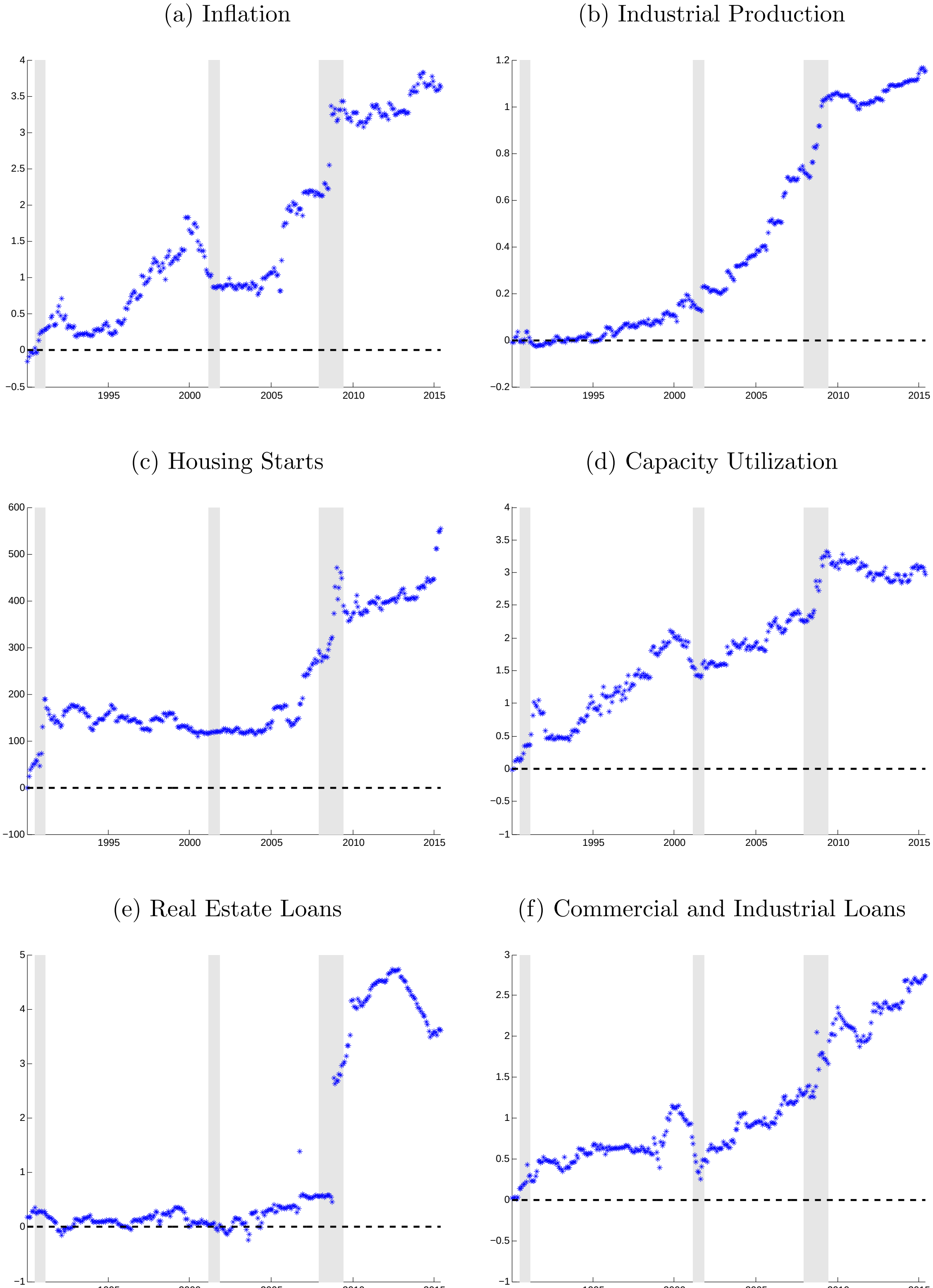
We compare the forecasts from our model to those from a VAR in Table 4. In the multivariate case, our methodology continues to do well. It forecasts better than the linear alternative in all but 2 cases and for 6 series, its forecasts are significantly better than those from a linear model.

Figure 15 shows the recursive one step ahead mean squared error differences between the nearest neighbor model and the VAR for the 6 series in which the nearest neighbor model forecasts significantly better than the VAR model. In all cases, the nearest neighbor method continues to do especially well during the Great Recession. For inflation, industrial production, capacity utilization, and commercial and industrial loans, the nearest neighbor model consistently outperforms the VAR model across all time periods. For housing starts and real estate loans, however, the gains seem to be more concentrated around the Great Recession.

8 Final thoughts

Our approach performs well during sharp changes in the data and still is competitive during normal times. We view our approach as a complement rather than a substitute to existing methods. It can be applied in different contexts. One possible extension is to use a weighted forecast of our approach and a linear

[15]We focus on the match to deviations from local mean specification.



The graphs show the relative performance of our 2-variable nearest neighbor model versus VAR in blue. Increases in these series mean that the nearest neighbor models are doing better. The two variables are the variable listed and the house price index. Shaded areas are NBER recession dates.

Figure 15: 2-variable nearest neighbor versus VAR model forecast comparison

Table 4: 2−variable nearest neighbor versus VAR model forecast comparison based on MSE (1 step ahead)

Inflation	Y^{**}
Federal funds rate	N
Unemployment	Y
Payroll employment	Y
Industrial production	Y^{**}
Personal consumption	Y
Real personal income	Y
Average hourly earnings	N
Housing starts	Y^{**}
Capacity utilization	Y^{**}
S&P500	Y
Real estate loans	Y^{*}
Commercial and industrial loans	Y^{**}

Note: Comparisons relative to the VAR model for the nearest neighbor model. The two variables are the variable listed and the house price index. "Y" means that our proposed model does better than the alternative. Based on the Diebold-Mariano test, an asterisk (*) and a double asterisk (**) mean that the forecast is better at 10 % and 5 %, respectively.

model. The weights can be based on the probability of a recession. Clearly, this alternative gives more emphasis to our algorithm when the economy is suffering a downturn. Alternatively, the forecasts can be combined using the Bayesian predictive synthesis recently advocated by McAlinn and West (2016). As we forecast better during sudden movements in the data, another possible application is to consider emerging economies, where wild fluctuations happen more often.

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A Data

All data excluding the excess bond premium and house price index runs from Jan 1959 to Jun 2015. The final two series begin in Jan 1973.

Series	Source
Civilian unemployment rate 16+	Bureau of Labor Statistics
Industrial production	Federal Reserve Board
PCE Chain price index	Bureau of Economic Analysis
Federal funds effective rate (Avg, annualized %)	Federal Reserve Board
S&P 500	FRED-MD
Real personal consumption expenditures	FRED-MD
Total nonfarm payrolls	FRED-MD
Real personal income	FRED-MD
Average hourly earnings	FRED-MD
Housing starts	FRED-MD
Capacity utilization manufacturing	FRED-MD
Real estate loans	FRED-MD
Commercial and industrial loans	FRED-MD
Excess bond premium	Simon Gilchrist website
House Price Index	Robert Shiller website
Real oil price (West Texas Intermediate, deflated by PCE prices)	FRED-MD

B Optimally selected linear baseline model

Following Ferrara, Marcellino, and Mogliani (2015), we use the BIC on the full sample data to select the optimal baseline model within the class of ARMA/ARIMA models. We perform augmented Dickey-Fuller tests for stationarity of the series. This test fails to reject the null of nonstationarity for the federal funds rate, unemployment, and capacity utilization. Among those 3 series, only for the federal funds rate does the BIC criterion select the ARIMA model over the ARMA model. We allow for up to 12 lags and 3 moving average terms in our model selection. m is the lag length and n is the moving average term length.

Series	Baseline Model ARMA(m,n)
Inflation	$1, 2$
Federal funds rate	$8, 1, 2$ (ARIMA)
Unemployment	$3, 1$
Payroll employment	$2, 1$
Industrial production	$4, 2$
Personal consumption	$1, 2$
Real personal income	$0, 1$
Average hourly earnings	$1, 1$
Housing starts	$1, 2$
Capacity utilization	$2, 1$
S&P 500	$0, 1$
Real estate loans	$1, 2$
Commercial and industrial loans	$1, 2$

We also show the optimally selected ARMAX/ARIMAX model. To select the number of lagged regressors of the exogenous variable, we begin with the selected ARMA/ARIMA model and consider regressor lags up to 12. Note that the excess bond premium and house price index data only begin in Jan 1973. This explains any potential discrepancies between the following ARMA/ARIMA results and those using the full data. m is the lag length, n is the moving average term length, and q is the X variable lag length where the X variable is the excess bond premium, the house price index, or the real oil price.

Series	Baseline Model ARMA(m,n,q) EBP	House price index	Real oil price
Inflation	$1, 2, 2$	$1, 2, 2$	$1, 2, 2$
Federal funds rate	$8, 1, 2, 4$ (ARIMAX)	$8, 1, 2, 1$ (ARIMAX)	$8, 1, 2, 1$ (ARIMAX)
Unemployment	$2, 2, 1$	$2, 2, 1$	$2, 2, 1$
Payroll employment	$1, 2, 1$	$1, 2, 1$	$1, 2, 12$
Industrial production	$1, 1, 1$	$1, 1, 1$	$1, 1, 1$
Personal consumption	$1, 2, 2$	$1, 2, 1$	$1, 2, 2$
Real personal income	$0, 1, 1$	$0, 1, 1$	$0, 1, 1$
Average hourly earnings	$1, 1, 1$	$1, 1, 2$	$1, 1, 1$
Housing starts	$1, 2, 11$	$1, 2, 10$	$1, 2, 11$
Capacity utilization	$2, 1, 1$	$2, 1, 1$	$2, 1, 1$
S&P 500	$0, 1, 1$	$0, 1, 1$	$0, 1, 12$
Real estate loans	$1, 2, 1$	$1, 2, 1$	$1, 2, 1$
Commercial and industrial loans	$1, 2, 3$	$1, 2, 1$	$1, 2, 2$

In the multivariate case, we select up to lag length 12. The second variable in the VAR is the house price index.

Series	VAR(l)
Inflation	3
Federal funds rate	3
Unemployment	4
Payroll employment	3
Industrial production	3
Personal consumption	1
Real personal income	2
Average hourly earnings	3
Housing starts	1
Capacity utilization	3
S&P 500	2
Real estate loans	3
Commercial and industrial loans	3

Table 5: Forecast comparison based on MSE (1-step ahead) (RMSE ratio relative to ARMA/ARIMA model forecast)

	NN1	NN2	MS-AR	NNX-B	NNX-H	NNX-O	ARMAX-B	ARMAX-H	ARMAX-O
Inflation	0.98^{**}	0.99	1.02	0.98^{*}	0.96^{**}	0.95^{**}	1.00	0.99	0.93^{**}
Federal funds rate	1.03	0.95	–	0.97	0.97	1.01	1.43	0.98	0.99
Unemployment	1.00	0.95^{**}	1.02^{**}	0.98^{*}	0.97^{**}	0.98	0.98	0.99	1.00
Payroll employment	0.96^{*}	0.97	1.00(1.04)†	0.98	0.96^{*}	0.99	0.96	1.00	1.02
Industrial production	0.96^{**}	0.96^{**}	0.98	0.97	0.96^{*}	0.98	0.97	1.00	1.00
Personal consumption	0.98	0.98^{*}	1.03^{**}	0.99	0.96^{*}	0.99	1.00	1.00	1.02
Real personal income	0.91^{**}	0.95^{**}	1.01	0.98	0.98^{**}	0.98^{*}	0.98	0.99	0.99
Average hourly earnings	1.00	1.00	1.01	0.97^{**}	0.97	0.96^{**}	1.00	1.01	0.96^{*}
Housing starts	0.99	0.99	0.99	0.98^{*}	0.98^{**}	1.00	1.02	1.01	1.01
Capacity utilization	0.99	0.98	0.98	0.97	0.98	0.99	0.98	1.00	1.00
S&P500	0.99	0.99	1.00	0.99	1.01	0.99	0.99	1.00	1.04
Real estate loans	0.99	0.98^{**}	1.00	0.98^{**}	0.98^{**}	0.98^{**}	1.00	0.99	1.00
Commercial and industrial loans	0.97^{**}	0.99	0.96^{**}	0.96^{**}	0.99	0.99	0.94^{**}	1.00	1.00

Note: Comparisons relative to ARMA/ARIMA model. NN1: match to level model; NN2: match to deviation model. The numbers are RMSE ratios relative to the baseline ARMA/ARIMA model forecast. Numbers below 1 indicate that the model under consideration forecasts better than the ARMA/ARIMA model. Based on the Diebold-Mariano test, an asterisk (*) and a double asterisk (**) mean that the forecast is better at 10 % and 5 %, respectively. We use Newey-West standard errors when making these calculations.

Note that while the comparisons NN1 and NN2 are made for models estimated on the data from 1959 until the end of the sample, the other comparisons are made for models estimated beginning in 1973 due to data limitation issues.

The MS-AR model does not estimate for the Federal funds rate.

†: The MS-AR model has difficulty estimating recursively for payroll employment. The model is able to estimate using the entire sample as well as using data only up to Jan 1990 (the first time period for the forecasting exercise). Forecasting using full sample parameter estimates leads to better performance versus the linear model whereas forecasting using parameter estimates with information up to Jan 1990 leads to poorer forecasting performance.

Table 6: NN - X versus ARMA/ARIMA model forecast comparison based on MSE for multiple horizons (months) (RMSE ratio relative to ARMA/ARIMA model forecast)

	3	6	12
Inflation	0.97	0.98	0.98
Federal funds rate	0.96	0.96	0.94
Unemployment	0.94	0.88^{*}	0.80^{**}
Payroll employment	0.95	0.92^{*}	0.91
Industrial production	0.96	0.98	0.98
Personal consumption	0.99	0.98^{*}	–
Real personal income	0.99	1.00	0.97^{**}
Average hourly earnings	0.99	1.00	0.99
Housing starts	0.99^{**}	0.98^{**}	0.99
Capacity utilization	0.97	0.99	0.99
S&P500	0.99	0.99	0.99
Real estate loans	0.98	0.98	0.96
Commercial and industrial loans	0.97^{*}	0.96^{**}	0.96^{*}

Note: Comparisons relative to the ARMA/ARIMA model for the $NNX-H$ model. The numbers are RMSE ratios relative to the baseline ARMA/ARIMA model forecast. Numbers below 1 indicate that the model under consideration forecasts better than the ARMA/ARIMA model. Based on the Diebold-Mariano test, an asterisk (*) and a double asterisk (**) mean that the forecast is better at 10 % and 5 %, respectively. We exclude results for personal consumption at horizon = 12 because the ARMAX model has difficulty estimating.

Table 7: ARMA/ARIMA - X versus ARMA/ARIMA model forecast comparison based on MSE for multiple horizons (months) (RMSE ratio relative to ARMA/ARIMA model forecast)

	3	6	12
Inflation	1.01	1.10	1.25*
Federal funds rate	1.06	0.97	0.93
Unemployment	0.96	0.83	0.83
Payroll employment	1.06	0.99	1.04
Industrial production	1.02	1.01	1.05
Personal consumption	1.00	1.03	–
Real personal income	0.99	0.95	0.99
Average hourly earnings	1.05*	0.99	0.99
Housing starts	1.04	1.04	1.07**
Capacity utilization	1.10	1.09	1.31**
S&P500	1.01	0.93	0.99
Real estate loans	0.99	0.96	0.92
Commercial and industrial loans	1.00	0.98	1.05

Note: Comparisons relative to the ARMA/ARIMA model for the $ARMAX/ARIMAX - H$ model. The numbers are RMSE ratios relative to the baseline ARMA/ARIMA model forecast. Numbers below 1 indicate that the model under consideration forecasts better than the ARMA/ARIMA model. Based on the Diebold-Mariano test, an asterisk (*) and a double asterisk (**) mean that the forecast is better at 10 % and 5 %, respectively. We exclude results for personal consumption at horizon = 12 because the ARMAX model has difficulty estimating.