

# Predicting National and Local House Price Fluctuations

Preliminary \*

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## Abstract

We develop a forecasting model for house price growth at both the local and national level. We adopt a Bayesian approach for exact dynamic factor analysis of data sets when both the cross-sectional and time series dimensions of the model are large. Our approach combines the approaches developed by Otrok and Whiteman (1998) and Kim and Nelson (1998), both of which rely on Markov-Chain Monte Carlo methods to sample from the joint posterior of the parameters and unobserved dynamic factors. Our application is to forecast house price movements in 240 Metropolitan Statistical Areas (MSAs) in the United States. Our objective is to provide forecasts for local house prices as well as for a national index of house prices. One novelty of our approach is that we combine local, regional and national factors in our forecasts of local and national house prices. We find that the best forecasting model, or weights given to the three types of factors, varies significantly by MSA.

JEL CLASSIFICATION:

KEY WORDS: Bayesian Factor Models; Forecasting; House Prices.

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# 1 Introduction

What direction are house prices headed? Does the answer to that question depend on whether you live in New York City or Charlottesville, Virginia? The answer to these two questions is of interest because it informs policymakers of potential risks to the economy, as well as the extent to which those risks may be localized versus national in nature. Knowledge of the variables that help predict house prices, such as mortgage rates, income or credit conditions is important to help us to better understand what moves house prices and how that might vary across housing markets. The challenge to answering this question is that housing markets have both a national component to them as well as region-specific or local components. In order to forecast house prices then, one needs to have a model that can measure all components.

To meet this challenge we employ a Bayesian dynamic factor model. There has been a recent interest in the dynamic factor literature (e.g., Quah and Sargent, 1993; Stock and Watson, 1999, 2002; Forni, Hallin, Lippi, and Reichlin 2001; and Kose, Otrok, and Whiteman, 2001), in using a large numbers of time series in an attempt to exploit cross-sectional covariation. It is believed that this cross-sectional covariation can be exploited for both forecasting purposes as well as measuring the nature of comovement in a dataset. The cited papers employ various types of "factor models" that characterize the covariation amongst a large vector of variables utilizing a much lower-dimension set of "factors" together with series-specific idiosyncratic components. In this paper, we employ a Bayesian approach to specifying and implementing a dynamic factor model for forecasting purposes.

The various approaches to estimating dynamic factor models that have appeared to date are motivated by difficulties with working with large cross sections and interest in exploiting cross-sectional information in forecasting particular time series. Stock and Watson (1999, 2002) utilize a two-step procedure whereby the unobserved factors are computed "offline" from the principal components of the vector of time series. That is, at each date, data available up to that date are used to estimate a covariance matrix of the cross-section, and the first principal component is constructed from the linear combination of the cross-section associated with the eigenvector corresponding to the largest eigenvalue of the estimated covariance matrix. Then observations on contemporaneous and lagged values of this "index" are included in regressions of variables of interest (e.g., inflation) on own lags. Consistency and asymptotic distribution theory (for large cross-section dimension rather than large time series dimension) are developed for estimators in such equations. Stock and Watson demon-

strate that the cross sectional information embodied in the principal components is helpful in forecasting.

Forni, Hallin, Lippi, and Reichlin (2001) employ a factor model in which the idiosyncratic components can be correlated, but are dominated by the common components (factors) when  $N$  is sufficiently large. They work in the frequency domain to estimate dynamic principal components. The authors argue that their procedure, which makes the factors inherently dynamic, in contrast to the Stock-Watson "static" factor procedure, improves "fit" and forecasts.

Kose, Otrok, and Whiteman (2001) build on Otrok and Whiteman (1998a) to implement a Bayesian procedure for estimating factor models with large cross sections but short time series. Their procedure involves a particular parameterization of the spectral density matrix. The empirical analysis is Bayesian, and utilizes Markov Chain Monte Carlo procedures. The application involves characterizing worldwide and region-specific comovement in output, consumption, and investment data for 60 countries over 36 years. The calculation exploits a feature of the Otrok-Whiteman (1998a) procedure that limits applicability to relatively short time series; here, we modify the procedure so that it is applicable to large time series dimensions as well as large cross sections.

The approach we take involves a structure along the lines of Kim and Nelson (1998) and Del Negro and Otrok (2007) who utilize Carter and Kohn's (1994) algorithm for drawing from the posterior of a state space model. Our factor analysis is explicitly dynamic, like that of Forni, Hallin, Lippi, and Reichlin (2001). Our model structure differs from those of Stock and Watson and Forni, Hallin, Lippi, and Reichlin in that we implement overidentifying restrictions to discover interpretable factors—here defined as regions—rather than the "reduced form" procedures involving static or dynamic principal components. Our parametric allows us to improve the interpretation of our forecasting results.

Before turning to our forecasting exercise we first present results for our factor model estimated on the full sample. We do this to document the diverse nature of house price movements across MSAs. We find that for the full sample the national factor accounts for, on average, 20 percent of house price growth movements. This average understates the potential importance of the national factor, as it accounts for more than 40 percent of house price movements in 25 MSAs. This result indicates that national conditions will clearly matter for a number of the MSAs—but not all. Our regional factors account for, on average, 60 percent of house price movements. This indicates that measurement of the region specific cycle will be critical to forecasting performance. The idiosyncratic components account

for 20 percent of house price movements on average. We show that there is considerable heterogeneity in this case, with a number of MSAs fully captured by the idiosyncratic component. This result indicates that for some MSAs, only local conditions matter, making forecasting difficult.

Our first forecasting exercise uses the dynamic factor model and the associated parameters. As the factors and idiosyncratic components are autoregressive processes generating forecasts is straightforward. The forecast in any particular housing market depends both on the forecast of the idiosyncratic component as well as the forecast of the national and regional components, with the latter weighted by the estimated factor loadings. All forecasts are 'out of sample' and are computed using rolling-estimates of the model. We focus on forecast horizons of up to 1 year. In all cases we compare the RMSE of the forecasts with a random walk forecast and a forecast of the unconditional mean.

Our second set of forecasts follows Stock and Watson (2002) and uses only the estimated factors themselves in the forecast. The target variable (perhaps house price growth in Phoenix one year in the future) is then regressed on lags of the factor(s) and possibly lags of the observable variable itself.

Our third forecasting exercise combines information from the factor model with other economic data to potentially improve forecast accuracy. At each date we combine the national housing factor, perhaps the regional factors, along with aggregate or local economic time series.

The paper proceeds as follows. Section 2 reviews the existing literature on forecasting house prices. In Section 3 we explain the dynamic factor model as well as show estimates of the model for the full sample. In Section 4 we present our main forecasting results. Section 5 concludes.

## 2 Literature Review

We review the existing literature on house price forecasting (to be added).

## 3 The Dynamic Factor Model

We begin with a review of the (standard) dynamic factor model we will use in forecasting. Dynamic factor models decompose the dynamics of observables  $y_{i,t}$ ,  $i = 1, \dots, n$ ,  $t =$

$1, \dots, T$  into the sum of two types unobservable components, one that affects all (or some)  $y_{i,t}$ s, namely the factors  $f_t$ , and one that is idiosyncratic, e.g. specific to each  $i$ :

$$y_{i,t} = a_i + b_i f_t + \epsilon_{i,t}, \quad (1)$$

where  $a_i$  is the constant and  $b_i$  is the exposure, or loading, of series  $i$  to the common factors. The framework accommodates multiple factors—in our application there will be a common national factor that all variables load on as well as a region-specific factor. Both the factors and idiosyncratic components follow autoregressive processes of order  $q_k$  and  $p_i$  respectively:

$$f_t^k = \phi_{k,1} f_{t-1}^k + \dots + \phi_{k,q} f_{t-q}^k + u_{k,t}, \quad \text{and} \quad (2)$$

$$\epsilon_{i,t} = \phi_{i,1} \epsilon_{i,t-1} + \dots + \phi_{i,p_i} \epsilon_{i,t-p_i} + \sigma_i u_{i,t}, \quad (3)$$

where  $\sigma_i$  is the standard deviation of the idiosyncratic component, and  $u_{i,t} \sim \mathcal{N}(0, 1)$  for  $i = 0$  and  $i = 1, \dots, n$  are the innovations to the law of motions 2 and 3, respectively.<sup>1</sup> These innovations are i.i.d. over time and across  $i$ . The factors' innovations are also assumed to be uncorrelated with one another. Note that expressions (1), (2), (3) can be viewed as the measurement and transition equations, respectively, in a state-space representation.

The model just described is the standard dynamic factor model estimated for example in Stock and Watson (1989). The model as described will decompose local house prices into components that are region specific and national in nature. We will then use these estimated components in a variety of forecasting exercises. It is important to note that our model is fully parametric. Nonparametric alternatives exist (e.g. Stock and Watson 2002, Forni et al 2005) and have been shown to be useful in combining data in a large dataset to forecast a few variables of interest. Our interest here is first understanding the relative importance of region and national components in house price fluctuations. This requires us to use a parametric approach to estimation so we can impose the needed zero restrictions to identify, say, the factor specific to MSAs in Florida. Second, we are interested in forecasting the whole panel of MSAs. As such, it is useful to have the sensitivity of each MSA to each factor to use in weighting forecasts.

### 3.1 Estimation

The model is estimated using a Gibbs sampling procedure. In essence, this amounts to reducing a complex problem – sampling from the joint posterior distribution – into a sequence of tractable ones for which the literature already provides a solution – sampling from

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<sup>1</sup>Note that  $\sigma_0$  is set to 1, which is a standard normalization assumption given that the scale of the loadings  $b_i$ s and  $\sigma_0$  cannot be separately identified.

conditional distributions for a subset of the parameters conditional on all the other parameters. Our Gibbs sampling procedure reduces to two main blocks. In the first block we condition on the factors, sample from the posterior of the constant term  $a_i$ , factor loadings  $b_i$ , the autoregressive parameters  $\{\phi_{i,1}, \dots, \phi_{i,p_i}\}$ , and the variance  $\sigma_i^2$ . It is important to observe that this step is done equation by equation. This keeps the state-space of the model tractable and allows us to estimate a model with a large cross-section of data. Next, we draw the factors  $f_t$  conditional on all other parameters using the state space representation of the model, as in Carter and Kohn (1994). We will stress that the procedure is computationally efficient and can accommodate datasets where  $T$  and  $n$  are relatively large: in most cases the computational cost increases only linearly in these dimensions. A curse of dimensionality problem often arises in state space models such as this since the idiosyncratic dynamics typically show up in the state equation along with the factor dynamics. A solution to this curse of dimensionality is to pre-whiten the data, that is, to pre-multiply each measurement equation by  $1 - \sum_{j=1}^p \phi_{n,j} L^j$ , so to get rid of the dynamics in the state-specific shocks (see Kim and Nelson 1999, and Quah and Sargent 1993), obtaining:

$$\left(1 - \sum_{j=1}^p \phi_{i,j} L^j\right) y_{i,t} = \left(1 - \sum_{j=1}^p \phi_{i,j}\right) i + \sum_{k=0}^K \beta_i^k \left(1 - \sum_{j=1}^p \phi_{i,j} L^j\right) f_t^k + u_{i,t}. \quad (4)$$

The estimation procedure is more fully described in Del Negro and Otrok (2007).<sup>2</sup>

The priors used in this paper are quite standard, and similar to those used in Kose, Otrok, and Whiteman (2005). The prior for constant  $a_i$  is normal with 2 and precision (the inverse of the variance) 1. The prior for the loadings  $\beta_i^f$  is fairly loose: it is Gaussian with zero mean and precision equal to 1/100. The prior for the idiosyncratic innovation variance  $\sigma_i^2$  is an inverted gamma with parameters 4 and 0.1. The priors for the parameters of the AR polynomial are Normal with mean zero and precision equal to 1 for the first lag, and then increasing geometrically at rate .75 for the subsequent lags. We choose a lag length equal to  $q = 3$  for the factors and  $p = 2$  for the idiosyncratic shocks. All priors are mutually independent.

### 3.2 Data

The house price data are published by the Office of Federal Housing Enterprise Oversight (OFHEO), and captures changes in the value of single-family homes. The HPI is a weighted repeat sales index: It measures average price changes in repeat sales or refinancings on the

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<sup>2</sup>Their procedure is derived from the work of Otrok and Whiteman 1998 and Kim and Nelson 1999.

same properties and weights them (see Calhoun, 1996, for an in-depth description of how the HPI is constructed). The price information is obtained from repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975. While the housing price data has been criticized for its construction, to our knowledge it is the best data available to the public at the MSA level. We will be working with growth rates of the housing price data so issues related to bias in the level estimates are not relevant. We compute growth rates using log-differences, in percent. The HPI data are nominal.

The HPI data are available from 1975, but in our estimation we use only data beginning in the first quarter of 1987. For the MSA level data that we use there is a tradeoff between the size of the time series and size of the cross-section. Before 1987 many MSAs do not have house price data reported. By starting later than 1987 we shorten the time series but pick up only a small number of MSAs. Our sample of MSAs is 240.

The regional factors are defined by geography. Our specification includes 13 regions. Most of the regions follow the Census definition, with the exception that we break South Atlantic and Mountain into North and South subregions. We also place Florida and California into their own regions. Each of the 240 MSAs is then placed in one of these regions.

1: Middle Atlantic (New York, New Jersey, Pennsylvania) 2: New England (Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut) 3: East North Central (Ohio, Indiana, Illinois, Michigan, Wisconsin) 4: West North Central (Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas) 5: South Atlantic [North] (Delaware, Maryland, District of Columbia, Virginia) 6: South Atlantic [South] (West Virginia, North Carolina, South Carolina Georgia) 7: Florida 8: East South Central (Kentucky, Tennessee, Alabama, Mississippi) 9: West South Central (Arkansas, Louisiana, Oklahoma, Texas) 10: Mountain Division [north] (Montana, Idaho, Wyoming, Colorado) 11: Mountain Division [south] (New Mexico, Arizona, Utah, Nevada) 12: Pacific (Washington, Oregon) 13: California

### 3.3 Full Sample Estimates of Model

We estimate the model for the full sample, including a national factor and the 13 regional factors. The factors are shown in Figure 1. The national factor tracks the national OFEHO price index well, showing the housing boom of the late 1990s and early 2000's, as well as the sharp decline in house prices in the recent past. The factors for Florida and California

show that there was an additional sharp decline in the MSAs in these states that cannot be accounted for by national house price movements. For the most part the factors are tightly estimated, indicating that the data are very informative about the state of the regional housing cycles. Given that we will use these factors for forecasting this is reassuring, as we hope that our predictive densities will be informative.

Table 1 reports the in-sample variance attributed to each factor. We can see that the regional factor is most important for understanding house price fluctuations, while national and idiosyncratic terms both explain a nontrivial amount of house price volatility. A key feature of this table is the heterogeneity across MSAs. There is a wide variety of experience in terms of exposure to national and regional cycles. This indicates that a forecasting model that uses equal weights across MSAs for various factors or predictors may perform poorly on average. Our objective is to exploit this heterogeneity to forecast well across all MSAs.

## 4 Forecasting Models

We consider a variety of forecasting models. In each case we compare the forecast of our model at forecast horizons of one quarter and four quarters out to two 'naive' forecasts: a random walk forecast and a forecast of the unconditional mean. It is of course simple to extend to longer horizons, however, given the number of MSAs we report forecasts for we limit ourselves to these two horizons that are typically of interest to policymakers. Note that our data is in the form of quarterly growth rates. Our random walk forecast is a random walk forecast of the *growth* of house prices. Our forecast of the unconditional mean is a forecast based on growth rates as well. This latter forecast corresponds to a random walk forecast in levels. Given the issues with the measurement of house prices levels discussed above this is the only formulation of the data we consider. In all cases forecast performance is based on out of sample forecasts. Our first sample is from 1987:1-1991:1. We estimate the full model in (1)-(3) for this period, then roll the sample forward one period to 1987:1-1991:2 and re-estimate the full model. In the end we get 43 out-of-sample forecast periods.<sup>3</sup>

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<sup>3</sup>We use 500 monte carlo draws in each subsample. This number is low and will be increased in the future. Estimation of the full rolling sample for this size takes more than a week due to the size of the model.



#### 4.1 Forecasts Based on Full Factor Model Model

Our first forecast is based on all of the parameters and factors estimated in equations (1)-(3). The forecast proceeds in the natural fashion. First each factor in (2) is forecast (at time  $T$ ) for periods  $T+1\dots T+4$ , using the estimated autoregressive parameters, and the estimate of the factor at the end of the period. The idiosyncratic components in (3) are forecast in a similar fashion, with the error terms for period  $T$ ,  $T-1$ ,  $T-2$  etc. calculated using (1) and the estimated factors. The final forecast of the observable is then the sum of the factor forecasts and idiosyncratic forecasts. The weight each factor gets in the forecast is given by the  $b_i$  in equation (1). This forecast is done for each draw from the posterior of the parameters, which then gives us the entire predictive density at each date. We then measure accuracy by choosing the mean of the predictive distribution as our point estimate, which implies the use of a quadratic loss function.

We construct forecasts for 5 different models. The first uses all factors and the idiosyncratic component as suggest by equations (1)-(3). We also report results for a model using only the regional factor, only the national factor, only the idiosyncratic factor, and only the national and regional factors. These additional forecasts help pinpoint what aspects of our factor model are contributing the most to forecast performance. These models are compared relative to the two naive forecasts.

In Table 2 we report the full set of relative RMSE at the one step ahead forecast horizon. The first thing to note from the table is the heterogeneity across MSAs. Clearly one model cannot consistently out perform either naive forecast. The full model forecast does well against the random walk forecast, beating it in 55 percent of the MSAs (and beating the unconditional mean forecast in 52 percent of MSAs). The idiosyncratic and national only forecasts perform poorly, while the region only and region plus national factor forecast do satisfactorily. What we take from this is that regional conditions are a vital ingredient in forecasting local house prices in the majority of MSAs.

At longer horizons the performance of the factor model declines relative to the random walk. Figure 2 plots a cumulative density function of the relative RMSE, with RMSE greater than one indicating that random walk model dominates. We can see that for the clear majority of MSAs (60 percent) the random walk model performs better. On the other hand (not shown) the parametric model does do better than the unconditional mean forecast at longer horizons. Extending to a forecast horizon of 8 periods the random walk model outperforms the factor model in 80 percent of the samples.

## 4.2 Forecasts with Factor Regressions

Our second forecasts follows Stock and Watson (2002) and regresses future observables (house prices) on the current and lagged estimates of the factor. The argument for this model is that it may be robust to model misspecification in the estimated parameters. This forecast is based on the estimated factors only, not the parameters in the model (1)-(3). Specifically the forecasting model (h periods in the future) is:

$$Ey_{i,T+h} = a_i + \theta_i(L)f_T + \phi(L)y_{i,T} \quad (5)$$

That is, the H period ahead forecast is constructed from a univariate regression of the house price in an MSA on the national factor, regional factor and its own lags. As in the first forecasting model we will experiment with excluding the different regressors. Here we will construct forecasts for h=1 and 4. Our main objective in this case is to see if we can improve upon the performance of the fully parametric estimate.

At the one step ahead horizon the models are fairly equal, with model 1 (the fully parametric factor model) beating the 'offline' regression approach in 53 percent of the MSAs (not shown). As the horizon increases to 4 periods the fully parametric factor model beats the second model 57 percent of the time. This is shown in the CDF in Figure 3. These results are for the full model, including both national and regional factors and own lags. When restricting the comparison to only the two regional models, model 2, the regression of the observable on the factor post factor estimation, domiantes. As shown by the CDF in Figure 4 the fully parametric model loses 78 percent of the time. Of course, the fully parametric model would do better when all factors are included.

## 4.3 Forecasts with other observable variables

We sllow for other observables in Stock-Watson style factor regression forecasts. We would like to know if these observables negate the performace of the factors. That is, do the factors proxy for an observable? We would also like to knwo how different forecasting variables perform across MSAs. RESULTS TO BE ADDED.

## 4.4 Forecasts of the OFHEO National House Price Index

National forecasts will be added.

## 5 Conclusion

We have developed a model to forecast house prices in a cross-section of 240 MSAs. We have adopted a number of approaches to forecasting. We find that in forecasting house prices accounting for national and regional cycles that vary in importance across MSA has an important impact on improving forecasting performance. One caveat to our work is that we assume that model parameters are stable over time. Del Negro and Otrok (2007) show that the role of the national factor in state level house price fluctuations increases post-2000. We view this as a potentially important extension of our paper. The time-varying factor model of Del Negro and Otrok (2008) is a useful starting point for undertaking this exercise.

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Figure 1: National and regional factors

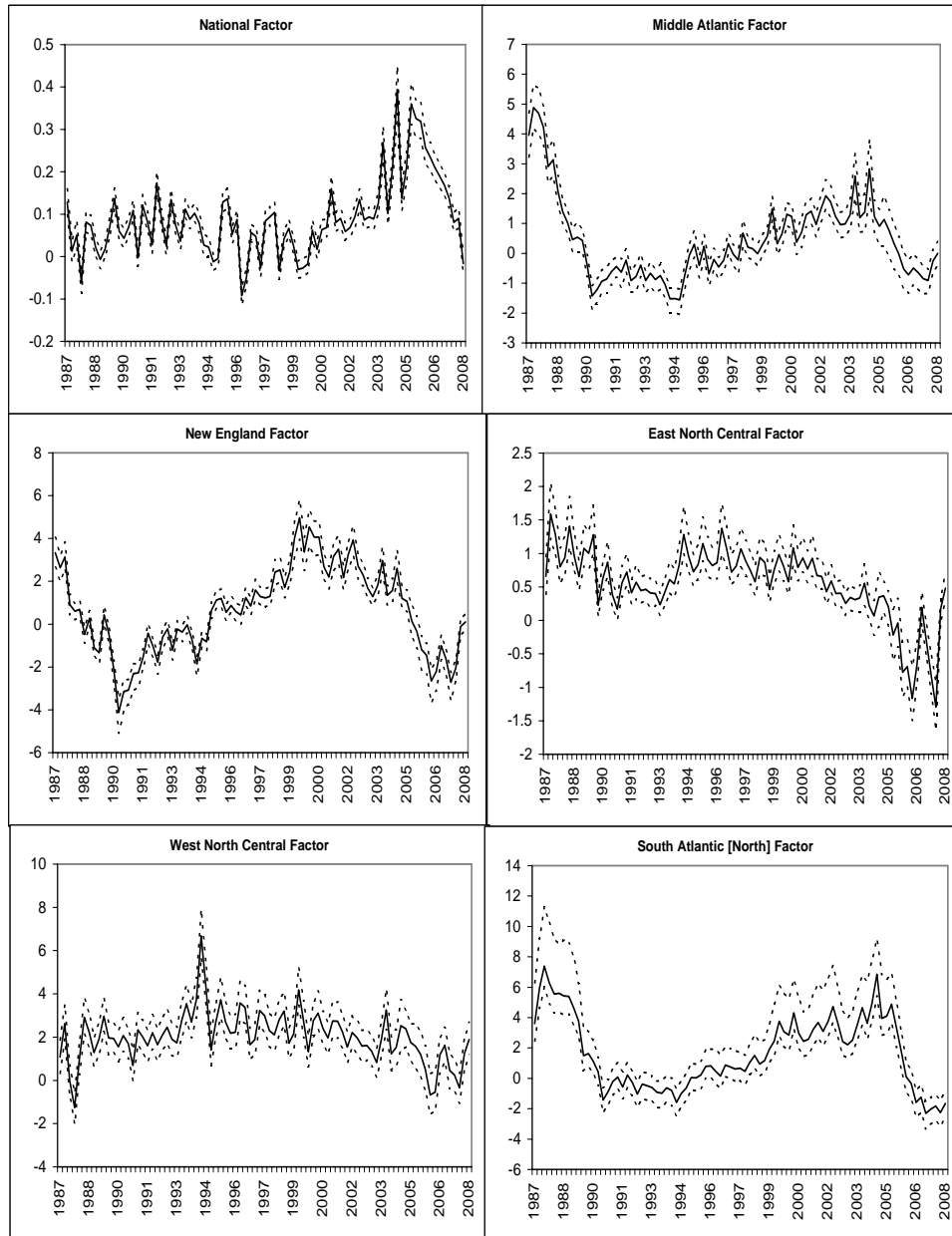


Figure 2: Regional factors

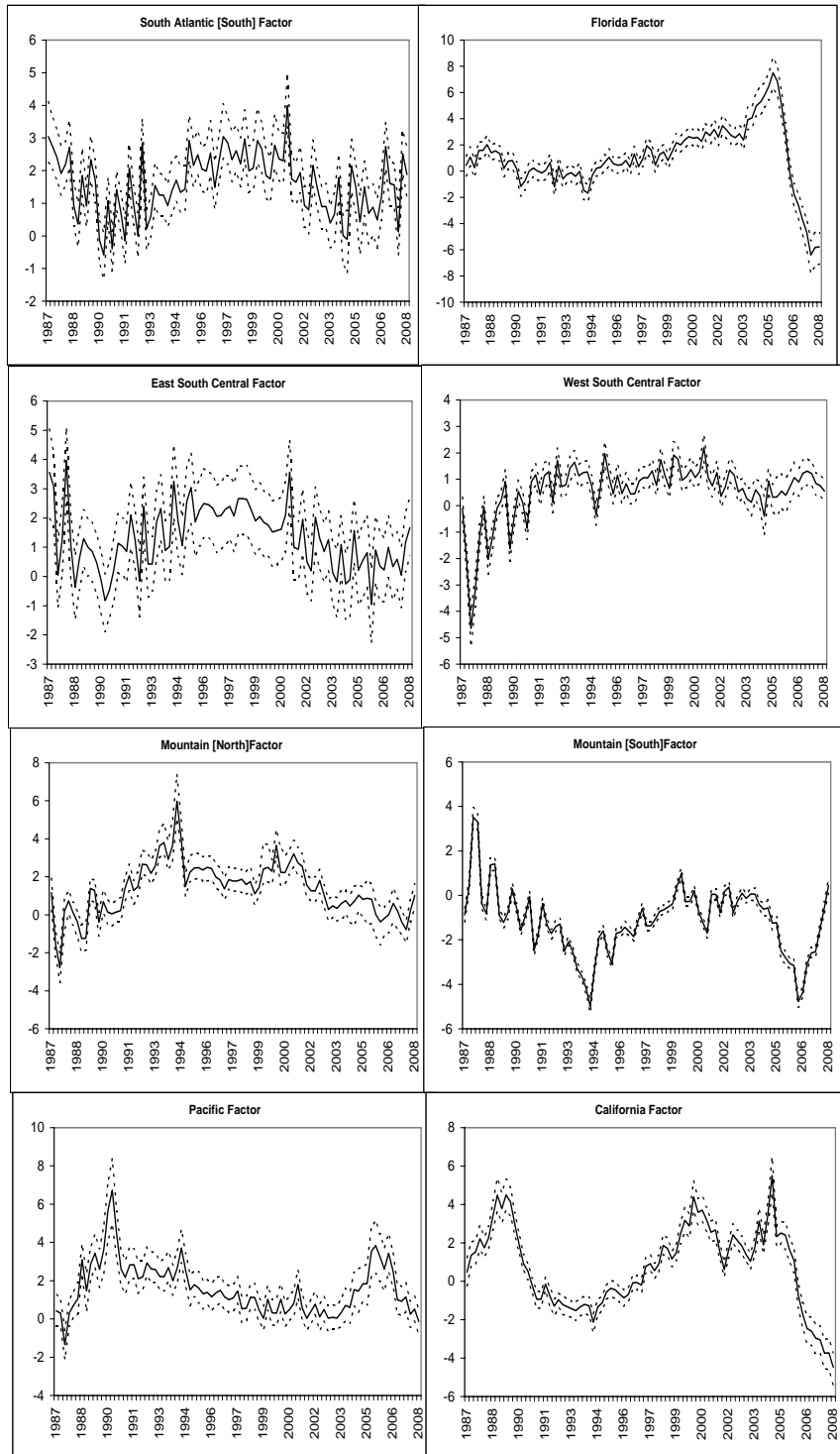


Figure 3: Table 1 of Variance Decompositions

Variance Decompositions: 1986:3-2008:1		National			Regional			Idiosyncratic			
		10%	50%	90%	10%	50%	90%	10%	50%	90%	
Atlantic Region	Albany-Schenectady-Troy, NY	32%	37%	41%	41%	45%	50%	17%	18%	19%	
	Allentown-Bethlehem-Easton, PA-NJ	15%	18%	22%	54%	58%	62%	22%	24%	25%	
	Atlantic City-Hammonton, NJ	25%	28%	32%	27%	30%	34%	40%	41%	43%	
	Binghamton, NY	12%	14%	15%	2%	3%	4%	83%	84%	85%	
	Buffalo-Niagara Falls, NY	6%	8%	10%	24%	27%	30%	63%	65%	67%	
	Camden, NJ (MSAD)	24%	29%	33%	58%	63%	68%	7%	8%	9%	
	Edison-New Brunswick, NJ (MSAD)	17%	21%	25%	48%	52%	56%	25%	27%	29%	
	Erie, PA	0%	0%	0%	0%	0%	0%	100%	100%	100%	
	Harrisburg-Carlisle, PA	34%	36%	39%	3%	4%	6%	58%	60%	62%	
	Lancaster, PA	27%	30%	34%	21%	25%	28%	44%	45%	47%	
	Nassau-Suffolk, NY (MSAD)	9%	13%	16%	44%	49%	53%	37%	39%	40%	
	New York-White Plains-Wayne, NY-NJ (MSAD)	18%	23%	27%	46%	50%	55%	25%	27%	29%	
	Newark-Union, NJ-PA (MSAD)	19%	23%	28%	42%	47%	51%	29%	30%	32%	
	Philadelphia, PA (MSAD)	23%	28%	33%	62%	66%	71%	4%	5%	6%	
	Pittsburgh, PA	6%	7%	9%	4%	6%	7%	86%	87%	88%	
	Poughkeepsie-Newburgh-Middletown, NY	12%	16%	20%	44%	48%	52%	35%	36%	38%	
	Reading, PA	26%	29%	32%	18%	21%	24%	49%	50%	52%	
	Rochester, NY	13%	16%	18%	20%	22%	25%	60%	62%	63%	
	Scranton-Wilkes-Barre, PA	12%	14%	16%	6%	7%	9%	77%	79%	80%	
	Syracuse, NY	12%	15%	17%	20%	23%	25%	61%	63%	64%	
	Trenton-Ewing, NJ	18%	22%	26%	48%	51%	55%	26%	27%	28%	
	Wilmington, DE-MD-NJ (MSAD)	26%	30%	35%	44%	49%	54%	19%	20%	21%	
	York-Hanover, PA	41%	44%	48%	14%	17%	20%	37%	38%	40%	
	<b>Regional Average</b>	<b>18%</b>	<b>23%</b>	<b>28%</b>	<b>29%</b>	<b>34%</b>	<b>38%</b>	<b>42%</b>	<b>45%</b>	<b>48%</b>	
	New England Region	Barnstable Town, MA	2%	3%	5%	78%	80%	82%	15%	16%	17%
		Boston-Quincy, MA (MSAD)	1%	2%	4%	92%	93%	95%	4%	4%	5%
Bridgeport-Stamford-Norwalk, CT		18%	22%	26%	53%	57%	61%	20%	21%	22%	
Burlington-South Burlington, VT		19%	23%	26%	21%	23%	26%	52%	54%	56%	
Cambridge-Newton-Framingham, MA (MSAD)		0%	1%	2%	90%	91%	92%	7%	8%	9%	
Hartford-West Hartford-East Hartford, CT		7%	10%	13%	40%	42%	45%	46%	48%	49%	
Manchester-Nashua, NH		3%	5%	8%	75%	78%	80%	16%	17%	18%	
New Haven-Milford, CT		19%	23%	27%	49%	52%	56%	23%	25%	26%	
Norwich-New London, CT		9%	12%	15%	33%	35%	38%	52%	53%	55%	
Peabody, MA (MSAD)		0%	1%	3%	90%	91%	92%	7%	8%	8%	
Portland-South Portland-Biddeford, ME		4%	7%	9%	56%	59%	61%	33%	34%	36%	
Providence-New Bedford-Fall River, RI-M		9%	13%	16%	63%	66%	69%	20%	21%	23%	
Rockingham County-Strafford County, NH		2%	3%	5%	74%	76%	77%	20%	21%	22%	
Springfield, MA		13%	17%	21%	41%	45%	48%	37%	38%	40%	
Worcester, MA		3%	5%	8%	81%	84%	86%	10%	11%	12%	
<b>Regional Average</b>		<b>7%</b>	<b>10%</b>	<b>13%</b>	<b>62%</b>	<b>65%</b>	<b>67%</b>	<b>24%</b>	<b>25%</b>	<b>27%</b>	
East North Central Region	Akron, OH	0%	0%	0%	25%	28%	31%	69%	72%	75%	
	Ann Arbor, MI	5%	7%	9%	54%	58%	61%	32%	35%	38%	
	Appleton, WI	0%	0%	1%	6%	7%	9%	91%	92%	94%	
	Bloomington-Normal, IL	0%	0%	1%	1%	2%	3%	97%	98%	99%	
	Canton-Massillon, OH	0%	0%	0%	19%	21%	24%	76%	79%	81%	
	Champaign-Urbana, IL	8%	9%	10%	10%	12%	14%	76%	79%	81%	
	Chicago-Naperville-Joliet, IL (MSAD)	18%	22%	26%	21%	24%	27%	48%	53%	57%	
	Cincinnati-Middletown, OH-KY-IN	0%	0%	0%	52%	56%	59%	41%	44%	48%	
	Cleveland-Elyria-Mentor, OH	0%	0%	0%	41%	45%	48%	52%	55%	58%	
	Columbus, IN	0%	0%	0%	4%	5%	6%	94%	95%	96%	
	Columbus, OH	0%	0%	0%	54%	57%	61%	39%	43%	46%	
	Dayton, OH	0%	0%	0%	32%	36%	39%	61%	64%	68%	
	Detroit-Livonia-Dearborn, MI (MSAD)	12%	14%	17%	57%	61%	64%	22%	25%	28%	
	Eau Claire, WI	0%	0%	1%	5%	6%	8%	92%	93%	95%	
	Elkhart-Goshen, IN	0%	0%	1%	1%	1%	2%	97%	98%	99%	
	Evansville, IN-KY	0%	1%	1%	7%	9%	11%	89%	91%	92%	
	Flint, MI	3%	4%	5%	51%	54%	58%	39%	42%	45%	
	Fort Wayne, IN	0%	0%	1%	14%	16%	18%	82%	84%	86%	
	Gary, IN (MSAD)	10%	12%	14%	9%	10%	12%	75%	78%	80%	
	Grand Rapids-Wyoming, MI	7%	9%	11%	39%	42%	45%	46%	49%	52%	
	Green Bay, WI	0%	0%	0%	4%	5%	7%	93%	95%	96%	
	Holland-Grand Haven, MI	6%	7%	9%	36%	39%	42%	51%	54%	57%	
	Indianapolis-Carmel, IN	0%	0%	0%	26%	29%	32%	68%	71%	74%	
	Janesville, WI	1%	2%	2%	2%	3%	4%	94%	95%	97%	
	Kalamazoo-Portage, MI	0%	0%	1%	24%	26%	29%	71%	73%	76%	
	La Crosse, WI-MN	2%	3%	4%	11%	13%	15%	81%	84%	86%	
	Lafayette, IN	2%	3%	4%	8%	7%	8%	88%	90%	92%	
	Lake County-Kenosha County, IL-WI (MSAD)	9%	12%	14%	26%	29%	32%	56%	60%	63%	
	Lansing-East Lansing, MI	0%	1%	1%	62%	65%	68%	31%	34%	37%	
	Lima, OH	0%	0%	1%	6%	7%	9%	91%	92%	94%	
	Madison, WI	1%	2%	3%	11%	13%	15%	83%	85%	87%	
	Mansfield, OH	0%	0%	0%	8%	10%	12%	88%	90%	92%	
	Milwaukee-Waukesha-West Allis, WI	16%	18%	21%	29%	32%	36%	46%	50%	53%	
	Monroe, MI	4%	6%	7%	37%	40%	43%	51%	54%	57%	
	Muskegon-North Shores, MI	9%	10%	12%	8%	10%	11%	78%	80%	82%	
	Niles-Benton Harbor, MI	0%	0%	1%	7%	8%	10%	90%	91%	93%	
	Oshkosh-Neenah, WI	0%	0%	0%	0%	0%	1%	99%	99%	100%	
	Peoria, IL	0%	0%	1%	5%	6%	8%	91%	93%	95%	
	Racine, WI	14%	17%	19%	19%	21%	24%	60%	62%	65%	
	Rockford, IL	24%	27%	29%	2%	3%	5%	68%	70%	72%	
	Saginaw-Saginaw Township North, MI	2%	3%	4%	13%	15%	17%	80%	82%	84%	
	Sheboygan, WI	3%	4%	5%	4%	5%	6%	89%	91%	92%	
	South Bend-Mishawaka, IN-MI	1%	2%	2%	12%	14%	16%	82%	84%	86%	
	Springfield, IL	5%	6%	7%	5%	7%	9%	85%	87%	89%	
	Springfield, OH	0%	0%	0%	6%	7%	9%	91%	93%	94%	
	Tolledo, OH	1%	1%	2%	46%	49%	53%	46%	49%	52%	
Warren-Troy-Farmington Hills, MI (MSAD)	10%	12%	15%	65%	68%	72%	17%	19%	22%		
Youngstown-Warren-Boardman, OH-PA	0%	0%	1%	11%	13%	15%	85%	87%	89%		
<b>Regional Average</b>	<b>4%</b>	<b>5%</b>	<b>5%</b>	<b>21%</b>	<b>23%</b>	<b>25%</b>	<b>70%</b>	<b>73%</b>	<b>75%</b>		

Figure 4: Table 1 of Variance Decompositions (cont)

<b>West North Central Region</b>	Cedar Rapids, IA	0%	0%	0%	8%	11%	15%	85%	89%	92%
	Columbia, MO	1%	1%	2%	8%	11%	14%	84%	87%	90%
	Davenport-Moline-Rock Island, IA-IL	0%	0%	1%	21%	25%	30%	70%	75%	79%
	Des Moines-West Des Moines, IA	5%	6%	8%	29%	34%	39%	54%	59%	64%
	Iowa City, IA	1%	1%	1%	3%	5%	7%	92%	94%	96%
	Kansas City, MO-KS	1%	1%	2%	25%	30%	36%	63%	69%	74%
	Lawrence, KS	0%	1%	1%	13%	17%	21%	78%	82%	86%
	Lincoln, NE	0%	0%	0%	34%	39%	44%	56%	61%	66%
	Minneapolis-St. Paul-Bloomington, MN-WI	4%	6%	8%	22%	27%	32%	62%	68%	72%
	Omaha-Council Bluffs, NE-IA	0%	0%	1%	29%	34%	39%	61%	66%	71%
	Rochester, MN	0%	0%	1%	2%	4%	7%	93%	95%	97%
	Springfield, MO	14%	16%	18%	7%	10%	13%	71%	74%	77%
	St. Louis, MO-IL	16%	19%	23%	14%	17%	21%	59%	63%	68%
	Topeka, KS	3%	3%	4%	5%	7%	10%	87%	89%	91%
	Waterloo-Cedar Falls, IA	2%	3%	3%	10%	14%	17%	80%	84%	87%
	Wichita, KS	5%	6%	8%	14%	19%	22%	71%	75%	79%
	<b>Regional Average</b>	3%	4%	5%	15%	19%	23%	73%	77%	81%
<b>South Atlantic [North] Region</b>	Baltimore-Towson, MD	50%	56%	61%	33%	39%	44%	4%	5%	6%
	Bethesda-Frederick-Gaithersburg, MD (M)	23%	28%	32%	61%	65%	70%	5%	7%	8%
	Charlottesville, VA	23%	26%	29%	18%	21%	24%	52%	54%	55%
	Richmond, VA	50%	55%	59%	17%	21%	26%	23%	24%	25%
	Roanoke, VA	20%	22%	24%	0%	1%	2%	76%	77%	79%
	Virginia Beach-Norfolk-Newport News, VA	63%	68%	72%	13%	17%	22%	13%	15%	16%
	Washington-Arlington-Alexandria, DC-VA	29%	35%	40%	57%	63%	68%	1%	3%	4%
<b>Regional Average</b>	37%	41%	45%	28%	32%	37%	25%	26%	28%	
<b>South Atlantic [South] Region</b>	Asheville, NC	16%	17%	19%	0%	1%	2%	80%	82%	83%
	Athens-Clarke County, GA	0%	0%	1%	7%	9%	11%	89%	91%	93%
	Atlanta-Sandy Springs-Marietta, GA	2%	4%	5%	70%	78%	86%	11%	18%	26%
	Augusta-Richmond County, GA-SC	27%	29%	32%	4%	5%	7%	63%	65%	68%
	Charleston-North Charleston-Summerville	17%	19%	22%	6%	9%	12%	69%	72%	74%
	Charlotte-Gastonia-Concord, NC-SC	2%	2%	3%	26%	31%	37%	61%	66%	71%
	Columbia, SC	11%	12%	14%	20%	22%	26%	62%	65%	68%
	Columbus, GA-AL	19%	20%	22%	2%	3%	5%	75%	77%	78%
	Dalton, GA	0%	0%	1%	3%	4%	5%	94%	96%	97%
	Durham, NC	0%	0%	0%	13%	15%	18%	81%	85%	87%
	Greensboro-High Point, NC	2%	2%	3%	16%	19%	22%	76%	79%	81%
	Greenville, NC	0%	0%	1%	2%	3%	4%	95%	96%	97%
	Greenville-Mauldin-Easley, SC	0%	1%	1%	12%	15%	18%	81%	85%	87%
	Macon, GA	4%	5%	6%	11%	13%	15%	80%	82%	84%
	Raleigh-Cary, NC	5%	7%	9%	6%	9%	13%	81%	84%	87%
	Rocky Mount, NC	0%	0%	0%	7%	9%	12%	88%	91%	93%
	Savannah, GA	22%	24%	26%	5%	7%	9%	67%	69%	71%
Wilmington, NC	39%	42%	44%	4%	6%	8%	50%	52%	55%	
Winston-Salem, NC	3%	4%	5%	18%	21%	24%	72%	75%	78%	
<b>Regional Average</b>	17%	19%	21%	17%	20%	23%	58%	61%	63%	
<b>Florida Region</b>	Bradenton-Sarasota-Venice, FL	28%	33%	37%	52%	57%	61%	9%	10%	12%
	Cape Coral-Fort Myers, FL	26%	30%	34%	47%	51%	55%	17%	19%	20%
	Deltona-Daytona Beach-Ormond Beach	44%	49%	53%	33%	37%	42%	13%	14%	15%
	Fort Lauderdale-Pompano Beach-Deerfield	39%	44%	48%	42%	47%	52%	8%	9%	10%
	Jacksonville, FL	41%	45%	48%	22%	25%	29%	29%	30%	31%
	Lakeland-Winter Haven, FL	44%	47%	50%	12%	15%	18%	36%	38%	39%
	Miami-Miami Beach-Kendall, FL (MSAD)	48%	52%	56%	20%	24%	28%	22%	24%	25%
	Orlando-Kissimmee, FL	56%	60%	64%	24%	28%	33%	10%	11%	12%
	Palm Bay-Melbourne-Titusville, FL	38%	42%	47%	40%	45%	50%	12%	13%	14%
	Pensacola-Ferry Pass-Brent, FL	25%	28%	31%	19%	23%	26%	48%	50%	51%
	Port St. Lucie, FL	23%	28%	31%	40%	44%	49%	27%	28%	30%
	Sebastian-Vero Beach, FL	20%	23%	25%	21%	24%	27%	52%	53%	55%
	Tallahassee, FL	26%	28%	30%	8%	10%	12%	60%	61%	63%
	Tampa-St. Petersburg-Clearwater, FL	45%	50%	54%	35%	39%	44%	10%	11%	12%
	West Palm Beach-Boca Raton-Boynton B	33%	38%	43%	47%	52%	58%	9%	10%	11%
<b>Regional Average</b>	24%	27%	30%	22%	25%	29%	46%	48%	49%	
<b>East South Central Region</b>	Birmingham-Hoover, AL	19%	21%	24%	27%	35%	42%	37%	44%	51%
	Chattanooga, TN-GA	9%	11%	13%	7%	12%	17%	72%	77%	82%
	Huntsville, AL	31%	33%	36%	5%	8%	12%	55%	59%	62%
	Jackson, MS	11%	13%	15%	13%	18%	23%	64%	69%	74%
	Knoxville, TN	20%	22%	23%	0%	2%	4%	74%	76%	78%
	Lexington-Fayette, KY	3%	4%	5%	10%	15%	20%	76%	81%	86%
	Louisville-Jefferson County, KY-IN	0%	0%	0%	8%	13%	19%	81%	87%	92%
	Memphis, TN-MS-AR	6%	7%	9%	30%	39%	49%	44%	53%	62%
	Mobile, AL	15%	17%	19%	4%	7%	12%	71%	75%	79%
	Nashville-Davidson--Murfreesboro--Frank	13%	16%	18%	23%	31%	40%	45%	53%	61%
	<b>Regional Average</b>	13%	14%	16%	13%	18%	24%	62%	67%	73%



Figure 5: Table 1 of Variance Decompositions (cont)

<b>West South Central Region</b>	Amarillo, TX	3%	4%	5%	15%	18%	21%	78%	79%	81%
	Austin-Round Rock, TX	2%	2%	3%	29%	33%	37%	61%	64%	68%
	Baton Rouge, LA	13%	16%	19%	28%	32%	37%	48%	52%	55%
	Beaumont-Port Arthur, TX	5%	6%	7%	7%	10%	12%	82%	84%	86%
	College Station-Bryan, TX	2%	2%	3%	18%	22%	25%	73%	76%	79%
	Corpus Christi, TX	12%	14%	16%	20%	23%	26%	61%	63%	66%
	Dallas-Plano-Irving, TX (MSAD)	7%	9%	11%	58%	63%	67%	25%	28%	32%
	El Paso, TX	41%	43%	46%	3%	4%	6%	50%	52%	54%
	Fayetteville-Springdale-Rogers, AR-MO	16%	18%	19%	0%	1%	2%	79%	81%	82%
	Fort Smith, AR-OK	1%	1%	2%	3%	4%	5%	93%	94%	96%
	Fort Worth-Arlington, TX (MSAD)	8%	10%	12%	54%	58%	62%	29%	32%	36%
	Houston-Sugar Land-Baytown, TX	6%	8%	9%	35%	39%	42%	50%	53%	57%
	Killeen-Temple-Fort Hood, TX	3%	4%	5%	3%	4%	6%	90%	92%	93%
	Lafayette, LA	7%	9%	11%	20%	24%	27%	64%	67%	70%
	Little Rock-North Little Rock-Conway, AR	20%	22%	25%	20%	23%	27%	52%	54%	57%
	Longview, TX	4%	4%	5%	5%	7%	9%	87%	89%	90%
	Lubbock, TX	3%	4%	5%	8%	10%	12%	84%	86%	88%
	Midland, TX	13%	16%	18%	7%	9%	11%	73%	75%	78%
	Monroe, LA	1%	1%	2%	5%	6%	8%	90%	92%	94%
	New Orleans-Metairie-Kenner, LA	18%	21%	23%	22%	26%	29%	51%	54%	58%
	Odessa, TX	10%	11%	12%	4%	5%	7%	82%	84%	85%
	Oklahoma City, OK	7%	9%	11%	48%	53%	57%	34%	38%	42%
	San Antonio, TX	29%	32%	36%	33%	37%	41%	29%	31%	34%
	Shreveport-Bossier City, LA	11%	12%	14%	17%	21%	24%	64%	67%	69%
	Tulsa, OK	4%	5%	7%	41%	45%	48%	47%	50%	53%
	Tyler, TX	4%	4%	5%	4%	6%	8%	88%	90%	91%
	<b>Regional Average</b>	10%	11%	13%	20%	22%	25%	64%	66%	69%
	<b>Mountain (north) Region</b>	Boise City-Nampa, ID	40%	43%	47%	4%	6%	8%	48%	51%
Boulder, CO		1%	1%	2%	41%	48%	55%	44%	51%	58%
Casper, WY		4%	5%	5%	1%	1%	3%	93%	94%	95%
Cheyenne, WY		3%	4%	5%	4%	6%	8%	88%	90%	92%
Colorado Springs, CO		4%	5%	7%	60%	68%	78%	19%	27%	34%
Denver-Aurora, CO		0%	1%	2%	57%	65%	74%	25%	34%	42%
Fort Collins-Loveland, CO		0%	0%	1%	53%	58%	63%	37%	41%	46%
Grand Junction, CO		11%	12%	14%	1%	2%	4%	84%	85%	87%
Greeley, CO		1%	1%	2%	20%	23%	27%	71%	76%	79%
Pueblo, CO		0%	0%	1%	13%	16%	19%	81%	83%	86%
<b>Regional Average</b>		6%	7%	9%	25%	29%	34%	59%	63%	67%
<b>Mountain (south) Region</b>	Albuquerque, NM	31%	36%	40%	7%	8%	11%	51%	56%	61%
	Farmington, NM	49%	53%	57%	19%	22%	26%	23%	25%	26%
	Las Cruces, NM	12%	13%	15%	3%	4%	5%	81%	83%	84%
	Las Vegas-Paradise, NV	35%	37%	40%	1%	2%	3%	59%	60%	62%
	Ogden-Clearfield, UT	36%	41%	45%	6%	8%	10%	47%	51%	55%
	Phoenix-Mesa-Scottsdale, AZ	6%	8%	11%	43%	48%	50%	44%	48%	47%
	Provo-Orem, UT	46%	50%	54%	0%	0%	0%	46%	50%	54%
	Reno-Sparks, NV	10%	13%	17%	58%	63%	66%	22%	24%	26%
	Salt Lake City, UT	15%	19%	24%	70%	74%	78%	5%	7%	8%
	Santa Fe, NM	11%	12%	14%	0%	1%	1%	86%	87%	88%
	Tucson, AZ	56%	59%	63%	0%	1%	2%	36%	40%	43%
<b>Regional Average</b>	28%	31%	34%	19%	21%	23%	46%	48%	51%	
<b>Pacific Region</b>	Bellingham, WA	19%	22%	24%	16%	23%	31%	48%	56%	61%
	Bend, OR	26%	28%	31%	10%	16%	22%	50%	55%	61%
	Bremerton-Silverdale, WA	35%	38%	40%	9%	13%	19%	44%	49%	52%
	Corvallis, OR	8%	10%	12%	19%	26%	34%	57%	64%	70%
	Eugene-Springfield, OR	22%	25%	27%	20%	26%	30%	45%	50%	54%
	Kennecook-Pasco-Richland, WA	2%	2%	3%	11%	15%	21%	77%	82%	85%
	Longview, WA	12%	14%	16%	4%	6%	9%	78%	80%	82%
	Medford, OR	28%	31%	35%	2%	5%	9%	60%	63%	66%
	Olympia, WA	35%	37%	40%	15%	19%	23%	41%	44%	47%
	Portland-Vancouver-Beaverton, OR-WA	37%	41%	45%	36%	44%	50%	11%	15%	21%
	Salem, OR	24%	28%	31%	21%	27%	32%	42%	45%	50%
	Seattle-Bellevue-Everett, WA (MSAD)	10%	12%	14%	13%	20%	30%	59%	68%	75%
	Spokane, WA	41%	44%	48%	19%	23%	28%	29%	32%	36%
	Tacoma, WA (MSAD)	45%	48%	51%	8%	13%	19%	33%	39%	43%
	Wenatchee, WA	19%	22%	25%	9%	14%	21%	58%	64%	68%
	<b>Regional Average</b>	24%	27%	29%	14%	19%	25%	49%	54%	58%
	<b>California Region</b>	Bakersfield, CA	49%	54%	59%	21%	25%	29%	19%	21%
Chico, CA		21%	25%	28%	36%	40%	45%	32%	35%	37%
Fresno, CA		39%	44%	49%	24%	28%	33%	25%	27%	30%
Los Angeles-Long Beach-Glendale, CA		20%	25%	29%	52%	57%	62%	16%	18%	21%
Madera, CA		27%	31%	34%	21%	24%	28%	42%	45%	47%
Merced, CA		14%	17%	20%	44%	48%	52%	32%	35%	37%
Modesto, CA		17%	21%	24%	59%	63%	68%	15%	16%	18%
Napa, CA		6%	8%	11%	68%	71%	74%	20%	21%	22%
Oakland-Fremont-Hayward, CA (MSAD)		7%	9%	12%	78%	81%	84%	7%	9%	11%
Oxnard-Thousand Oaks-Ventura, CA		7%	10%	13%	63%	67%	71%	20%	23%	26%
Redding, CA		28%	32%	36%	26%	30%	35%	35%	38%	40%
Riverside-San Bernardino-Ontario, CA		26%	30%	35%	53%	58%	63%	11%	12%	13%
Sacramento-Arden-Arcade-Roseville, CA		11%	15%	18%	65%	70%	74%	44%	46%	48%
Salinas, CA		10%	13%	16%	72%	76%	79%	10%	11%	12%
San Diego-Carlsbad-San Marcos, CA		5%	8%	11%	78%	81%	85%	9%	11%	13%
San Francisco-San Mateo-Redwood City		1%	2%	3%	61%	66%	70%	28%	32%	37%
San Jose-Sunnyvale-Santa Clara, CA		1%	1%	2%	53%	57%	61%	38%	42%	46%
San Luis Obispo-Paso Robles, CA		5%	7%	9%	73%	75%	78%	17%	18%	20%
Santa Ana-Anaheim-Irvine, CA (MSAD)		11%	14%	18%	64%	68%	73%	15%	17%	20%
Santa Barbara-Santa Maria-Goleta, CA		5%	8%	11%	66%	69%	72%	22%	23%	25%
Santa Cruz-Watsonville, CA		1%	2%	3%	71%	74%	77%	21%	24%	27%
Santa Rosa-Petaluma, CA		2%	4%	6%	65%	68%	70%	7%	8%	10%
Stockton, CA		14%	18%	22%	66%	71%	74%	10%	11%	13%
Vallejo-Fairfield, CA		11%	14%	18%	72%	76%	80%	8%	10%	12%
Visalia-Porterville, CA		49%	54%	58%	17%	20%	25%	24%	26%	28%
<b>Regional Average</b>		15%	19%	22%	55%	59%	63%	20%	22%	24%

Figure 6: Table 2 of RMSE 1 Qtr Horizon

		RMSE(Model)/RMSE(RW)					RMSE(Model)/RMSE(UC Mean)					
		Full Model	National only	regional Only	Idiosyncratic Only	National and regional	Full Model	National only	regional Only	Idiosyncratic Only	National and regional	
Atlantic Region	Albany-Schenectady-Troy, NY	1.05	1.39	1.09	1.47	1.02	1.28	1.69	1.33	1.79	1.25	
	Allentown-Bethlehem-Easton, PA-NJ	0.93	1.39	0.98	1.46	0.90	1.11	1.65	1.17	1.74	1.08	
	Atlantic City-Hammonton, NJ	1.04	1.29	1.06	1.39	1.01	1.14	1.41	1.16	1.52	1.10	
	Binghamton, NY	1.09	1.09	1.06	1.16	1.04	0.80	0.80	0.78	0.85	0.78	
	Buffalo-Niagara Falls, NY	1.08	1.20	1.05	1.26	1.04	0.84	0.94	0.82	0.98	0.82	
	Camden, NJ (MSAD)	0.94	1.40	0.98	1.47	0.91	1.25	1.88	1.30	1.96	1.21	
	Edison-New Brunswick, NJ (MSAD)	0.75	1.33	0.88	1.24	0.84	1.07	1.90	1.25	1.77	1.20	
	Erie, PA	0.92	0.97	0.99	0.93	0.98	0.57	0.60	0.62	0.58	0.61	
	Harrisburg-Carlisle, PA	1.08	1.17	1.15	1.19	1.11	0.89	0.96	0.94	0.97	0.91	
	Lancaster, PA	1.06	1.25	1.15	1.33	1.06	1.18	1.39	1.28	1.47	1.18	
	Nassau-Suffolk, NY (MSAD)	0.62	1.35	0.89	1.00	0.87	0.87	1.90	1.25	1.41	1.22	
	New York-White Plains-Wayne, NY-NJ (MSAD)	0.73	1.35	0.92	1.19	0.88	0.97	1.80	1.23	1.59	1.17	
	Newark-Union, NJ-PA (MSAD)	0.79	1.36	0.91	1.29	0.87	1.03	1.77	1.19	1.68	1.14	
	Philadelphia, PA (MSAD)	0.91	1.43	0.98	1.48	0.91	1.17	1.83	1.24	1.89	1.16	
	Pittsburgh, PA	1.18	1.25	1.19	1.17	1.22	0.88	0.93	0.89	0.87	0.91	
	Poughkeepsie-Newburgh-Middletown, NY	0.77	1.30	0.94	1.19	0.88	0.82	1.55	1.18	1.42	1.03	
	Reading, PA	1.02	1.31	1.17	1.32	1.06	1.01	1.30	1.15	1.31	1.07	
	Rochester, NY	1.14	1.37	1.09	1.40	1.09	0.85	1.02	0.81	1.04	0.81	
	Scranton-Wilkes-Barre, PA	1.01	1.12	1.12	1.09	1.07	0.75	0.83	0.83	0.80	0.80	
	Syracuse, NY	1.09	1.46	1.12	1.48	1.09	0.93	1.24	0.95	1.26	0.92	
	Trenton-Ewing, NJ	0.89	1.33	0.92	1.35	0.88	1.05	1.59	1.09	1.60	1.05	
	Wilmington, DE-MD-NJ (MSAD)	0.95	1.34	1.03	1.40	0.95	1.28	1.81	1.39	1.89	1.28	
	York-Hanover, PA	1.04	1.20	1.15	1.24	1.07	1.06	1.22	1.17	1.26	1.09	
	New England Region	Barnstable Town, MA	0.62	1.25	0.60	1.32	0.57	1.21	2.43	1.17	2.56	1.12
		Boston-Quincy, MA (MSAD)	0.53	1.23	0.56	1.24	0.54	0.88	2.03	0.92	2.04	0.89
		Bridgeport-Stamford-Norwalk, CT	0.85	1.28	0.89	1.32	0.84	1.07	1.62	1.12	1.67	1.06
		Burlington-South Burlington, VT	1.14	1.33	1.19	1.38	1.12	1.05	1.22	1.09	1.27	1.03
		Cambridge-Newton-Frammingham, MA (MSAD)	0.58	1.15	0.59	1.16	0.58	0.94	1.87	0.95	1.88	0.93
Hartford-West Hartford-East Hartford, CT		0.91	1.34	0.92	1.69	0.85	1.15	1.68	1.16	2.13	1.07	
Manchester-Nashua, NH		0.61	1.30	0.63	1.30	0.59	1.10	2.34	1.14	2.35	1.06	
New Haven-Milford, CT		0.87	1.28	0.86	1.60	0.78	1.40	2.07	1.39	2.58	1.26	
Norwich-New London, CT		0.99	1.35	1.01	1.52	0.94	0.98	1.35	1.01	1.51	0.94	
Peabody, MA (MSAD)		0.54	1.19	0.55	1.20	0.54	0.88	1.92	0.88	1.93	0.86	
Portland-South Portland-Biddeford, ME		0.76	1.40	0.82	1.45	0.77	0.99	1.80	1.05	1.88	1.00	
Providence-New Bedford-Fall River, RI-M		0.81	1.34	0.82	1.45	0.78	1.22	2.02	1.24	2.18	1.17	
Rockingham County-Strafford County, NH		0.57	1.26	0.58	1.26	0.54	1.08	2.38	1.09	2.39	1.03	
Springfield, MA		0.93	1.40	0.94	1.76	0.86	1.19	1.79	1.33	2.25	1.25	
Worcester, MA		0.62	1.34	0.65	1.35	0.62	1.09	2.36	1.15	2.38	1.10	
East North Central Region		Akron, OH	0.84	1.26	0.88	1.09	0.90	0.78	1.16	0.81	1.00	0.83
		Ann Arbor, MI	1.00	1.54	1.02	1.43	1.04	0.99	1.52	1.01	1.42	1.03
		Appleton, WI	1.12	1.42	1.08	1.49	1.08	0.81	1.03	0.78	1.07	0.78
		Bloomington-Normal, IL	1.04	1.49	1.07	1.47	1.06	0.59	0.85	0.61	0.84	0.61
		Canton-Massillon, OH	0.92	1.24	0.95	1.14	0.97	0.70	0.94	0.72	0.86	0.73
	Champaign-Urbana, IL	1.66	2.07	1.50	2.30	1.47	1.20	1.50	1.09	1.67	1.07	
	Chicago-Naperville-Joliet, IL (MSAD)	1.22	1.96	1.52	1.78	1.45	1.18	1.90	1.47	1.72	1.40	
	Cincinnati-Middletown, OH-KY-IN	1.25	2.08	1.24	2.07	1.25	1.16	1.94	1.16	1.93	1.16	
	Cleveland-Elyria-Mentor, OH	0.89	1.47	0.92	1.37	0.95	0.84	1.40	0.87	1.30	0.90	
	Columbus, IN	0.87	0.86	0.87	0.86	0.71	0.78	0.70	0.79	0.79	0.73	
	Columbus, OH	1.20	2.05	1.18	2.03	1.19	1.02	1.76	1.01	1.73	1.02	
	Dayton, OH	1.20	1.70	1.05	1.88	1.05	1.00	1.42	0.88	1.57	0.88	
	Detroit-Livonia-Dearborn, MI (MSAD)	0.81	1.30	0.92	1.19	0.91	1.17	1.87	1.32	1.72	1.32	
	Eau Claire, WI	1.06	1.46	1.08	1.55	1.07	0.66	0.91	0.68	0.97	0.67	
	Elkhart-Goshen, IN	1.03	1.17	1.08	1.13	1.08	0.69	0.78	0.72	0.75	0.72	
	Evansville, IN-KY	1.24	1.76	1.28	1.71	1.28	0.79	1.13	0.82	1.09	0.82	
	Flint, MI	0.89	1.34	0.89	1.31	0.91	0.76	1.15	0.76	1.13	0.78	
	Fort Wayne, IN	1.31	1.70	1.20	1.78	1.22	0.94	1.22	0.86	1.28	0.88	
	Gary, IN (MSAD)	1.28	1.56	1.19	1.79	1.13	1.07	1.31	1.00	1.50	0.95	
	Grand Rapids-Wyoming, MI	0.94	1.21	0.91	1.19	0.91	0.97	1.25	0.85	1.23	0.94	
	Green Bay, WI	1.00	1.39	1.02	1.43	1.01	0.72	1.00	0.73	1.02	0.73	
	Holland-Grand Haven, MI	1.00	1.68	0.99	1.70	0.99	0.81	1.36	0.80	1.37	0.80	
	Indianapolis-Carmel, IN	0.99	1.48	0.97	1.45	1.00	1.00	1.50	0.98	1.47	1.01	
	Janesville, WI	0.99	1.33	1.02	1.35	0.99	0.75	1.00	0.77	1.01	0.75	
	Kalamazoo-Portage, MI	1.10	1.91	1.14	1.88	1.14	0.72	1.25	0.74	1.23	0.75	
	La Crosse, WI-MN	1.33	1.99	1.31	2.10	1.28	0.95	1.43	0.94	1.50	0.92	
	Lafayette, IN	0.72	0.97	0.78	0.78	0.79	0.54	0.71	0.58	0.58	0.58	
	Lake County-Kenosha County, IL-WI (MSAD)	1.52	2.16	1.57	2.22	1.51	1.23	1.76	1.28	1.81	1.23	
	Lansing-East Lansing, MI	1.15	1.97	1.19	1.89	1.20	0.89	1.53	0.92	1.46	0.93	
	Lima, OH	1.16	1.57	1.21	1.53	1.22	0.78	1.08	0.82	1.04	0.83	
	Madison, WI	1.15	1.51	1.14	1.55	1.12	0.75	0.99	0.75	1.01	0.73	
	Mansfield, OH	0.92	1.16	0.99	1.08	0.99	0.55	0.70	0.59	0.65	0.60	
Milwaukee-Waukesha-West Allis, WI	1.28	1.78	1.34	1.82	1.29	0.92	1.29	0.96	1.32	0.93		
Monroe, MI	0.79	1.23	0.78	1.22	0.80	0.68	1.05	0.67	1.04	0.68		
Muskegon-North Shores, MI	0.97	1.28	0.97	1.34	0.96	0.70	0.93	0.70	0.97	0.70		
Niles-Benton Harbor, MI	1.01	1.42	1.06	1.40	1.05	0.70	0.99	0.73	0.97	0.73		
Oshkosh-Neenah, WI	0.93	1.05	1.00	1.02	1.00	0.58	0.66	0.63	0.64	0.63		
Peoria, IL	0.90	1.35	0.97	1.27	0.96	0.62	0.93	0.67	0.88	0.66		
Racine, WI	1.31	1.52	1.27	1.63	1.23	0.97	1.13	0.94	1.21	0.91		
Rockford, IL	0.98	1.15	1.14	1.21	1.03	0.78	0.81	0.80	0.85	0.77		
Saginaw-Saginaw Township North, MI	0.94	1.11	0.96	1.08	0.96	0.70	0.83	0.71	0.81	0.72		
Sheboygan, WI	1.10	1.38	1.12	1.38	1.11	0.67	0.84	0.69	0.85	0.69		
South Bend-Mishawaka, IN-MI	0.96	1.40	1.08	1.31	1.09	0.58	0.85	0.66	0.80	0.68		
Springfield, IL	1.13	1.37	1.15	1.28	1.12	0.84	1.02	0.85	0.95	0.83		
Springfield, OH	0.88	1.09	0.86	0.99	0.88	0.68	0.83	0.66	0.76	0.68		
Toledo, OH	1.12	1.52	1.09	1.52	1.11	0.87	1.19	0.85	1.18	0.87		
Warren-Troy-Farmington Hills, MI (MSAD)	0.73	1.37	0.85	1.25	0.84	1.17	2.18	1.35	1.99	1.33		
Youngstown-Warren-Boardman, OH-PA	0.98	1.37	1.02	1.28	1.04	0.70	0.98	0.73	0.91	0.74		

Figure 7: Table 2 of RMSE 1 Qtr Horizon (cont)

<b>West North Central Region</b>	Cedar Rapids, IA	1.14	1.38	0.99	1.04	1.01	0.76	0.92	0.66	0.69	0.67
	Columbia, MO	1.35	1.59	1.16	1.92	1.12	1.01	1.19	0.87	1.44	0.84
	Davenport-Moline-Rock Island, IA-IL	1.19	1.89	1.18	1.91	1.17	0.77	1.23	0.76	1.23	0.76
	Des Moines-West Des Moines, IA	1.26	2.11	1.28	2.09	1.28	0.84	1.41	0.86	1.40	0.86
	Iowa City, IA	1.17	1.52	1.13	1.42	1.13	0.73	0.95	0.71	0.89	0.71
	Kansas City, MO-KS	0.84	1.73	1.12	1.36	1.12	0.90	1.87	1.21	1.47	1.21
	Lawrence, KS	1.28	2.16	1.23	2.26	1.22	0.87	1.47	0.84	1.54	0.83
	Lincoln, NE	1.08	1.41	1.02	1.46	1.02	0.73	0.95	0.69	0.98	0.68
	Minneapolis-St. Paul-Bloomington, MN-W	0.93	1.69	1.17	1.41	1.16	1.07	1.94	1.34	1.62	1.34
	Omaha-Council Bluffs, NE-IA	1.08	1.80	1.07	1.86	1.06	0.75	1.26	0.74	1.30	0.74
	Rochester, MN	1.17	1.31	1.09	1.34	1.12	1.12	1.25	1.05	1.28	1.07
	Springfield, MO	1.38	1.84	1.31	1.96	1.23	1.14	1.52	1.08	1.62	1.02
	St. Louis, MO-IL	0.89	1.77	1.16	1.50	1.12	1.00	2.00	1.31	1.69	1.27
	Topeka, KS	1.22	1.80	1.19	1.86	1.18	0.87	1.28	0.84	1.32	0.84
Waterloo-Cedar Falls, IA	1.25	1.86	1.16	1.91	1.18	0.76	1.13	0.70	1.16	0.71	
Wichita, KS	1.20	1.90	1.19	1.92	1.20	0.80	1.27	0.80	1.28	0.80	
<b>South Atlantic [North] Region</b>	Baltimore-Towson, MD	0.94	1.44	1.02	1.50	0.95	1.44	2.20	1.56	2.29	1.45
	Bethesda-Frederick-Gaithersburg, MD (M	0.86	1.46	0.85	1.57	0.81	1.02	1.73	1.01	1.86	0.95
	Charlottesville, VA	0.98	1.32	1.01	1.41	0.96	0.89	1.20	0.92	1.28	0.87
	Richmond, VA	1.02	1.36	1.02	1.50	0.94	1.56	2.08	1.57	2.30	1.44
	Roanoke, VA	1.08	1.16	1.06	1.26	1.02	0.93	1.00	0.92	1.09	0.88
	Virginia Beach-Norfolk-Newport News, VA	0.76	1.26	1.00	1.12	0.95	1.43	2.38	1.90	2.12	1.79
Washington-Arlington-Alexandria, DC-VA	0.80	1.51	0.85	1.55	0.80	1.22	2.29	1.30	2.36	1.21	
<b>South Atlantic [South] Region</b>	Asheville, NC	1.29	1.48	1.25	1.66	1.19	0.98	1.13	0.95	1.26	0.90
	Athens-Clarke County, GA	1.18	1.66	1.16	1.70	1.16	0.78	1.10	0.77	1.13	0.77
	Atlanta-Sandy Springs-Marietta, GA	1.09	2.25	1.17	2.16	1.15	1.35	2.79	1.45	2.67	1.43
	Augusta-Richmond County, GA-SC	1.23	1.41	1.32	1.42	1.27	0.90	1.03	0.96	1.03	0.92
	Charleston-North Charleston-Summerville	1.22	1.53	1.26	1.58	1.21	1.48	1.84	1.52	1.91	1.46
	Charlotte-Gastonia-Concord, NC-SC	1.08	1.57	1.11	1.63	1.08	0.83	1.21	0.85	1.25	0.83
	Columbia, SC	1.40	1.99	1.52	2.00	1.46	1.14	1.62	1.24	1.63	1.19
	Columbus, GA-AL	1.20	1.39	1.23	1.47	1.17	0.91	1.05	0.93	1.12	0.89
	Dalton, GA	0.99	1.42	1.13	1.31	1.12	0.61	0.87	0.70	0.80	0.69
	Durham, NC	1.31	1.79	1.32	1.83	1.27	0.92	1.26	0.93	1.29	0.89
	Greensboro-High Point, NC	0.90	1.52	1.11	1.28	1.09	0.54	0.92	0.67	0.77	0.65
	Greenville, NC	0.95	1.12	1.02	1.09	1.01	0.59	0.69	0.63	0.67	0.63
	Greenville-Mauldin-Easley, SC	0.98	1.19	1.01	1.10	1.01	0.63	0.76	0.65	0.71	0.65
	Macon, GA	0.98	1.43	1.10	1.36	1.07	0.64	0.93	0.71	0.88	0.70
	Raleigh-Cary, NC	1.05	1.62	1.18	1.58	1.14	0.94	1.45	1.06	1.42	1.02
	Rocky Mount, NC	0.85	1.18	1.02	0.96	1.02	0.52	0.72	0.62	0.59	0.62
Savannah, GA	1.29	1.60	1.29	1.75	1.21	1.19	1.48	1.19	1.61	1.12	
Wilmington, NC	1.15	1.33	1.28	1.34	1.19	1.62	1.86	1.80	1.89	1.67	
Winston-Salem, NC	1.14	1.51	1.17	1.51	1.13	0.78	1.02	0.79	1.03	0.77	
<b>Florida Region</b>	Bradenton-Sarasota-Venice, FL	0.81	1.24	0.80	1.31	0.78	1.35	2.05	1.34	2.18	1.29
	Cape Coral-Fort Myers, FL	0.86	1.24	0.87	1.33	0.83	1.21	1.74	1.22	1.87	1.17
	Deltona-Daytona Beach-Ormond Beach,	0.78	1.25	0.80	1.33	0.77	1.25	2.00	1.28	2.11	1.22
	Fort Lauderdale-Pompano Beach-Deerfie	0.71	1.23	0.78	1.24	0.74	1.27	2.22	1.39	2.23	1.33
	Jacksonville, FL	0.60	1.25	0.62	1.26	0.61	0.90	1.86	0.92	1.88	0.90
	Lakeland-Winter Haven, FL	0.87	1.15	0.87	1.24	0.83	1.34	1.76	1.33	1.91	1.27
	Miami-Miami Beach-Kendall, FL (MSAD)	0.80	1.24	0.85	1.29	0.80	1.42	2.22	1.52	2.31	1.43
	Orlando-Kissimmee, FL	0.77	1.24	0.80	1.30	0.76	1.58	2.56	1.65	2.67	1.56
	Palm Bay-Melbourne-Titusville, FL	0.81	1.27	0.84	1.32	0.82	1.37	2.14	1.42	2.23	1.38
	Pensacola-Ferry Pass-Brent, FL	0.81	1.14	0.85	1.08	0.85	1.18	1.65	1.24	1.57	1.24
	Port St. Lucie, FL	0.87	1.25	0.89	1.30	0.86	1.22	1.75	1.25	1.82	1.21
	Sebastian-Vero Beach, FL	0.95	1.18	0.89	1.28	0.87	1.00	1.24	0.93	1.35	0.91
	Tallahassee, FL	0.94	1.16	0.93	1.27	0.89	0.89	1.11	0.88	1.21	0.85
	Tampa-St. Petersburg-Clearwater, FL	0.62	1.30	0.66	1.34	0.63	1.38	2.88	1.46	2.97	1.39
	West Palm Beach-Boca Raton-Boynton B	0.65	1.27	0.70	1.33	0.66	1.11	2.16	1.19	2.26	1.13
<b>East South Central Region</b>	Birmingham-Hoover, AL	1.34	1.85	1.48	1.81	1.42	0.92	1.27	1.01	1.24	0.98
	Chattanooga, TN-GA	1.34	1.82	1.41	1.82	1.36	0.99	1.34	1.04	1.34	1.00
	Huntsville, AL	1.38	1.64	1.44	1.71	1.37	1.25	1.49	1.30	1.55	1.25
	Jackson, MS	1.24	1.64	1.33	1.69	1.28	0.86	1.13	0.92	1.17	0.88
	Knoxville, TN	1.32	1.43	1.30	1.58	1.22	1.20	1.30	1.18	1.43	1.11
	Lexington-Fayette, KY	1.14	1.36	1.13	1.43	1.10	0.91	1.08	0.90	1.14	0.88
	Louisville-Jefferson County, KY-IN	0.99	1.08	1.00	1.04	1.00	0.70	0.75	0.70	0.73	0.70
	Memphis, TN-MS-AR	1.27	1.81	1.33	1.80	1.31	0.81	1.16	0.85	1.15	0.84
	Mobile, AL	1.10	1.33	1.15	1.35	1.11	1.01	1.22	1.06	1.24	1.02
	Nashville-Davidson--Murfreesboro--Frank	1.06	1.78	1.30	1.69	1.24	1.17	1.95	1.42	1.86	1.36

Figure 8: Table 2 of RMSE 1 Qtr Horizon (cont)

West South Central Region	Amarillo, TX	1.06	1.17	1.08	1.17	1.06	0.71	0.78	0.72	0.78	0.71
	Austin-Round Rock, TX	1.25	1.32	0.95	1.52	0.94	1.63	1.72	1.24	1.99	1.22
	Baton Rouge, LA	1.12	1.19	1.06	1.32	1.01	1.29	1.38	1.22	1.52	1.16
	Beaumont-Port Arthur, TX	0.94	1.14	1.06	1.08	1.03	0.60	0.72	0.67	0.68	0.66
	College Station-Bryan, TX	0.88	1.15	0.97	1.11	0.96	0.81	0.81	0.68	0.78	0.67
	Corpus Christi, TX	1.02	1.30	1.09	1.30	1.05	0.74	0.95	0.80	0.95	0.76
	Dallas-Plano-Irving, TX (MSAD)	0.98	1.48	1.07	1.36	1.08	1.51	2.29	1.65	2.10	1.67
	El Paso, TX	1.12	1.20	1.17	1.29	1.10	0.99	1.08	1.04	1.14	0.97
	Fayetteville-Springdale-Rogers, AR-MO	0.83	1.32	1.27	1.48	1.21	1.43	1.41	1.36	1.58	1.29
	Fort Smith, AR-OK	0.96	1.08	1.04	1.02	1.03	0.58	0.66	0.63	0.62	0.63
	Fort Worth-Arlington, TX (MSAD)	1.04	1.53	1.04	1.51	1.05	1.27	1.86	1.27	1.84	1.28
	Houston-Sugar Land-Baytown, TX	1.09	1.55	1.10	1.51	1.09	1.12	1.59	1.13	1.55	1.12
	Killeen-Temple-Fort Hood, TX	0.95	1.06	1.02	1.05	1.01	0.61	0.68	0.65	0.67	0.65
	Lafayette, LA	1.11	1.47	1.21	1.52	1.13	0.83	1.10	0.91	1.14	0.85
	Little Rock-North Little Rock-Conway, AR	1.10	1.35	1.16	1.38	1.11	0.83	1.02	0.87	1.04	0.84
	Longview, TX	1.00	1.04	1.03	1.06	1.02	0.65	0.67	0.67	0.69	0.66
	Lubbock, TX	0.88	1.24	1.08	1.08	1.07	0.53	0.74	0.64	0.64	0.63
	Midland, TX	1.07	1.08	1.06	1.17	1.03	0.92	0.93	0.91	1.01	0.88
	Monroe, LA	0.87	1.10	0.97	1.05	0.96	0.57	0.72	0.64	0.69	0.63
	New Orleans-Metairie-Kenner, LA	1.19	1.27	1.12	1.48	1.04	1.52	1.62	1.43	1.89	1.33
	Odessa, TX	0.98	1.04	1.03	1.05	1.01	0.65	0.69	0.68	0.69	0.66
	Oklahoma City, OK	0.93	1.52	1.04	1.52	0.99	1.04	1.71	1.17	1.71	1.12
	San Antonio, TX	1.11	1.62	1.19	1.63	1.13	1.08	1.57	1.16	1.58	1.10
	Shreveport-Bossier City, LA	1.19	1.32	1.10	1.53	1.04	0.92	1.03	0.85	1.19	0.81
	Tulsa, OK	1.04	1.33	1.03	1.35	1.03	0.80	1.02	0.79	1.04	0.79
	Tyler, TX	0.94	1.23	1.00	1.21	0.97	0.66	0.86	0.70	0.85	0.68
	Mountain [north] Region	Boise City-Nampa, ID	1.09	1.26	1.24	1.26	1.16	1.49	1.73	1.70	1.73
Boulder, CO		0.84	1.35	0.91	1.26	0.92	0.93	1.48	1.00	1.39	1.01
Casper, WY		1.52	1.38	1.27	1.68	1.19	1.30	1.17	1.08	1.43	1.01
Cheyenne, WY		1.45	1.46	1.23	1.72	1.18	1.00	1.01	0.85	1.19	0.82
Colorado Springs, CO		1.36	2.26	1.44	2.32	1.37	1.12	1.85	1.18	1.90	1.12
Denver-Aurora, CO		0.77	1.52	0.98	1.26	0.99	1.14	2.25	1.45	1.86	1.46
Fort Collins-Loveland, CO		0.96	1.56	0.98	1.56	0.98	0.78	1.25	0.79	1.26	0.79
Grand Junction, CO		1.12	1.28	1.20	1.22	1.17	0.78	0.89	0.83	0.85	0.81
Greeley, CO		0.92	1.39	0.86	1.42	0.86	0.89	1.34	0.83	1.37	0.84
Pueblo, CO		1.10	1.35	1.10	1.30	1.10	0.69	0.85	0.69	0.82	0.69
Mountain [south] Region		Reno-Sparks, NV	0.84	1.12	1.16	0.87	1.12	1.16	1.55	1.60	1.20
	Albuquerque, NM	0.93	1.21	1.13	1.15	1.06	1.50	1.96	1.83	1.87	1.71
	Farmington, NM	1.42	1.35	1.29	1.60	1.23	1.22	1.16	1.10	1.37	1.05
	Las Cruces, NM	1.23	1.25	1.22	1.36	1.17	0.99	1.00	0.98	1.09	0.94
	Las Vegas-Paradise, NV	0.84	1.14	1.17	0.90	1.13	1.12	1.51	1.56	1.20	1.51
	Ogden-Clearfield, UT	0.83	1.06	0.81	1.12	0.79	0.95	1.22	0.92	1.28	0.91
	Phoenix-Mesa-Scottsdale, AZ	0.74	1.15	1.16	0.82	1.10	1.49	2.31	2.31	1.65	2.20
	Provo-Orem, UT	0.78	1.09	0.83	1.09	0.79	0.91	1.27	0.97	1.27	0.92
	Salt Lake City, UT	0.87	1.22	0.93	1.27	0.88	1.33	1.86	1.42	1.93	1.34
	Santa Fe, NM	1.09	1.21	1.17	1.17	1.14	0.73	0.81	0.79	0.78	0.77
	Tucson, AZ	0.96	1.22	1.21	1.09	1.14	1.25	1.60	1.58	1.42	1.49
Pacific Region	Bellingham, WA	0.93	1.45	1.05	1.45	1.02	1.08	1.70	1.23	1.69	1.19
	Bend, OR	0.97	1.34	1.08	1.36	1.00	1.61	2.22	1.78	2.25	1.66
	Bremerton-Silverdale, WA	1.08	1.46	1.19	1.52	1.12	1.10	1.49	1.21	1.55	1.14
	Corvallis, OR	0.78	1.09	0.78	1.09	0.77	0.69	0.97	0.69	0.97	0.69
	Eugene-Springfield, OR	0.75	1.24	0.80	1.29	0.77	1.02	1.68	1.09	1.74	1.04
	Kennewick-Pasco-Richland, WA	1.24	1.56	1.23	1.63	1.26	0.83	1.04	0.82	1.09	0.84
	Longview, WA	0.86	1.14	0.88	1.17	0.86	0.69	0.92	0.71	0.95	0.69
	Medford, OR	1.18	1.41	1.22	1.48	1.17	1.37	1.65	1.42	1.73	1.37
	Olympia, WA	0.99	1.34	1.04	1.43	0.98	0.98	1.33	1.03	1.41	0.97
	Portland-Vancouver-Beaverton, OR-WA	0.85	1.42	0.90	1.47	0.85	1.29	2.16	1.38	2.24	1.30
	Salem, OR	0.77	1.21	0.78	1.26	0.75	0.90	1.42	0.91	1.47	0.88
	Seattle-Bellevue-Everett, WA (MSAD)	0.96	1.82	1.23	1.60	1.18	1.22	2.30	1.56	2.03	1.50
	Spokane, WA	0.94	1.40	0.98	1.48	0.93	1.43	2.13	1.50	2.25	1.41
	Tacoma, WA (MSAD)	1.22	1.59	1.29	1.71	1.20	1.36	1.76	1.43	1.90	1.34
Wenatchee, WA	0.95	1.19	0.96	1.22	0.95	0.72	0.91	0.73	0.93	0.72	
California Region	Bakersfield, CA	0.90	1.18	1.16	1.05	1.09	1.62	2.11	2.07	1.88	1.96
	Chico, CA	0.95	1.32	1.04	1.30	0.99	1.11	1.55	1.22	1.53	1.17
	Fresno, CA	0.89	1.22	1.24	0.98	1.18	1.74	2.37	2.43	1.90	2.31
	Los Angeles-Long Beach-Glendale, CA (MSAD)	0.79	1.41	0.92	1.47	0.87	1.18	2.12	1.39	2.21	1.31
	Madera, CA	1.00	1.21	1.17	1.18	1.09	1.19	1.44	1.39	1.40	1.30
	Merced, CA	0.90	1.28	1.00	1.27	0.95	1.57	2.26	1.76	2.23	1.66
	Modesto, CA	0.84	1.36	0.97	1.32	0.93	1.32	2.14	1.53	2.08	1.46
	Napa, CA	0.84	1.41	0.83	1.42	0.83	0.82	1.36	0.81	1.38	0.80
	Oakland-Fremont-Hayward, CA (MSAD)	0.75	1.48	0.72	1.56	0.71	1.02	2.02	0.98	2.14	0.97
	Oxnard-Thousand Oaks-Ventura, CA	0.80	1.41	0.83	1.46	0.81	0.98	1.73	1.01	1.79	0.99
	Redding, CA	1.00	1.28	1.20	1.20	1.14	1.33	1.70	1.60	1.60	1.51
	Riverside-San Bernardino-Ontario, CA	0.73	1.36	0.95	1.25	0.90	1.39	2.57	1.79	2.37	1.71
	Sacramento-Arden-Arcade-Roseville, CA	0.80	1.41	0.87	1.37	0.86	1.11	1.95	1.20	1.91	1.19
	Salinas, CA	0.75	1.32	0.81	1.24	0.79	1.01	1.79	1.09	1.69	1.07
	San Diego-Carlsbad-San Marcos, CA	0.78	1.46	0.79	1.49	0.80	1.03	1.93	1.04	1.98	1.06
	San Francisco-San Mateo-Redwood City, CA	0.73	1.48	0.76	1.57	0.76	0.99	2.00	1.03	2.12	1.03
	San Jose-Sunnyvale-Santa Clara, CA	0.77	1.35	0.89	1.42	0.89	1.00	1.77	1.17	1.86	1.17
	San Luis Obispo-Paso Robles, CA	0.84	1.60	0.79	1.75	0.79	1.03	1.97	0.98	2.17	0.98
	Santa Ana-Anaheim-Irvine, CA (MSAD)	0.75	1.47	0.82	1.48	0.79	1.05	2.04	1.14	2.06	1.10
	Santa Barbara-Santa Maria-Goleta, CA	0.85	1.43	0.85	1.43	0.85	1.02	1.71	1.01	1.72	1.01
	Santa Cruz-Watsonville, CA	0.74	1.46	0.70	1.55	0.70	1.10	2.16	1.03	2.29	1.03
	Santa Rosa-Petaluma, CA	0.75	1.47	0.72	1.53	0.72	0.99	1.95	0.96	2.03	0.96
	Stockton, CA	0.75	1.36	0.85	1.32	0.82	1.18	2.14	1.33	2.08	1.28
	Vallejo-Fairfield, CA	0.71	1.43	0.80	1.35	0.78	1.17	2.38	1.33	2.24	1.29
	Visalia-Porterville, CA	0.96	1.16	1.17	1.07	1.10	1.57	1.89	1.92	1.76	1.81

Figure 9: Figure 2: Relative RMSE at 4qtr Horizon

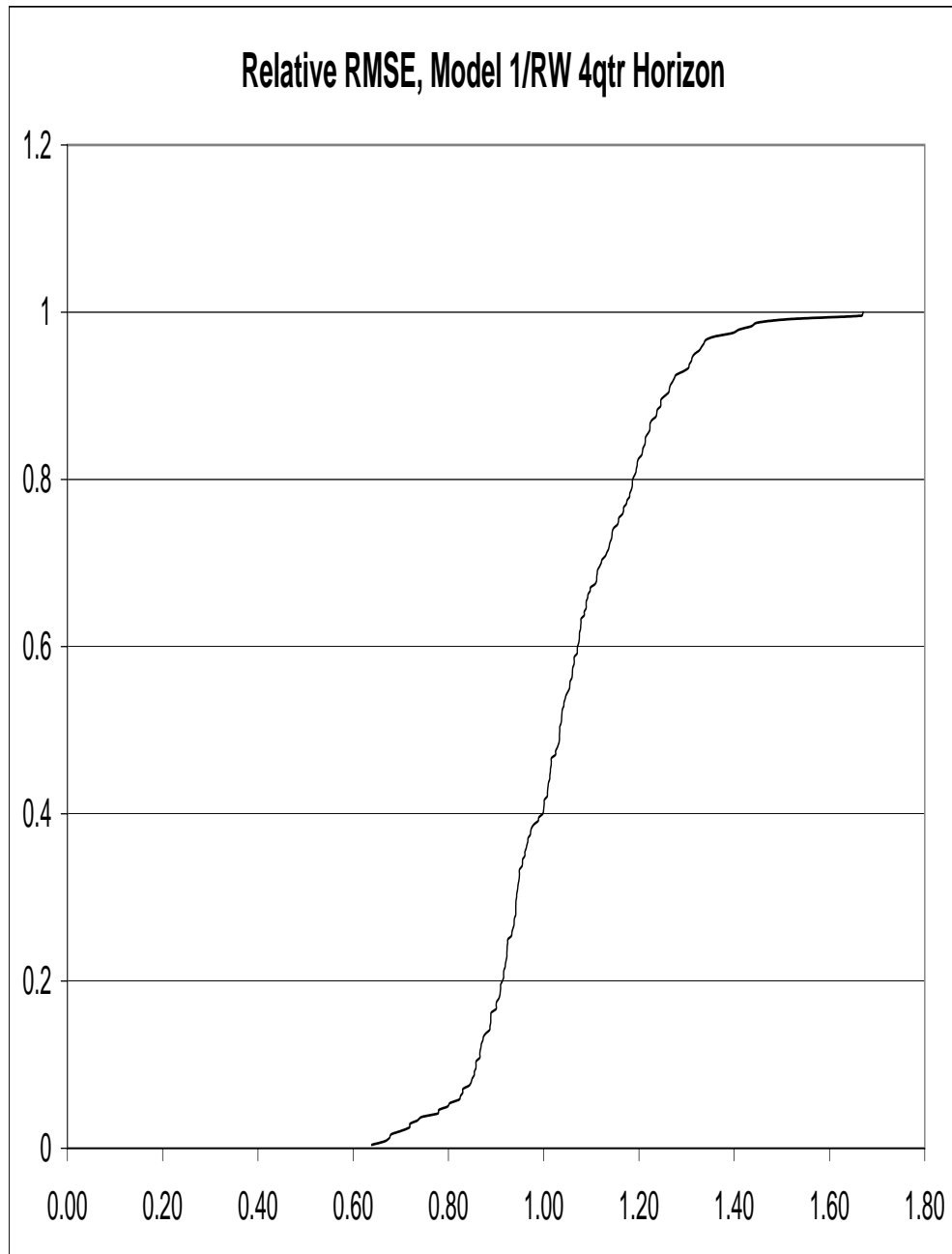


Figure 10: Figure 3: Relative RMSE at 4qtr Horizon

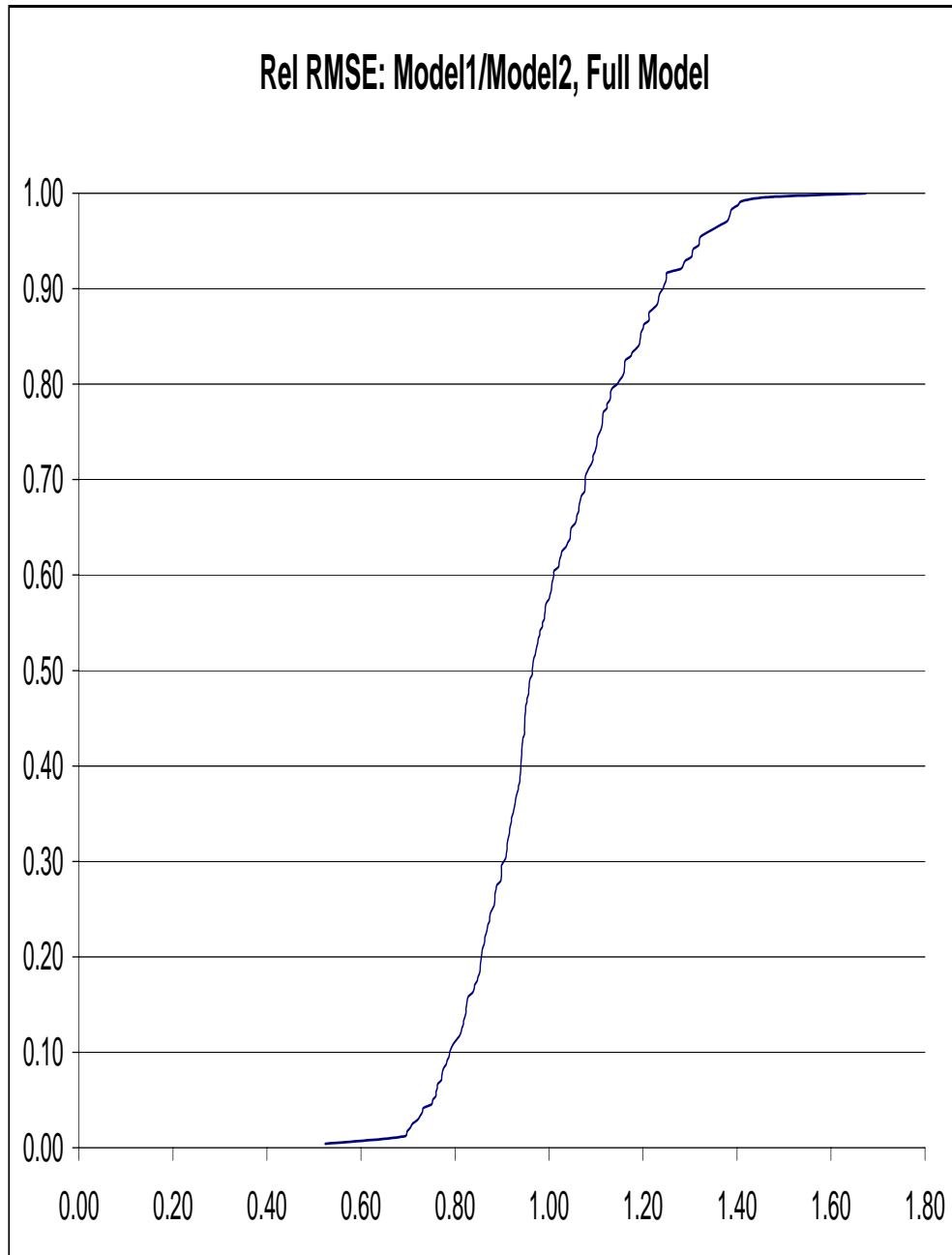


Figure 11: Figure 4: Relative RMSE at 4qtr Horizon

