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Adaptive Diffusion Models for the Growth of Robotics in New York State Industry

STUART BRETSCHNEIDER and BARRY BOZEMAN

ABSTRACT

Forecasts are developed for the diffusion of robotics in the state of New York through the year 2015. The chief objective is to compare static approaches with dynamic models for forecasting diffusion processes of various time horizons. Results for a Bass–Mansfield model are compared to those for a dynamic time-varying parameter model. The results indicate the advantages and disadvantages of a robust heuristic approach which smooths data as opposed to providing an optimal fit.

I. Introduction

New York's traditional industrial base has been in an apparent state of decline since the early 1970s. In 1972, the manufacturing industries provided 22.8% of all nonagricultural employment; by 1982, that percentage had dropped to only 18.8%. During that ten-year period, the number of people employed in durable goods manufacture fell from 750,300 to 701,200, and nondurable goods manufacturing employment correspondingly dropped from 852,000 to 660,000. Blue-collar employment is expected to continue to decline, falling 1.2% by the mid-1980s [24].

As a means of regaining their competitive edge, many U.S. firms have turned to automated manufacturing processes and have achieved some qualified success [13]. Similarly, a number of New York firms have begun to rely on automation to increase productivity and to reduce costs. One result of this has been an increased interest in automation and robotics. Of particular interest has been the rate of diffusion of robotics technology, because it is expected to (at some point) have a significant effect on levels of employment and productivity for many manufacturing industries.

The purposes of this paper are twofold: (1) to develop forecasts of the diffusion of robotics in the state of New York through the year 2015; and (2) to compare static approaches with dynamic models for forecasting diffusion processes over extended forecast horizons, 10, 20, or 30 years ahead. The next section of the paper provides some

STUART BRETSCHNEIDER is Senior Research Associate, Technology and Information Policy Program, and Associate Professor of Public Administration, Maxwell School, Syracuse University, Syracuse, N.Y.

BARRY BOZEMAN is Director, Technology and Information Policy Program, and Professor of Public Administration, Maxwell School, Syracuse University, Syracuse, N.Y.

Address reprint requests to Prof. Barry Bozeman, The Maxwell School, Syracuse University, 103 College Place, Syracuse, New York 13244-4010.

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basic background for understanding robotics. This is followed by a review of the Bass-Mansfield model for forecasting technological substitution. The traditional approach is extended here to include underlying models in which the rate of substitution is allowed to vary over the forecast period. Such dynamic models are often referred to as *time-varying parameter models*. The fourth section of the paper reviews the data and assumptions necessary to apply diffusion models to forecasting robotics through the year 2015 for the state of New York. Results for forecasting robotics through the year 2015 are presented for both the static and dynamic diffusion models. This article concludes with some observations about the problems of forecasting technological substitution by use of either technique.

II. Description of Robotics Technology

One definition of a robot "is a mechanical device that can be programmed to perform some task of manipulation or locomotion under automatic control" [22]. Robots are composed of a manipulator, which physically performs the task, a control system, and a power supply.

Robots are currently limited in accuracy, force, and versatility and are used primarily in repetitive, "preprogrammable" or easily programmed tasks such as spot welding, grinding, spray painting, or materials handling [2, pp. 35–38]. The main thrust in robotics research and development is now directed at increasing the sensory and intelligence capabilities of the machines [23]. Engelberger [10] drafted a list of desirable capabilities for future robots:

1. Rudimentary sense of vision;
2. Tactile senses;
3. Computer interpretation of sensory data;
4. Mechanical hand-to-hand coordination;
5. Mobility;
6. Minimized spatial intrusion;
7. Energy-conserving musculature;
8. General-purpose hands;
9. Self-diagnostic fault tracing;
10. Man-robot voice communication; and
11. Inherent safety (safe human-robot work area).

The attainment of these goals is anticipated by the generational descriptions outlined in Table 1. The current state of the art can be characterized as at the beginning edge of the Generation 1.5 robot technology.

The pace at which these capabilities will be attained is uncertain. Concerning machine vision, current models perform tasks such as inspecting photographs of spot welds to determine whether or not imperfections exists. Skepticism exists about the attainment of 20/20 vision and eye-manipulator coordination before the year 2000, if ever [10]. Tactile sensory perception and the computer interpretation of both tactile and visual data are not likely for many years. The full duplication of human hand functions is even further away [14]. Near-term innovations will occur in such tasks as assembly, inspection, and continuous welding. These advances have important implications for New York State.

TABLE 1
Evolution of Robot Technology

Generation 1 Robot: This is a robot in use today. It is characterized by being a programmable, memory-controlled machine with several degrees of freedom. It can be equipped with grippers or special handling attachments, which can hold and operate hand tools, welding guns, and power tools, and can perform work-piece and material-handling manipulation and transfer functions.

Generation 1.5 Robot: This is a robot that will be sensory controlled and will have capabilities for performing "make" and "test" functions. It will work on principles of electro-optics pressure torque, force-sensitive touch, and proximity. It will be capable of recognizing and manipulating work pieces, parts, and tools. The motion paths of the robot will be memory controlled with overrides of preprogrammed control depending on sensory input.

Generation 2 Robot: This is a future robot that will have hand-eye coordination through its own vision. The robot will see objects and will be able with hand interactions to perform manipulative functions.

Generation 3 Robot: A "factory-intelligence-controlled" robot that will provide artificial intelligence to help solve "factory" problems.

Source: Tver and Bolz [22].

III. Traditional Diffusion Models

Viewing the diffusion of robotics technology in New York for Generation 1 and Generation 1.5 robots as a "new" product, we can consider application of the Mansfield-Bass model [3, 4, 11, 18]. In mathematical terms:

$$dN(t + 1) / dt = N(t + 1) - N(t) = [a + bN(t)][\bar{N} - N(t)], \tag{1}$$

where $N(t)$ is the current number of adopters at time t from a fixed population of potential adopters, $\bar{N}$, a is the coefficient of innovation, and b is the coefficient of imitation. The model explains the incremental number of adopters in a time period t as a function of spontaneous adoption, innovativeness, and the influence of those already using the new product on the remaining nonadopters (that is, imitation). Several major attempts have focused on extending the basic theory presented in Equation (1) by making a and b explicit functions of other factors thought to directly influence the rate of diffusion [16, 17]. One approach suggested by Hernes [15] was to make a and b explicit functions of time. Recent work by Bretschneider and Mahajan [8] illustrated the use of a heuristic procedure in estimating such models when a and b were expressed as implicit functions of time. We may characterize such approaches by the following dynamic-diffusion model:

$$dN(t + 1) / dt = [a(t) + b(t)N(t)][\bar{N} - N(t)], \tag{2}$$

where $a(t)$ and $b(t)$ are time-varying parameters. The procedure illustrated by Bretschneider and Mahajan [8] adaptively estimated the parameter paths for both $a(t)$ and $b(t)$ from data using feedback techniques without a priori specification of a structure for the time path of the parameters. The two major advantages of such an approach were improved forecast performance in the short run and estimated parameter paths that could be explored separately in order to find potential causes for accelerating or decelerating rates of innovation and imitation (see [7]).

IV. Data and Assumptions

In order to apply the models presented in Equation (1) or Equation (2), we need knowledge of the total population for which the innovation is aimed ($\bar{N}$) and some data on the early adoption of the innovation. Such data, even at the national level, is sparse. Table 2 summarizes the currently available data on the industrial robot population for the United States, including the sources of each estimate by year. We have estimated the total population of industrial robots in the U.S. for the year 2000 at slightly over 1.5 million. This estimate was developed by assuming that 40% of all industrial jobs could potentially be met by either Generation 1 or Generation 1.5 robots, and that, on average, one robot could replace three regular positions [2]. Using Bureau of Labor Statistics [26], we made projections of the numbers of basic laborers, nontransport operatives, and metal-working craftsmen in manufacturing for the year 2000. The estimate of potential robots was calculated as 40% of the sum of these projected positions divided by three. This, then, provides an estimate of the total potential population for Generation 1 and Generation 1.5 robots through the year 2000. Implicit in this calculation is the view that all such positions can potentially be replaced by either Generation 1 or Generation 1.5 robots.

Due to the absence of specific data for New York State, we decided to build a model using U.S.-level data and then apportion a share of the total to New York. One strategy for apportioning New York State's share of total U.S. robots is to apply the proportion of New York's manufacturing jobs to the total number of U.S. manufacturing jobs. This approach does not adequately reflect the higher concentration of robots in specific industries. Consequently, a weighted average of New York's proportion of total U.S. manufacturing was calculated based on specific industries known to have high concentrations of robots; fabricated metals, machinery, electronics, and transportation. Within these four groups the New York State percentage of the United States as a whole ranged from 3.4% to 8.4%, with the weighted average at 6.4% [25].

V. Estimation

Given the data in Table 1 and an estimate of the fixed population ($\bar{N}$), direct estimation of Equation (1) is possible using ordinary least squares. We rewrite Equation (1) as:

$$dN(t+1) / dt = a\,[\bar{N} - N(t)] + b\,N(t)[\bar{N} - N(t)], \tag{3}$$

and we estimate a and b by simply transforming the raw data on cumulative adopters in period t into changes in cumulative adopters between periods $[N(t+1) - N(t)]$ and form the two independent variables $\bar{N} - N(t)$ and $N(t)[\bar{N} - N(t)]$. Following this approach, hypothesis tests are possible on a and b directly. The empirical results of applying Equation (3) to the data were:

$$dN(t+1) / dt + -0.00002153\,[\bar{N} - N(t)] + 0.0000002832\,N(t)[\bar{N} - N(t)].$$

The estimate of a was found to not be statistically different from 0, whereas the estimate of b was statistically significant at an alpha level of .0001. This result implied that the predominant effect was one of imitation and not innovation. When a is found to be not significantly different from 0, the Bass Model becomes identical to the Mansfield Model:

$$dN(t+1) / dt = b\,N(t)[\bar{N} - N(t)]. \tag{4}$$

TABLE 2
U.S. Robotic Population

Year	Number	Source
1970	200	J. Engelberger [10]
1971	580[a]	
1972	950[a]	
1973	1,330[a]	
1974	1,700[a]	
1975	2,000[a]	
1976	2,000	Eikonix [9]
1977	2,400	Eikonix [9]
1978	2,500[a]	
1979	3,700[b]	Robotics Industry Association (1986)
1980	4,300[b]	Robotics Industry Association (1986)
1981	4,700[b]	Robotics Industry Association (1986)
1982	6,300[b]	Robotics Industry Association (1986)
1983	9,400[b]	Robotics Industry Association (1986)
1984	14,500[b]	Robotics Industry Association (1986)
1985	20,000[b]	Robotics Industry Association (1986)

[a]Interpolated values.
[b]Telephone interview.

One consequence of this analysis was that Equation (4) was deemed a more appropriate model for forecasting diffusion of robots than was Equation (1), hence, our interest shifts to estimation of b, the coefficient of imitation.

In considering forms of the dynamic-diffusion model, we find that preliminary results similarly tend to favor a Mansfield specification over that of the Bass model.[1] Two alternatives for forecasting dynamic-parameter models are available, neither of which allow for traditional approaches of statistical inference. Both are based on notions of feedback that adjust parameter estimates for time t based on previous estimates using data through time $t - 1$ and the size of the one-step-ahead forecast error. Specifically,

$$\hat{b}(t) = \hat{b}(t - 1) + A(e(t)), \tag{5}$$

where $\hat{b}(t)$ is an estimate of b at time t, and $e(t)$ is the one-step-ahead forecast error associated with applying the model using $\hat{b}(t - 1)$. The first approach, known as the adaptive-estimation procedure (AEP), was applied to diffusion models by Bretschneider and Mahajan [8]. The reader is directed to that work for a detailed description of the means for implementing the procedure.

A second approach advocates the use of recursively weighted least squares to estimate $b(t)$ [27]. This approach can be viewed as a feedback approach when formulated as a Kalman Filter. A first-order Markov chain model is stipulated as a model of motion or a system model for the time-varying parameter $b(t)$. To estimate a dynamic form of Equation (4) using Kalman Filtering, the model of motion is

$$b(t) = b(t - 1) + e1(t), \tag{6}$$

[1]Preliminary estimates of $a(t)$ for Equation (2) resulted in negative values.

with a measurement relationship

$$dN(t + 1) / dt = b(t)\, N(t)[\bar{N} - N(t)] + e2(t), \tag{7}$$

where $e1(t)$ and $e2(t)$ are random terms. We normally assume that $e1(t)$ and $e2(t)$ are uncorrelated normal random deviates. Under these circumstances the standard Kalman Filter recursive equations can be applied to estimate the parameter path for $b(t)$ (see [12]).

Adaptive estimation procedures defined by Equation (5) imply the need for initial estimates of the parameter b at time 0, $b(0)$. Application of Kalman Filtering further requires initial estimates for the variance of $e1$ and $e2$, plus the variance of the parameter estimate at time 0. The AEP approach similarly requires initial estimates of the rate of adaptation and variances but in the form of a smoothing and damping parameter. In both cases, these initial conditions strongly influence the resulting parameter path estimates. Heuristic procedures were applied to obtain "reasonable" estimates of these initial conditions. The first four observations were used to obtain an OLS estimate of b based on Equation (1), and these estimates were used as an initial value of $b(0)$ for both AEP and Kalman Filtering. The estimate of the variance of the parameter's $b(0)$ was used as the initial estimate of the parameter's variance, as well as an estimate of the variance in $e1$, whereas mean square error associated with fitting the first four observations was used as an initial estimate of the variance of $e2$. For alternative approaches to estimating initial conditions, see Sarris [21] and Gelb [12]. In applying AEP, smoothing and damping parameters play a role similar to those of initial variance terms in the Kalman Filter. For this application, the smoothing factor was set at .01 and the damping factor at .10. See Pack, Pike and Downing [19] for procedures on selection of these parameters using AEP.

Table 3 presents the estimates of $b(t)$ obtained using both recursive feedback approaches. The most striking distinction between the results is that the Kalman Filter estimates exhibit greater variance from time period to time period than do those produced by AEP. This reflects the tendency of AEP to smooth results and illustrates the advantage of heuristic selection of small damping factors to control the rate of change between time periods, as opposed to "optimally" estimating random fluctuations [6]. Both sets of results

TABLE 3
Estimated Parameter Paths For Coefficient of Imitation

Year	AEP Estimates	Kalman Filter Estimates
1971	0.00000021059	0.00000042707
1972	0.00000022090	0.00000041702
1973	0.00000022400	0.00000029714
1974	0.00000021859	0.00000020152
1975	0.00000020283	0.00000012641
1976	0.00000018214	0.00000001500
1977	0.00000016393	0.00000011471
1978	0.00000014753	0.00000003463
1979	0.00000016229	0.00000028561
1980	0.00000014606	0.00000011191
1981	0.00000013145	0.00000006162
1982	0.00000014460	0.00000021513
1983	0.00000015906	0.00000031593
1984	0.00000017496	0.00000035055
1985	0.00000019246	0.00000024639

indicate a decline in the effect of imitation between 1971 and 1981, followed by a rapid increase in 1982 through 1985. One interpretation of these results is that in the last few years, an acceleration in imitation behavior has occurred due to changing economic conditions. People are more willing to try new approaches during periods of real growth. Although 1982 was a recession year, the growth in robots during 1982 more than likely reflected prior commitments (made as many as 18 months earlier) to purchasing robots. Although sustained growth from 1983 through 1985 reflected the rapid growth of robots in those years, the growth cannot be explained purely by diffusion.

VI. Forecast

Making use of our estimates in forecasting can be done in several ways. Using the OLS estimate of b based on all the data, we assume that the value of b is constant over the sample and will remain constant over the forecast horizon. Using this approach, calculation of forecasts are accomplished by applying the following formula

$$N(t + 1) = N(t) + \hat{b}\, N(t)[\overline{N} - N(t)]. \tag{8}$$

By substituting the most recent forecast back into Equation (8), one may bootstrap forecasts forward over any future forecast period desired.

In the case of the feedback approaches, we have a parameter path and have assumed that the coefficient is not constant either within the sample or over the future time period. The simplest approach to forecasting using feedback results is to apply Equation (8), substituting the last, most current estimate of $b(t)$ for the constant value. Here we assume that despite changes in the coefficient within the historic sample, it will remain constant over the forecast horizon. Figure 1 presents the results of applying these approaches to forecasting the diffusion of robots. Annual estimates of the level of robots were multiplied by 6.4% to obtain an estimate for New York State.

An alternative to this approach is to extrapolate the parameter path estimates as a polynomial function of time over the forecast period. This approach takes advantage of our knowledge that the imitation process appears to be accelerating in the early 1980s. The most appropriate model for extrapolating the parameter paths presented in Table 3 was that of a quadratic function of time. This approach adequately captured the initial decline in the value of the parameter, followed by a reversal in trend. We can also tie such variation to more causal factors such as a quadratic function of industrial production lagged one or two years. Though such an approach is useful, forecasting industrial production over a twenty-year period is then necessary to forecast the coefficient of imitation to in turn forecast diffusion of industrial robots.[2] Figure 2 graphically displays the extrapolated values of $b(t)$ based on fitting quadratic time-trend models to the estimates in Table 3. Forecasts of New York State robots can be obtained by applying Equation (8) again to the data and substituting each forecasted value of $b(t)$ into the equation before calculating the next forecast. Figure 3 presents the results of forecasting that applies each model using extrapolated values for $b(t)$. OLS, AEP, and Kalman Filtering forecasts for the U.S. robot population are again adjusted for an estimate of New York State's share of manufacturing jobs (6.4%).

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[2]Both of the estimated-parameter paths showed significant correlation with lagged values of GNP, national disposable income, and industrial production.

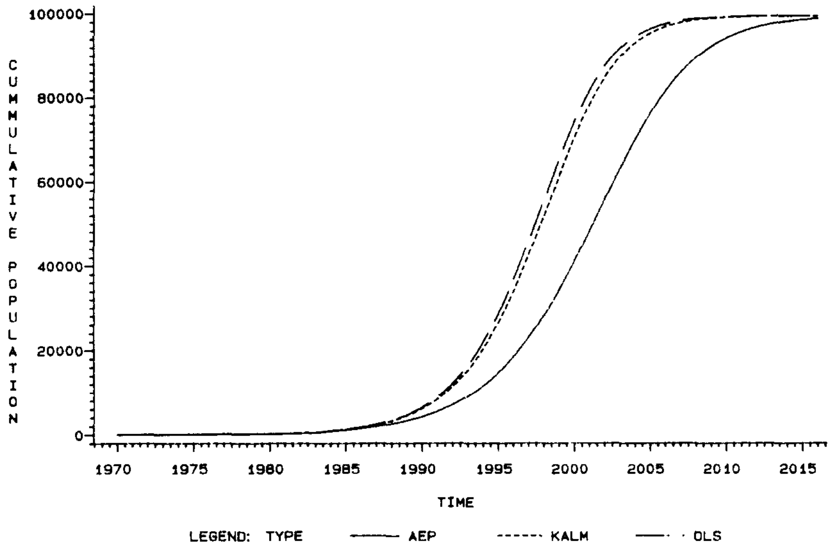

Fig. 1. Standard Diffusion Forecasts of Industrial Robots in New York State Through 2015.

Using the most recent estimate of $b(t)$ from the sample (see Figure 1), the OLS model implies the most rapid diffusion, whereas the AEP estimate generates the slowest diffusion. The results of the forecasts based on the Kalman Filtering estimates behave similarly to the OLS results. When using extrapolated values for $b(t)$, we found that the Kalman Filter forecasts jump up almost immediately to saturate the population, whereas the AEP approach demonstrates the effect of a slower acceleration in the coefficient (see Figure 3). Starting out at a rate slower than that predicted by the OLS estimate, the AEP

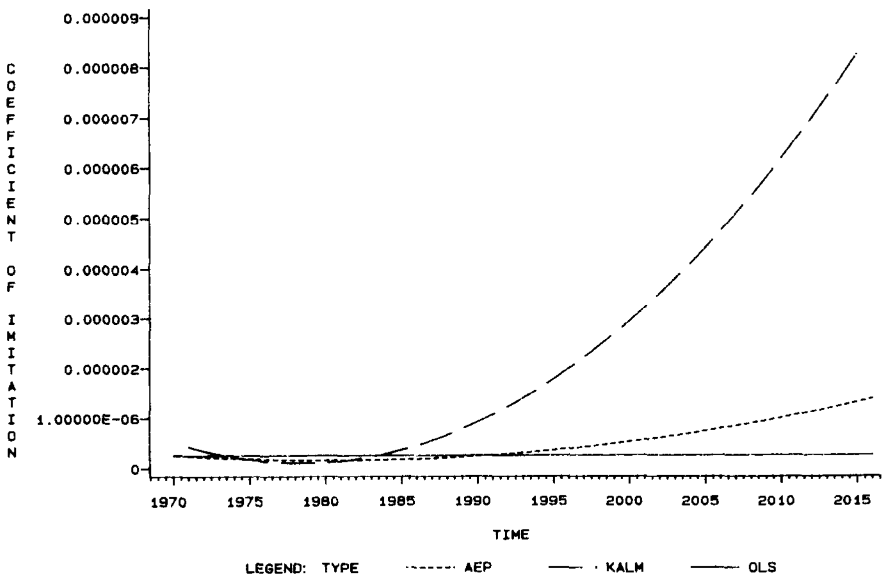

Fig. 2. Forecasted Values for Coefficient of Imitation (Quadratic Model).

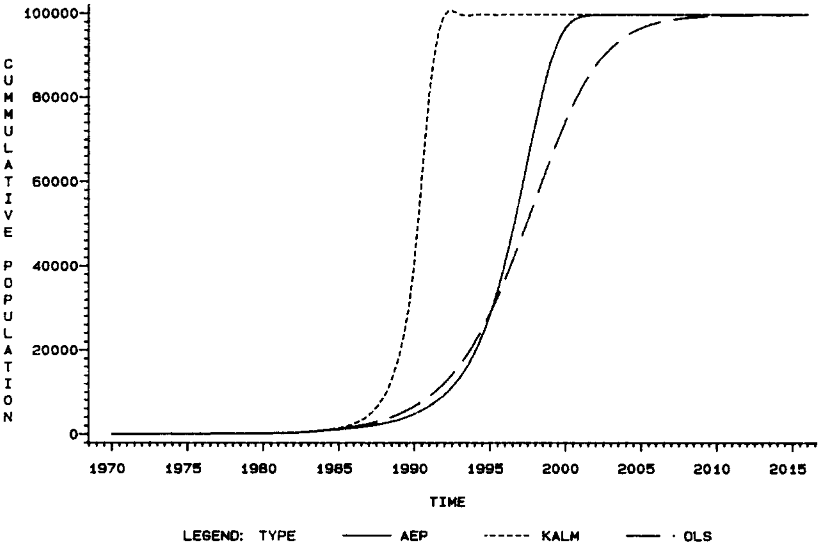

Fig. 3. Dynamic Diffusion Forecasts of Industrial Robots in New York State Through 2015.

forecasts eventually accelerate enough to reach saturation prior to the OLS forecasts by about nine years.

Each model predicts market saturation for robots at different times, ranging from 1992 to 2010. The AEP approach using dynamic forecast estimates market saturation around 2001. Which of these is most accurate depends upon how much acceleration is expected in the rate of imitation over the next decade. As mentioned above, the true determinant of acceleration relates directly to economic growth, particularly growth in specific components of the manufacturing sector—those most directly affected by the use of Generation 1 and Generation 1.5 robots. The rapid acceleration demonstrated using Kalman Filter estimates reflects some of the eccentricities of applying "optimal" filters in a heuristic fashion. Particularly important are the specification of initial conditions, which here have led to greater variance in estimated parameters across time and ultimately have led to a very large rate of acceleration. The AEP approach, developed heuristically, appears to give more robust results that have greater face validity.

VII. Conclusions

In applying diffusion models to the forecasting of technological substitution, we urge the reader to remember that such forecasts usually look ten, 20, or more years into the future. The structural nature of the diffusion model places a cap on the maximum value of a forecast based on the initial estimate of the population through which the new technology is to diffuse. Hence, the critical issue in technological forecasting is the rate of substitution. The use of dynamic-diffusion models reflect this point by allowing the rate of innovation and imitation to change over time, subject to various factors simultaneously. The application of empirical techniques to estimating such changing coefficients, such as Kalman Filtering and AEP, not only provide a basis for improved forecasting, they also provide intermediate results useful for investigating the causes of accelerating or decelerating rates of substitution.

In the application presented here, various projections for the diffusion of robotics in New York State reflect the strengths and weaknesses of the two heuristic estimation approaches. Kalman Filtering results lack some face validity, partially because of poor initialization and partially due to the application of optimality criteria in estimation (see [12]). The AEP approach, on the other hand, reflects the advantage of robust heuristics that smooth data as opposed to optimally fitting it. The result is forecasts that are less radical.

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