Not-for-publication appendix to Monitoring and Forecasting Currency Crises[†]

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More details on the 'Preliminary Data Analysis' section

More details on the Diffusion Index Analysis' section

Let X_t denote an n-dimensional time series variable that contain useful information to predict future values of the exchange rate. The researcher focuses on predicting the cumulated change in the logarithm of the nominal exchange rate h-steps ahead, $e_{t+h}^{h} \equiv \ln(e_{t+h}/e_t)$, where ln is the natural logarithm operator. The most general DI forecast model is:

$$X_t = \Lambda_t F_t + \eta_t \tag{1}$$

$$e_{t+h}^{h} = \alpha_h + \sum_{j=1}^{m} \beta_{hj}' F_{t-j+1} + \sum_{j=1}^{p} \gamma_{hj} e_{t-j+1} + \epsilon_{t+h} \tag{2}$$

where $e_t = e_t^1$, $t = 1, 2..T$, F_t represents the $r \times 1$ vector of common factors and η_t is the $n \times 1$ idiosyncratic disturbance, which can be correlated and serially correlated, but otherwise satisfies the usual assumptions of exogeneity (see Stock and Watson (1998)). By focusing on the common factor, the diffusion index captures most of the variability in the data without being too much influenced by the idiosyncratic components. In what follows, various versions of (2) are considered: a simple DI model (referred to as "DI") where $r \neq 0$, $m = 1$, $p = 0$; the DI model with lagged dependent variables (referred to as "DI-AR") where $r \neq 0$, $m = 1$, $p \neq 0$; the DI model with lagged factors (referred to as "DI, Lag") where $r \neq 0$, $m > 1$, $p = 0$; the most general DI model with lagged dependent variables and lagged factors (referred to as "DI-AR, Lag") where $r \neq 0$, $m > 1$, $p \neq 0$

Table A1(a-b) show the results. We report the forecasting performance of the diffusion index method in terms of its Root Mean Square Forecast Error (RMSFE) *relative* to the RMSFE of a simple autoregressive process ("ar"). The autoregressive process with p lags is simply:

$$e_{t+h}^{h} = \rho_0 + \sum_{j=1}^{p} \rho_j e_{t-j+1} + \epsilon_{t+h} \tag{3}$$

The number of lags is selected by BIC. In all the tables, forecasting starts in 1994:1 for Malaysia, and 1995:1 in Philippines, South Korea, Taiwan and Thailand.

Entries less than 1 in Table A1 mean that the DI is better than the autoregressive process in terms of forecasting. As it is clear from Table A1(a), for most countries and most horizons of prediction it is possible to find a DI that is better than the autoregressive process in terms of forecasting.

We also perform formal test of forecast comparison between the DI forecasts and the forecasts based on the simple AR model. The test we use is the Diebold and Mariano (1995) and West (1996) test, referred to as DMW (all models are non-nested except the DI-AR and the AR models, for which we use critical values from Clark and McCracken (2001)).[1] The test statistic is the following:

$$n\left(\frac{1}{n}\sum_{t=m}^{T-1}\Delta L_{m,t+h}\right)'\widehat{\Omega}^{-1}\left(\frac{1}{n}\sum_{t=m}^{T-1}\Delta L_{m,t+h}\right) \tag{4}$$

where $\Delta L_{m,t+h}$ is the difference of the squared forecast errors of the two models, and $\widehat{\Omega}$ is an estimate of the long-run variance of $\left(\frac{1}{n}\sum_{t=m}^{T-1}\Delta L_{m,t+h}\right)$. For simplicity, we abstract from the possibility of parameter estimation uncertainty in the DMW test. The p-values of the DMW test are reported in parentheses under the corresponding RMSE ratio. The results show that, except in a few cases, the performance of the DI model is not significantly better than that of the AR model, whereas the AR model is never significantly better than the DI.

Table A1(b) shows the results if one adds the lagged exchange rate among the explanatory variables (the "DI, Lag" model). As in Stock and Watson (2002), the number of lags of the exchange rate is selected recursively by BIC. That is, first we select by BIC the number of lags of the exchange rate for a given number of explanatory factors, then the number of factors is chosen according to a BIC criterion again. Note that in a few cases, adding lags help, but this result does not hold uniformly over all countries. Unreported analysis regarding the models "DI-AR", and "DI-AR, Lag" found similar results, except that the latter did not perform very well for some countries.

INSERT TABLES A1 (a,b)

We also compare the performance of the DI method with that of the more traditional leading indicators used in KR, and briefly summarized in Table 4. More details are, again, available in the Appendix. Let the $j-th$ leading indicator be denoted by "L_j". We estimate the following model:

$$e_{t+h}^{h}=\alpha_h+\sum_{j=1}^{l}\beta_h' L_{j,t-j+1}+\sum_{j=1}^{p}\gamma_{jt}e_{t-j+1}+\epsilon_{t+h} \tag{5}$$

[1] Since recursive forecasts are at least $h-1$ serially correlated, where h is the horizon of the forecast, the long run covariance matrix is estimated with h lags.

where the number of lags "p" is chosen according to the BIC criterion. Table 5(a) compares the forecasts of each of the available Leading Indicators and the DI models in terms of RMSEs relative to an AR process. We consider DI models where the number of factors is either one ("DI_1") or chosen by BIC ("DI_{BIC}"). The DMW p-values are reported in parentheses below the corresponding RMSE ratio. The table shows that the Leading Indicators are indeed useful for forecasting future exchange rates.

However, the best Leading Indicator may be different for different countries and different forecast horizons, whereas one of the advantages of the DI model is that the choice of the variables is automatically provided within the method. Thus, to be realistic, in Table 5(b) we compare a model that uses all Leading Indicators and compare its performance to the DI. We find that a simple DI_1 model forecasts better than the Leading Indicator model in 66% of the cases. The DMW p-values reported in parentheses refer to either the comparison between the DI and the Leading Indicator model (in the columns labeled "DI") or the comparison between the Leading Indicators and the AR model (in the columns labeled "L_{all}"). Some of the DI forecasts are statistically better than the Leading Indicator, and only one is statistically worse.

INSERT TABLES 4 AND 5(a,b)

We also consider the alternative test for conditional predictive ability proposed by Giacomini and White (2003, referred to as GW). The null hypothesis of this test is that the h-steps ahead forecast loss differential between two models in not predictable on the basis of explanatory variables known at the time in which the forecast is made. In particular, the test statistic is constructed as:

$$\frac{1}{n}\left(\sum_{t=m}^{T-1} Z_t \Delta L_{m,t+h}\right)' \widehat{\Omega}^{-1} \left(\sum_{t=m}^{T-1} Z_t \Delta L_{m,t+h}\right) \tag{6}$$

where $\Delta L_{m,t+1}$ is the difference between the squared forecast errors of the two models, Z_t is a vector of p_z explanatory variables known at time t, and is a consistent estimate of the long run variance of $Z_t \Delta L_{m,t+h}$. Giacomini and White (2004) show that, under some regularity conditions, (6) has an asymptotic chi-square distribution with a number of degrees of freedom equal to the number of explanatory variables used, p_z. In the our implementation, we use as control variables the past values of the Leading Indicators when comparing the DI model with the AR model, and we use past values of the dependent variable when comparing the DI model with the all Leading Indicator model. Table 6 shows the p-values of the GW test. For this test, when the p-value is less than the desired size it is not possible to conclude, on the basis of the sign of the test statistic, which forecasting method is better when the control variables are more than one, as in that case the test statistic has a one-sided chi-square distribution. However, the advantage of the GW test is that it is possible to test for conditional predictive ability and to evaluate jointly the forecast and the forecasting method, that is the model and the estimation procedure altogether. The GW test clearly does generally reject the null hypothesis of conditionally equal predictive ability when comparing the DI forecasts with the AR forecasts, but generally does not when comparing the DI forecasts with the LI forecasts.

Table A1(a). Diffusion Indexes forecasting performance

	h	6	12	24	6	12	24	6	12	24
r			Philippines			Malaysia			South Korea	
1		1.00	1.02	**1.02**	**1.07**	**0.92**	1.00	**0.75**	1.01	0.73
		(0.91)	(0.30)	**(0.62)**	**(0.20)**	**(0.47)**	(0.94)	**(0.24)**	(0.97)	(0)
2		**0.99**	1.03	1.15	1.11	0.99	1.06	0.80	0.92	0.59
		(0.82)	(0.40)	(0.14)	(0.05)	(0.93)	(0.18)	(0.29)	(0.75)	(0)
3		1.00	1.08	1.21	1.14	1.07	1.05	0.95	0.70	0.79
		(0.93)	(0.04)	(0)	(0.08)	(0.74)	(0.36)	(0.75)	(0.40)	(0.24)
4		1.07	1.09	1.21	1.21	1.14	1.07	0.88	0.69	0.69
		(0.25)	(0.09)	(0)	(0.07)	(0.51)	(0.33)	(0.56)	(0.42)	(0.07)
8		1.19	**0.96**	1.14	1.43	1.40	**0.96**	1.05	0.74	0.50
		(0.06)	**(0.76)**	(0.17)	(0.01)	(0.19)	**(0.53)**	(0.77)	(0.43)	(0)
12		1.29	1.20	1.09	1.36	1.29	0.97	1.32	**0.64**	**0.50**
		(0.02)	(0.03)	(0.23)	(0.02)	(0.14)	(0.66)	(0.18)	**(0.31)**	**(0.01)**
			Taiwan			Thailand				
1		1.06	1.04	0.81	**0.94**	**1.06**	**1.01**			
		(0.47)	(0.49)	(0.18)	**(0.27)**	**(0.19)**	**(0.88)**			
2		**1.00**	**0.97**	**0.71**	1.03	1.40	1.15			
		(0.97)	**(0.61)**	**(0.03)**	(0.69)	(0.09)	(0.24)			
3		1.01	1.06	0.99	1.41	1.27	1.34			
		(0.87)	(0.41)	(0.88)	(0.15)	(0.04)	(0.18)			
4		1.09	1.25	1.11	1.28	1.34	1.34			
		(0.40)	(0.20)	(0.41)	(0.13)	(0.12)	(0.18)			
8		1.12	1.29	1.18	1.20	1.08	1.21			
		(0.20)	(0.01)	(0.24)	(0.19)	(0)	(0.14)			
12		1.15	1.63	1.51	1.20	1.13	1.33			
		(0.19)	(0.13)	(0.13)	(0.21)	(0)	(0.13)			

Table A1(b). Diffusion index with lagged factors

h	6	12	24	6	12	24	6	12	24
r		Philippines			Malaysia			South Korea	
1	1.00	**1.02**	**1.02**	**1.07**	**0.92**	**1.00**	**0.75**	1.01	0.73
	(0.91)	**(0.30)**	**(0.62)**	**(0.20)**	**(0.47)**	**(0.94)**	**(0.24)**	(0.97)	(0)
2	**0.99**	1.03	1.15	1.11	0.99	1.06	0.80	0.92	**0.59**
	(0.82)	(0.40)	(0.14)	(0.05)	(0.93)	(0.18)	(0.29)	(0.75)	**(0)**
3	1.00	1.08	1.21	1.14	1.07	1.05	0.95	0.70	0.79
	(0.93)	(0.04)	(0)	(0.08)	(0.74)	(0.36)	(0.75)	(0.40)	(0.24)
4	1.07	1.09	1.21	1.21	1.14	1.07	0.88	**0.69**	0.69
	(0.25)	(0.09)	(0)	(0.07)	(0.51)	(0.33)	(0.56)	**(0.42)**	(0.07)
		Taiwan			Thailand				
1	1.06	1.04	0.81	**0.94**	**1.06**	**1.01**			
	(0.47)	(0.49)	(0.18)	**(0.27)**	**(0.19)**	**(0.88)**			
2	**1.00**	**0.97**	**0.71**	1.03	1.40	1.15			
	(0.97)	**(0.61)**	**(0.03)**	(0.69)	(0.09)	(0.24)			
3	1.01	1.06	0.99	1.41	1.27	1.34			
	(0.87)	(0.41)	(0.88)	(0.15)	(0.04)	(0.18)			
4	1.09	1.25	1.11	1.28	1.34	1.34			
	(0.40)	(0.20)	(0.41)	(0.13)	(0.12)	(0.18)			

Table A2(a). Leading Indicators vs. Diffusion Index forecasts.

h	6	12	24	6	12	24
	Malaysia			*South Korea*		
DI_{BIC}/ar	1.40	1.30	0.99	1.32	0.68	0.46
	(0.01)	(0.14)	(0.91)	(0.18)	(0.34)	(0.01)
DI_1/ar	1.07	0.92	1.00	0.75	1.01	0.73
	(0.20)	(0.47)	(0.94)	0.24)	(0.97)	(0.00)
L_1/ar	0.98	0.90	0.99	0.59	0.63	0.74
	(0.96)	(0.91)	(0.95)	(0.90)	(0.90)	(0.87)
L_3/ar	- -	- -	- -	0.59	0.61	0.77
	- -	- -	- -	(0.90)	(0.90)	(0.89)
L_4/ar	- -	- -	- -	0.72	0.94	0.93
	- -	- -	- -	(0.91)	(0.98)	(0.95)
L_6/ar	0.97	0.90	0.96	0.56	0.56	0.68
	(0.94)	(0.91)	(0.87)	(0.90)	(0.89)	(0.85)
L_7/ar	0.98	0.93	1.01	0.62	0.65	0.72
	(0.95)	(0.93)	(0.95)	(0.91)	(0.91)	(0.85)
L_8/ar	0.98	0.95	1.00	0.59	0.60	0.69
	(0.96)	(0.93)	(0.95)	(0.90)	(0.89)	(0.85)
L_9/ar	0.98	0.96	1.01	0.62	0.62	0.66
	(0.96)	(0.93)	(0.95)	(0.90)	(0.90)	(0.85)
L_{10}/ar	- -	- -	- -	- -	- -	- -
	- -	- -	- -	- -	- -	- -
L_{12}/ar	0.95	0.92	1.00	0.57	0.57	0.68
	(0.90)	(0.90)	(0.91)	(0.90)	(0.89)	(0.85)
L_{14}/ar	0.98	0.93	0.99	0.61	0.63	0.74
	(0.95)	(0.92)	(0.83)	(0.90)	(0.89)	(0.85)

Table A2(a) (continued)

h	6	12	24	6	12	24	6	12	24
		Taiwan			*Thailand*			*Philippines*	
DI_{BIC}/ar	1.21	1.63	1.36	1.22	1.09	1.31	1.10	1.14	1.11
	(0.01)	(0.08)	(0.17)	(0.23)	(0.01)	(0.13)	(0.17)	(0.01)	(0.14)
DI_1/ar	1.06	1.04	0.81	0.94	1.06	1.01	1.00	1.02	1.02
	(0.47)	(0.49)	(0.18)	(0.27)	(0.19)	(0.88)	(0.91)	(0.30)	(0.62)
L_1/ar	- -	- -	- -	0.92	1.01	0.99	0.99	1.09	1.00
	- -	- -	- -	(0.92)	(0.95)	(0.88)	(0.96)	(0.82)	(1.00)
L_3/ar	1.13	1.13	1.06	0.93	1.02	1.01	1.00	1.05	1.09
	(0.89)	(0.85)	(0.83)	(0.90)	(0.82)	(0.51)	(0.98)	(0.80)	(0.85)
L_4/ar	1.09	1.06	0.99	0.93	1.03	0.99	1.00	1.02	0.95
	(0.91)	(0.90)	(0.88)	(0.91)	(0.85)	(0.62)	(0.99)	(0.95)	(0.69)
L_6/ar	- -	- -	- -	0.93	1.02	1.00	0.95	0.99	1.00
	- -	- -	- -	(0.92)	(0.86)	(0.96)	(0.81)	(0.83)	(1.00)
L_7/ar	0.92	0.86	0.87	0.93	1.03	1.00	0.95	1.02	1.09
	(0.86)	(0.74)	(0.68)	(0.91)	(0.94)	(0.96)	(0.85)	(0.87)	(0.82)
L_8/ar	- -	- -	- -	0.90	1.02	1.02	1.03	1.07	1.02
	- -	- -	- -	(0.90)	(0.95)	(0.82)	(0.92)	(0.82)	(0.90)
L_9/ar	- -	- -	- -	0.93	1.04	1.01	0.98	1.01	1.00
	- -	- -	- -	(0.91)	(0.69)	(0.91)	(0.93)	(0.91)	(0.99)
L_{10}/ar	1.02	1.01	0.87	- -	- -	- -	- -	- -	- -
	(0.99)	(0.99)	(0.90)	- -	- -	- -	- -	- -	- -
L_{12}/ar	0.93	0.91	0.73	1.02	1.09	1.02	0.96	1.00	1.01
	(0.86)	(0.85)	(0.79)	(0.89)	(0.86)	(0.76)	(0.89)	(0.99)	(0.96)
L_{14}/ar	1.03	1.02	0.91	- -	- -	- -	1.04	1.09	0.95
	(0.96)	(0.93)	(0.71)	- -	- -	- -	(0.94)	(0.95)	(0.71)

Table A2(b). All leading indicators vs. DI forecasts.

Country	h	DI_{BIC}/ar	L_{all}/ar	DI_1/ar
Malaysia	6	**1.40**	**1.03**	1.07
		(0.05)	**(0.05)**	(0.20)
	12	1.30	0.85	0.92
		(0.17)	(0.47)	(0.47)
	24	0.99	0.92	1.00
		(0.47)	(0.34)	(0.94)
South Korea	6	1.32	1.00	0.75
		(0.13)	(0.99)	(0.24)
	12	0.68	1.23	1.01
		(0.11)	(0.52)	(0.97)
	24	**0.46**	0.89	**0.73**
		(0.00)	(0.58)	**(0.00)**

Table A2(b). All leading indicators vs. DI forecasts.

Country	h	DI_{BIC}/ar	L_{all}/ar	DI_1/ar
Taiwan	6	1.21	1.08	1.06
		(0.09)	(0.43)	(0.47)
	12	1.63	1.15	1.04
		(0.14)	(0.15)	(0.49)
	24	**1.36**	0.61	0.81
		(0.03)	(0.14)	(0.18)
Thailand	6	1.22	0.98	0.94
		(0.31)	(0.80)	(0.27)
	12	1.09	1.14	1.06
		(0.49)	(0.15)	(0.19)
	24	1.31	1.01	1.01
		(0.15)	(0.54)	(0.88)
Philippines	6	1.10	1.49	1.00
		(0.16)	(0.07)	(0.91)
	12	1.14	1.42	1.02
		(0.28)	(0.09)	(0.30)
	24	1.11	**1.18**	1.02
		(0.60)	**(0.02)**	(0.62)

Table A3. Giacomini and White's forecast comparison test (p-values)

h	6	12	24	6	12	24	6	12	24
	Philippines			Malaysia			South Korea		
DI_1/ar	0.70	0	0	0.85	0.03	0	0.45	0.03	0
DI_1/L_{all}	0.43	0.98	0.11	0.50	0.56	0.53	0.47	0.85	0.91
DI_2/ar	0.06	0	0	0.49	0.30	0.00	0.92	0.84	0
DI_2/L_{all}	0.45	0.98	0.17	0.65	0.64	0.47	0.55	0.51	0.25
DI_{BIC}/ar	0.87	0	0	0.11	0.03	0	0.93	0.54	0
DI_{BIC}/L_{all}	0.54	0.99	0.13	0.47	0.47	0.84	0.52	0.97	0.83
	Taiwan			Thailand					
DI_1/ar	0	0	0	0.14	0	0			
DI_1/L_{all}	0.57	0.97	0.40	0.70	0.64	0.27			
DI_2/ar	0	0	0	0.27	0.19	0			
DI_2/L_{all}	0.53	0.33	0.65	0.76	0.77	0.39			
DI_{BIC}/AR	0	0	0	0.27	0.06	0			
DI_{BIC}/L_{all}	0.59	0.32	0.09	0.30	0.11	0.17			

Tables A4 shows the Brier score test statistic to quantitatively evaluate the predictions in Section 5 of the paper. The Brier score is the most common verification method for probabilistic forecasts. It is similar to the MSE, measuring the difference between a forecast probability of an event and its occurrence, expressed as 0 or 1 depending on whether the event occurred or not. The lower the Brier score, the better the forecast. Table 8 shows that there are not big differences in the Brier scores of different models, which confirms the earlier findings.

Table A4. Brier's score statistic

Country	mo.	ar	di_{BIC}	di_1	L_1	L_3	L_4	L_5	L_6	L_7	L_8	L_9	L_{10}	L_{11}
Mala	1	0.01	0.01	0.01	0.01	- -	- -	0.01	0.01	0.01	0.01	- -	0.01	0.01
	6	0.13	0.14	0.14	0.13	- -	- -	0.13	0.14	0.13	0.13	- -	0.13	0.13
	12	0.21	0.22	0.22	0.20	- -	- -	0.20	0.20	0.21	0.19	- -	0.20	0.21
	24	0.34	0.37	0.38	- -	- -	- -	0.38	0.37	0.35	0.36	- -	0.34	- -
S.Korea	1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	- -	0.01	0.01
	6	0.08	0.08	0.07	0.07	0.08	0.08	0.08	0.07	0.07	0.07	- -	0.08	- -
	12	0.17	- -	0.17	0.17	0.16	0.16	0.17	0.17	0.17	0.17	- -	0.17	0.17
	24	0.41	0.41	0.41	0.41	0.41	0.42	0.41	0.42	0.41	0.41	- -	- -	0.42
Taiwan	1	0	0	0	- -	0	0	- -	0	- -	- -	0	0	0
	6	0	0.01	0	- -	0	0	- -	0	- -	- -	0	0	0
	12	0.04	0.04	0.04	- -	0.04	0.04	- -	0.04	- -	- -	0.04	0.04	0.04
	24	0.10	0.09	0.09	- -	0.10	0.10	- -	0.10	- -	- -	0.10	0.10	0.10
Thai	1	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	- -	0.01	- -
	6	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.10	0.09	- -	0.09	- -
	12	0.19	0.20	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	- -	0.19	- -
	24	0.47	0.49	0.49	0.48	0.48	0.48	0.48	0.47	0.48	0.48	- -	0.48	- -
Phil.	1	0	0	0	0	0	0	0	0	0	0	- -	0	0
	6	0.10	0.09	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	- -	0.10	0.10
	12	0.23	0.21	0.23	0.22	0.22	0.22	0.23	0.23	0.22	0.22	- -	0.23	0.23
	24	0.56	- -	0.56	- -	- -	0.55	0.57	- -	0.56	- -	- -	- -	0.57

Additional notes regarding the calculation of signal to noise ratios (constructed as in Note 16 of KR, page 489).

Table A5. Signal to noise tables

	DI	
	Crisis occurs	No crisis occurs
	Taiwan 2	*Taiwan* 2
	Thailand 4	*Thailand* 0
Signals a crisis	*Philippines* 4	*Philippines* 2
	Malaysia 4	*Malaysia* 1
	South Korea 0	*South Korea* 0
	Taiwan 2	*Taiwan* 2
	Thailand 0	*Thailand* 4
Do not signal a crisis	*Philippines* 0	*Philippines* 2
	Malaysia 0	*Malaysia* 3
	South Korea 2	*South Korea* 4
	AR	
	Crisis occurs	No crisis occurs
	Taiwan 0	*Taiwan* 2
	Thailand 4	*Thailand* 0
Signals a crisis	*Philippines* 4	*Philippines* 2
	Malaysia 4	*Malaysia* 2
	South Korea 0	*South Korea* 0
	Taiwan 4	*Taiwan* 2
	Thailand 0	*Thailand* 4
Do not signal a crisis	*Philippines* 0	*Philippines* 2
	Malaysia 0	*Malaysia* 2
	South Korea 4	*South Korea* 4
	Leading	
	Crisis occurs	No crisis occurs
	Taiwan 1	*Taiwan* 3
	Thailand 4	*Thailand* 2
Signals a crisis	*Philippines* 4	*Philippines* 3
	Malaysia 4	*Malaysia* 2
	South Korea 0	*South Korea* 0
	Taiwan 3	*Taiwan* 1
	Thailand 0	*Thailand* 2
Do not signal a crisis	*Philippines* 0	*Philippines* 1
	Malaysia 0	*Malaysia* 2
	South Korea 4	*South Korea* 4

Additional references:

Lopez, Jose' (2001), "Evaluating the Predictive Accuracy of Volatility Models", *Journal of Forecasting,* 20, pp. 87-109.