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MONEY DEMAND, FINANCIAL DISTRESS, AND EXCHANGE-RATE UNCERTAINTY IN INDONESIA

Paul D. Mc Nelis *)

This paper examines the demand for currency and quasi-money in Indonesia with linear and neural network models. The goal is to predict better the recent financial distress, reflected by the flight into currency and decline of quasi-money.

The results show that neural network approaches, much more than linear models, are capable of accurate out-of-sample predictions for both monetary aggregates. However, for the very turbulent period of November and December of 1997, even the neural network models show large out-of-sample forecast errors.

When a proxy for exchange-rate uncertainty supplements the network models, the out-of-sample currency demand becomes quite accurate, even for the last month of 1997. The quasi-money demand forecast also improve, although not as dramatically as those of currency demand.

The analysis shows that a credible program, which reduces uncertainty in exchange-rate expectations, may mitigate the flight into currency from broad money, and the ensuing demonetization of the financial sector.

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I. Introduction

In this paper I examine the monthly demand for currency and quasi money in Indonesia, from 1984 through 1997.

This is an empirical exercise with immediate policy implications. Since the later part of 1997, the increase in currency demand has come at the expense of broad money. It thus represents a demonetization of the banking sector, or a reversal of the process of "financial deepening" in Indonesia. It is a clear sign of financial distress. If such a process continues, it cannot help but undermine the long term growth process of Indonesia.[1]

The flight from quasi money into currency was sudden, which traditional linear or error-correction models did not forecast very well. For this reason, I make use of neural networks, and contrast the results given by this approach with those given by linear models, for in sample and out of sample accuracy.

It turns out that most important variable for explaining the sudden switch from quasi money to currency in the out of sample forecast is exchange-rate uncertainty. Several proxy variables for this uncertainty measure significantly improve the neural-network out of sample forecasts.

The policy implication of this paper is that the monetary authority of Indonesia will have take credible and quick steps to reduce exchange-rate uncertainty and volatility, if it wishes to reserve the continuing demonetization process of the banking sector.

A related benefit is that this method may be an effective early warning system for financial distress. If the forecasts of shifts in currency demand are in tandem with forecast a fall in quasi money, the central bank may be able to anticipate this demonetization with appropriate policies for restoring confidence in the financial sector.

The use of neural networks represents a departure from the purely linear rational expectations approach to macroeconomics, into "bounded rationality", in which economics agents "learn" and respond to changes in economic fundamentals only after these changes reach critical thresholds.

Kamin and Rogers (1996) examined the currency demand in Mexico prior to the crisis of 1994. They also found that high monetary base of currency growth prior to the crisis reflected

[1] See Levine (1997 for a survey of the literature on financial development and long-run economic growth.

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a "shock" or shift in the demand for money away from broader aggregates toward narrow money. They also found that the monetary authority did not depart significantly from its "normal" reaction function in the face of the currency demand shock. They concluded that effective response to the crisis would have entailed a major departure from the usual stance of monetary policy measured by the estimated reaction function.

However, Kamin and Rogers analyzed the demand for currency with quarterly data, using traditional linear error-correction methods. In this paper I use monthly data. Nor did they examine an explicit demand for quasi-money. Unfortunately, purely linear models, even those based on cointegration and error-correction, do not perform well with the higher frequency monthly financial data.

In the next section I examine the data and note several "stylized facts" about the Indonesian financial sector. I then take up in Section III the linear error-correction model, and evaluate how it performs, in sample, with the Indonesian monthly data for currency and quasi-money demand. Then in Section IV, I discuss the neural network model for currency demand and quasi-money. Section V takes up the out- of sample performance of the linear and neural network models for currency and quasi money, and shows the crucial role of exchange-rate uncertainty for predictive accuracy. The last section concludes with a broader policy discussion of the results.

II. Indonesian Monetary Aggregates and Asset Prices

Figure 1 pictures the evolution of currency and quasi-money for the past three years.

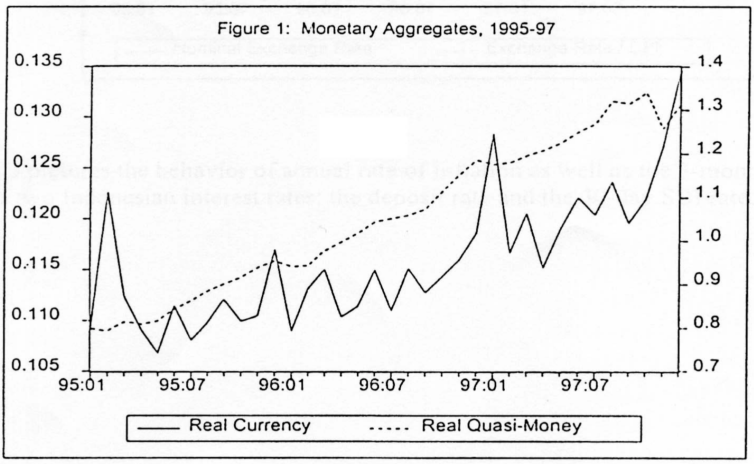

Figure 1

One cannot help but notice the jump in currency demand after the start of the financial crisis in July 1997, and the corresponding fall in quasi-money, The key question : could the behavior of these monetary aggregates have been anticipated, on the basis of available macroeconomic data, or did this phenomenon represent a totally unpredictable shock to the financial sector?

The time paths of the nominal exchange rate and the nominal exchange rate deflated by the CPI appear in Figure 2. Again, both the variables appear quite calm before the storms of July 1997.

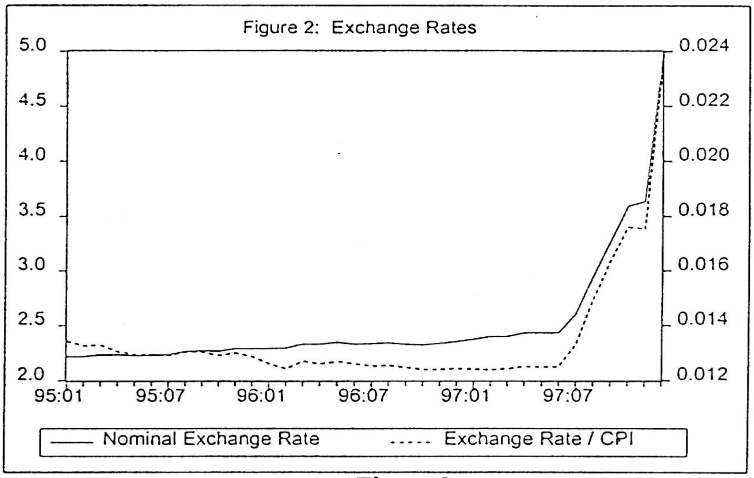

Figure 2

Figure 3 pictures the behavior of annual rate of inflation as well as the 3 month LIBOR and the two Indonesian interest rates : the deposit rate and the 30-day SBI rate.

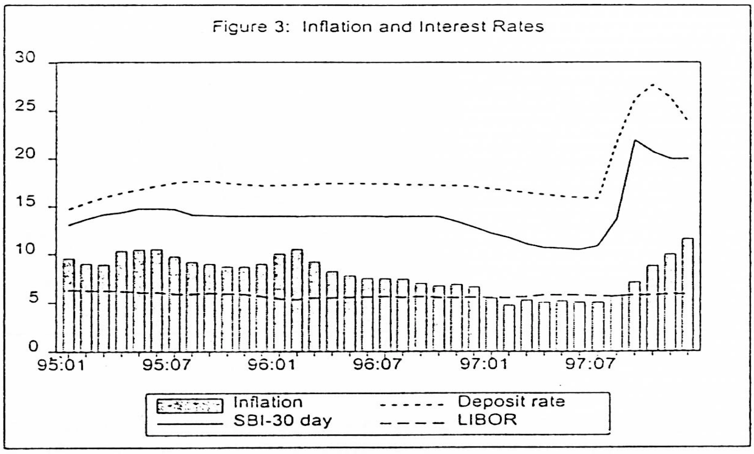

Figure 3

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Figure 3 shows that by early 1997 inflation had fallen to annual levels near 5 percent. The 30-day SBI rate was approximately equal to the LIBOR rate adjusted for inflation. After July 1997 both of the Indonesian interest rates rose sharply, as did the rate of inflation.

Figure 4 pictures the evolution of the index of quasi-money to net foreign assets of the Government of Indonesia since 1989.

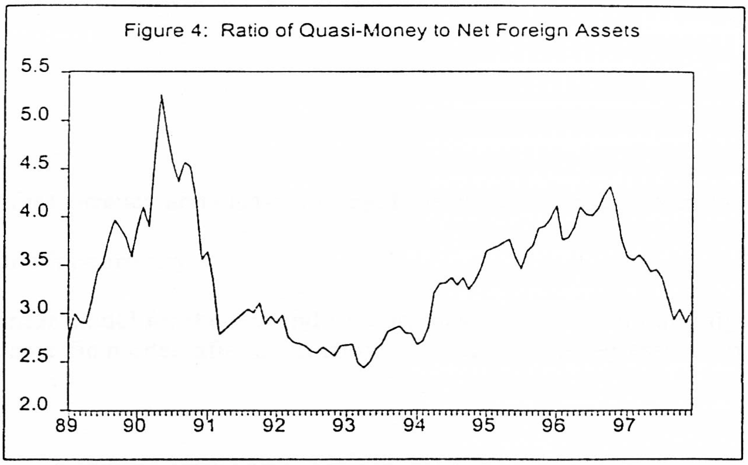

Figure 4

Calvo and Mendoza (1996) use this ratio, as well as the corresponding ratio for M2, as “indices of vulnerability”. The authors point out that it is the *instability* of this ratio, rather than the *level*, that is dangerous[(Calvo and Mendosa (1996) : p. 243).]. There is a greater risk that sudden and large shocks to quasi-money would mean a large loss of reserves, and undermine the currency band or peg.

One sees in Figure 4 the abrupt run up in this ratio between 1994 and 1996 and the rapid decline in 1997. This ratio has been anything but stable in Indonesia.

III. Demand for Currency and Quasi-Money : Linear Models and Forecasts

A. The demand for currency

The linear model for the demand for currency makes use of monthly data. The results of the specific model, after elimination of insignificant regressors, appears in Table I.

Linear Error Correction Model of Currency Demand
1984 : 1996

Argument	**Estimate**	**T-Stat**	**Marg.Sig**
[m / py](-1)	-0.1370	-3.5143	0.0003
R(-1)	-0.1514	-2.6624	0.0043
D[m / p](-1)	-0.3778	-6.7428	0.0000
D[m / p](-4)	-0.2009	-3.6046	0.0002
D[m / p](-12)	0.2871	4.8981	0.0000
D[y](-5)	-0.2647	-5.4294	0.0000
D[R](-3)	0.1851	1.9196	0.0284
Dum (8)	-0.0646	-2.4383	0.0080
Idul Fitri	0.0854	2.7256	0.0036
constant	0.7725	10.7305	0.0000

Diagnostics:	**Estimate**	**Marg. Sig**
R-Sq	0.6072	
HQ	31.27	
DW	1.9892	
Q(1)-e^1	0.0450	0.831935
Q(1)-e^2	20.1448	7.18E-06
J-B	1.3354	0.512876
Engle-Ng	12.6065	0.00557

Table 1.

In this equation, lower case m represents the logarithmic value of currency in circulation, upper case R is the level of the deposit rate, y is the logarithmic of real gdp. D is the first difference operator, while Dum (8) is the August monthly dummy variable, and Idul Fitri is the dummy for the date of the Idul Fitri celebration.[2]

[2] Idul Fitri is the celebration at the end of Ramadhan, the annual period of fasting in Indonesia and Islamic countries. Since the calender date of Ramadhan changes each year, this effect cannot be captured by a monthly dummy variable.

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The results show that all of the coefficients are significant for the estimation period 1984 through 1996 : 12.

The overall in-sample explanatory power, given by the R-Sq coefficient, is quite good, at. 60.[3] The Durbin-Watson significant, given by D-W, and the Leung-Box Q-statistic, for the level of the residuals, cannot reject serial independence. However, the same Q-statistic, for the squared residuals, rejects serial independence, indicating the presence of heteroskedasticity. The Jarque-Bera statistic, discussed in Bera and Jarque (1980) does not reject normality of the regression residuals, whereas the Engle-Ng (1993) test rejects symmetry in the residuals.

Overall, the currency demand equation performs well with the in sample pre-crisis data.

B. The demand for quasi-money

The demand for quasi money appears in Table 2.

Linear Demand for Quasi-Money
1985.1 : 1996.12

Argument	**Estimate**	**T-Stat**	**Marg. Sig**
[qm / res](-1)	0.0088	1.7781	0.0388
D[qm](-1)	0.2503	3.0324	0.0014
D[res](-3)	0.0219	1.6642	0.0492
[R-R* -Dep](-12)	-0.0003	-2.1815	0.0154
AUGUST	0.0112	2.1570	0.0164
constant	0.0027	0.5313	0.2980

Diagnostics:	**Estimate**	**Marg.Sig.**
R-Sq	0.1510	
HQ	111.6472	
DW	1.9736	
Q(1)-e^1	0.0126	0.9106
Q(1)-e^2	1.7791	0.1823
J-B	29.4577	0.0000
Engle-Ng	3.3735	0.3375

Table 2

3 The HQ statistic is Hannan_quinn information criterion, used for selecting models. It is given by the formula, n ln(ssr) + ln(ln(n)) k, where n is the number of observations, k the nunber of regressors, and ssr is the sum of squared residuals. One should chose a model, among alternative specifications, with the lowest Hannan-Quinn criterion. I refer back to Hannan-Quinn criterion. I refer back to the Hannan-Quinn criterion for the linear model after discussing the corresponding statistic for the neural network model.

The demand for quasi-money depends upon the logarithm of the ratio of the level of lagged quasi-money to the level of lagged reserves, since these variables are co-integrated. It also depends on the first lag of the change in the logarithm of real quasi-money, on the third lag of the change in the logarithm of real reserves, denominated in domestic currency, on lag 12 of the difference between the domestic interest rate R and the foreign interest rate R* less the annualized rate of depreciation, on an August dummy, and a constant term.

The overall explanatory power of the demand for quasi money is, as expected, lower than that of the demand for currency. All of the coefficients, except for the covered interest parity deviation, are significant, and the regression diagnostics do not reject serial independence, normality, and symmetry in the regression residuals.

IV. Neural Network Analysis of Money Demand

A. Design of a neural network

Figure 5, below, pictures the "architecture" of a feedforward neural network, relating inputs x to an observed output y.

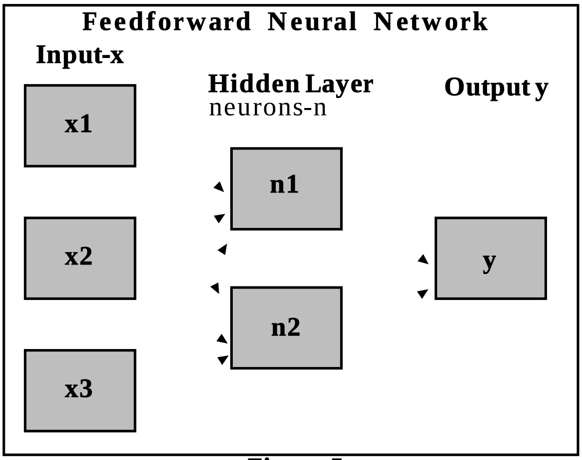

Figure 5

The hidden layers simply transform the input variables x by one or more "squasher functions". The advantage of the neural network approach over the linear approach is that estimation involves not only sequential processing of the data, using inputs x to forecast the output y, but also simultaneous parallel processing, since the inputs are processes by several "neurons" in the hidden layer.

The neural network approach is an outgrowth of Weierstrass Theorem, which tells us that any continuous function g (x,y) may be approximated with greater accuracy by a polynomial expansion of progressively higher orders. Unfortunately, with polynomial approximation, the number of parameters grows exponentially with the number of arguments in the function. A neural network, by contract, delivers the same degree of accuracy with fewer parameters, or greater accuracy with the same number of parameters.

The mathematical expression for a neural network is given by the following system of equations:

$$y_t = \gamma_0 + \sum_{i=1}^{i*} \gamma_i N_{i.i}$$

$$N_{t,i} = \frac{1}{1 + e^{-\pi_{t,i}}}$$

$$n_{t,i} = b_i + \sum_{j=1}^{i*} \omega_{ij} X_{t,j}$$

Equation 1 : FF Network

In this typical feedforward network, there are j* regressors, and i* neurons. Each neuron is formed by a linear combination of the inputs, with coefficients or weights given by $\{w_{ij}\}$ and $\{b_i\}$. The linear combinations are then "squashed" by the logistic or logsigmoid function given by the second expression in Equation 1. Finally, the squashed neurons are recombined with weights y to produce forecasts of the output y.

The intuition behind the logsigmoid squasher is that is captures "threshold behavior" in economic behavior, or reaction of people to news. The logsigmoid squasher has the following graphical representation:

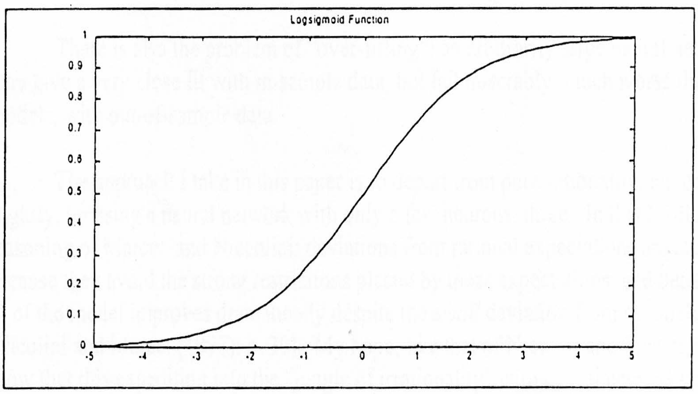

Figure 6

Figure 6 shows that at extremely low or high values of a set of input variables, there is little reaction. However, as the inputs gradually increase from the low values, or fall from the high values, people begin to "learn", to react little by little, to changes in the news or fundamentals. After a certain threshold point, people will adjust very quickly to changes, positive or negative, in the fundamentals.

The use of a logsigmoid squasher function necessitates pre-processing or re-scaling of the data if they take on large values, since the input data will simply trigger output values of unity beyond certain values. One simple rescaling mechanism is to transform the z = [x y] data set in the following way :

$$\boxed{z^*_t = \frac{z_t - \min(z)}{\max(z) - \min(z)}}$$

Equation 2 : Rescaling Mechanism

The use of the logsigmoid function as the specification of the "neurons" in the middle layer implies "bounded rationality" in economic behavior. When people react to news or changes in economic fundamentals, they do indeed adjust their behavior, but in the short run, they react only after the changes reach critical thresholds or trigger points. This behavior is in contrast to pure rational or linear adaptive behavior by economic agents, and represents a departure from the pure rational expectations approach to macroeconomics.

The problem with the neural network approach, of course, is that there are no a priori restrictions to limit the number or neurons. Rationals wxpectations macroeconomics teaches us quite rightly to beware of modelers bearing too many "free parameters". If a theory or model can be adjusted to explain everything, in the end, it explains nothing.

There is also the problems of "over-fitting" : an arbitrarily large neural network may give a very close fit with in-sample data, but fail miserably, much worse than linear models, with out of sample data.

The approach I take in this paper is to depart from pure rationality, but only slightly, by using a neural network with only a few neurons, three. In this I follow the reasoning of Marcet and Niccolini : deviations from rational expectations are attractive because they avoid the strong restrictions placed by these expectations, and because the fit of the model improves dramatically despite the small deviation from rationality [Nicolini and Marcet (1997) : p. 30]. My hope, like that of Nicolini and Marcet, is to show that this expedition into the "jungle of irrationality" with neural networks can be a safe and productive experience (Nicolini and Marcet (1997) : p. 30).

B. Demand for Currency

The neural network estimates for currency demand appear in Table 3.

Demand for Currency: Neural Network Estimates

Inputs to Neurons

Input:		[m / py](-1)	r(-1)	D[m / p](-1)	D[m / p](-4)	D[m / p](-12)	D[y](-5)	D[r](-3)	Dum(8)	Idul Fitri
Neuron:	1	22.0825	-2.7685	-13.3127	-17.3712	3.1234	-3.6592892	-30.598	3.32366	6.198518
	2	-0.4076	-0.7320	-0.8935	-0.5091	0.5106	-0.73967603	0.276258	-0.14023	0.310213
	3	24.2379	-3.8291	-14.8276	-19.5943	2.9559	-4.72237327	-33.3342	34.69806	7.248473

Neurons to Output:

1	2	3
2.9338	10.6526	-2.8931

Partial Derivatives Evaluated At Mean:

Input:	[m / py](-1)	r(-1)	D[m / p](-1)	D[m / p](-4)	D[m / p](-12)	D[y](-5)	D[r](-3)	Dum(8)	Idul Fitri
	-5.0916	0.5585	2.6923	3.8341	-0.3700	0.7310	6.8743	-8.6406	-1.3905

Diagnostics:	Estimate	Marg. Sig
R-Sq	0.7410	
HQ	5.1582	
DW	2.0719	
Q(1)-e^1	0.2561	0.6128
Q(1)-e^2	12.5065	0.0004
J-B	0.3247	0.8502
Engle-Ng	15.1974	0.0017

Table 3.

Table 3 shows that the fit of the model improves dramatically, to a value of 74 from. 6 in the linear model. The Hannan-Quinn criterion at 5 is much lower than the corresponding value for the linear model, 15.

The partial derivatives evaluated at the mean are different from the pure linear regression coefficients. The diagnostics of the model cannot reject serial independence in favor of first-order autocorrelation. However there is also evidence of heteroskedasticity and asymmetry in regression residuals.

C. Demand for quasi-money

Table 4 gives the neural network estimates for the demand for quasi-money.

Demand for Quasi-Money : Neutral Network Estimates					
Inputs to Neurons					
	Input:				
Neuron:	[qm/res](-1)	D[qm](-1)	D[res](-3)	[R-R*-Dep](-12)	AUGUST
1	-3.3111	45.219	-28.4717	-5.9779	-26.8606
2	-127.8175	105.9160	70.7640	5.7473	-5.4477
3	0.2028	0.9887	-0.5361	-0.3305	0.1656
Neurons to Output:					
	1	2	3		
	-0.5674	19.7046	1.4256		
Partial Derivatives Evaluated At Mean:					
	Input:				
Neuron:	[qm/res](-1)	D[qm](-1)	D[res](-3)	[R-R*-Dep](-12)	AUGUST
	-0.5674	19.7046	1.4256	-0.1233	-0.0343
Diagnostics:	Estimate	Marg. Sig			
R-Sq	0.3538				
HQ	97.9971				
DW	1.8994				
Q(1)-e^1	0.3674	0.5444			
Q(1)-e^2	0.0373	0.8469			
J-B	33.9232	0.0000			
Engle-Ng	2.1142	0.5490			

Table 4.

The results show that the neural network explanatory power dominates that of the linear model, both by the R^2 and the Hannan-Quinn criteria. Table 4 also shows that the partial derivatives are rather close to the linear regressions coefficients, and that the diagnostics show residuals that are serially independent, homoskedastic, and symmetric.

The superior performance of the network models, with only three neurons, relative to the linear specification, shows that there are significant non-linearities in the demand for currency and the demand for quasi-money.

The most important performance measure of any estimation method, of course, is its out-of-sample forecasting accuracy. This is the subject of the following section.

V. Out-of-Sample Performance of Linear and Network Models

The basic statistics for the out of sample performance of the two models appear in Table 5.

Out-of-Sample Performance of Linear and Network Models				
	Currency Demand		Quasi-Money Demand	
	Linear	Network	Linear	Network
RMSQ	0.804446674	0.17291846	0.396757727	0.2129442
DM-Stat		16.1323288		4.913696598
Mar.Sig		0		4.46875E-07

Table 5.

The currency demand and quasi money out of sample forecasts are for the entire year, 1997.

The RMSQ, or root mean squared error statistic, shows that the network model outperforms the linear model for both currency demand and quasi money demand. However, the Diebold-Mariono (1995) statistic shows that the network forecast errors are “significantly better” than the linear forecast errors, only for the currency demand model, not for the quasi money demand model.

The out-of-sample forecast errors for the two models appear in Figures 7 and 8, respectively.

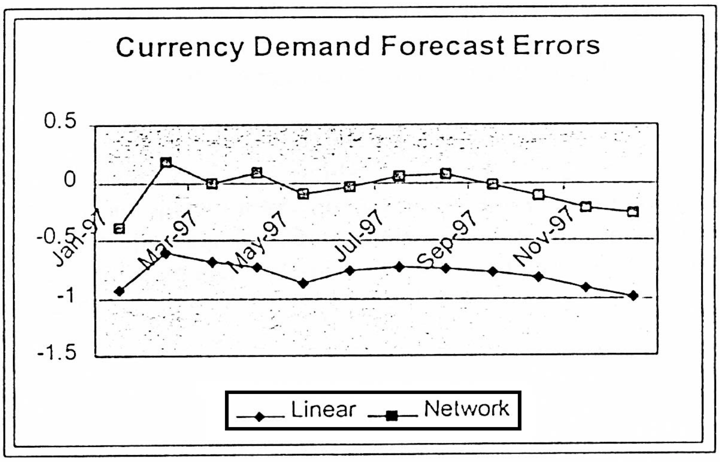

Figure 7.

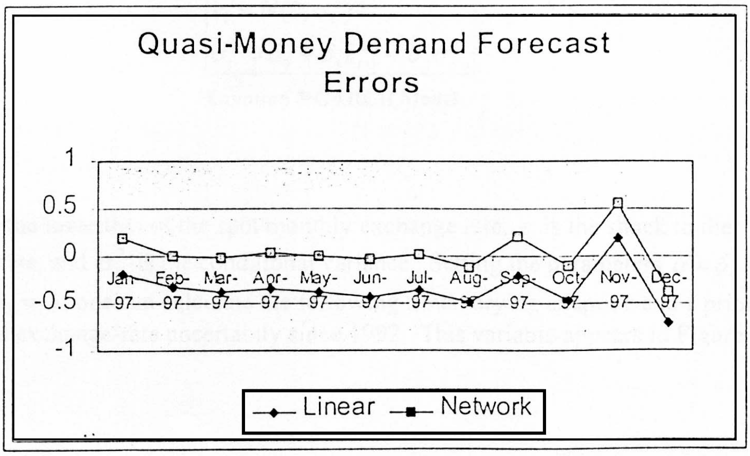

Figure 8.

What is really striking in figures 7 and 8 is that the neural network out-of-sample forecasts are on the mark, until November and December of 1997, for both currency and quasi money. By contrast, up until this time, the forecast errors of the linear models are persistently negative. Thus the linear model systematically over predicts currency and quasi money demand for most of 1997.

What these forecast errors show is that the neural network does remarkably well for out of sample data up to ten moths for currency and four months for quasi money. Only in November and December of 1997 does the network model deteriorate. The currency and quasi-money forecast errors of November and December of 1997 represent shocks of such magnitude and change that even the highly non linear network model breaks down.

Clearly, there is a "missing variable", which began to have strong effects on the demand for currency and quasi-money in November and December of 1997, but prior to that time, did not have appreciable effects. One candidate that comes to mind is exchange-rate variability, or exchange rate risk, proxied by the following time varying GARCH specification.

$$\Delta e_t = \alpha + \varepsilon_t$$
$$\varepsilon_t = N(0, \sigma^2_t)$$
$$\sigma_t^2 = \delta_0 + \delta_t \varepsilon^2_{t-1} + \delta_2 \sigma^2_{t-1}$$

Equation 3: GARCH Model

Where e is the logarithm of the spot monthly exchange rate, ε is the shock to the exchange rate, and σ^2 is the conditional variance. Setting the parameters $\alpha = \delta_0 = 0$, and $\delta_1 = \delta_2 = 5$, one can calculate the following time varying adaptive and a priori estimate of exchange rate uncertainty since 1992. This variable appears in Figure 9.

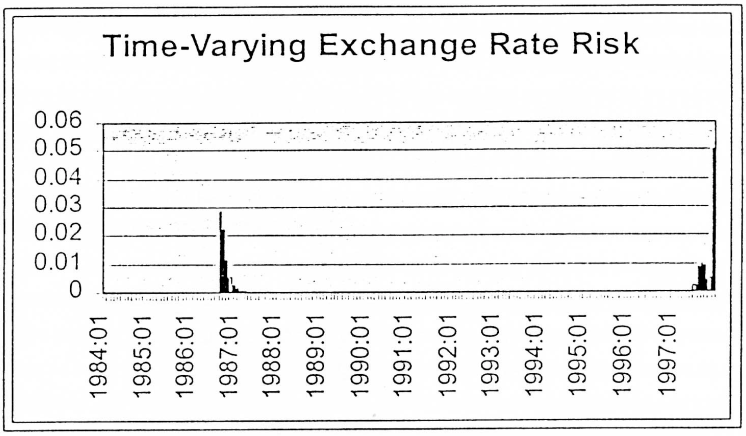

Figure 9.

This time varying-exchange-rate variable is relatively flat for most of the estimation period, but in two periods, in 86-87, and at the end of 97, there are large jumps.

The forecasting power of the network for currency is vastly improved when this additional variable is added to the list of inputs or regressors. Figure 10 shows the forecast errors of the original network and augmented network models.[4]

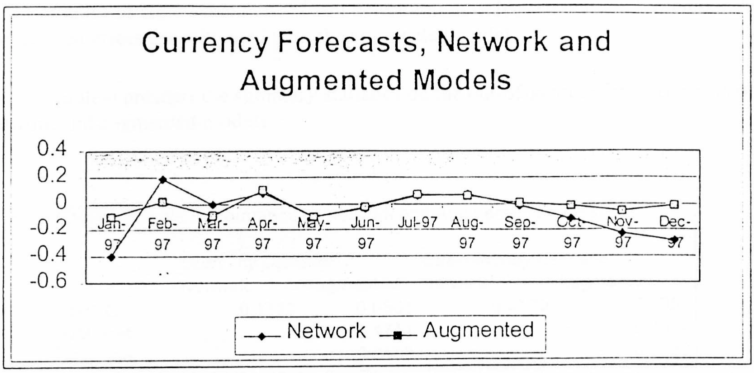

Figure 10

4 Alternative time-varying proxy variables were also used for exchange rate uncertainly. These variables were based on lagged squared first differences. Their performance was about as good as the GARCH.

There is no longer a dramatic drop in the forecasting performance of the network in November and December. The risk variable makes a major difference.

What about the forecasts of quasi-money? Figure 11 pictures the forecast errors of the original and augmented models.

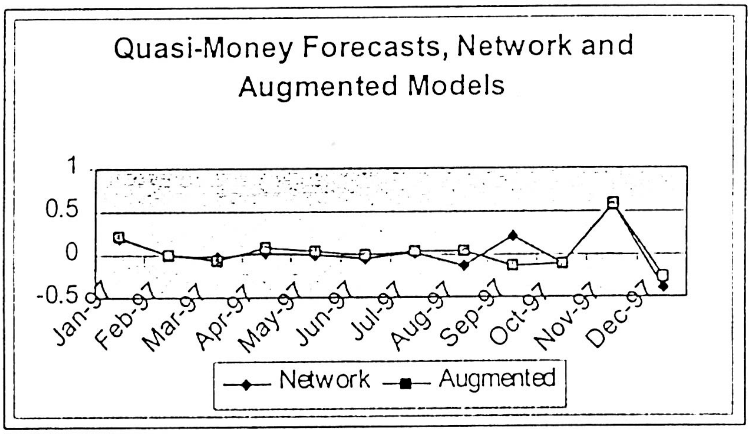

Figure 11.

Figure 11 shows that there is still deterioration in November and December, but the forecast errors are mitigated with the augmented model.

Table 6 presents the summary statistics on the out-of-sample errors of the network and augmented models.

Out-of-Sample Performance of Linear and Network Models				
	Currency Demand		Quasi-Money Demand	
	Network	Augmented	Network	Augmented
RMSQ	0.1729	0.0653	0.2179	0.2051
DM-Stat		2.1711		0.4514
Mar.Sig		0.0150		0.3259

Table 6.

VI. Conclusion

The policy implications of the above analysis are hard to escape. Policies which mitigate exchange-rate uncertainty may play a crucial role in reversing the flight into currency from quasi-money, and the ensuing demonetizations of the Indonesian financial sector.

Of course, reducing uncertainty about the exchange rate involves the credibility of the monetary authority it self toward maintaining a fixed exchange rate or one with a limited band.

In Latin America, such exchange rate based stabilization plans were common in the mid-1980. In Argentina and Brazil these plans were known as heterodox shocks, and involved temporary wage and price controls as well as exchange-rate fixes. However, these plans were eventually doomed, due to the lack of fiscal discipline by the new democratically elected governments, which took office after years of military dictatorship in both of these countries.[5]

In the 90's, similar exchange rate based stabilization plans were again tried. Argentina adopted a currency board under Domingo Cavallo, while Brazil adopted a rather tight exchange-rate intervention band under Fernando Henrique Cardoso. However, there was no thought of wage / price controls. In contrast to the failed exchange rate based stabilization plans adopted earlier, both economies were considerably more open in the 1990.

While Indonesia is not coming out of an experience of chronic high inflation or near-hyperinflation, as many Latin American countries were in the 1980's and early 1990's, it is facing the problem of a large dollar debt overhang.

One method that was used by Mexico was the FICORCA Plan, adopted in 1983, and administered initially by Ernesto Zedillo, the current President of Mexico [Zedillo (1993)]. Such a plan involved the government assuming the dollar obligations of indebted domestic firms, while the firms in turn negotiated payment in local currency to the central bank. The program was voluntary, and applied only to the rescheduled foreign debt.

A similar plan, called sucretization, was tried in Ecuador in 1984. In this plan the government reserved the process of dollarization by assuming domestic dollar debts and receiving payment in domestic currency, the sucre. This plan had the unexpected payoff of leading to an increase in the demand for domestic deposits, an appreciation of the domestic currency in the parallel markets, and a dramatic fall in inflation within one year.[6]

5 For further analysis of these "incredible reforms", see Calvo (1986,1989), and Calvo Vegh (193).

6 See McNelis and Nickelsburg (1990) for more about the Ecuador plan and a comparison of dollarization problems in Peru during this period.

In contrast to Ecuador, Mexico, and Peru, Indonesia does not suffer a significant dollarization problem. However, as the Ecuadorian experience indicates, an exchange-rate based debt-relief plan may have beneficial macroeconomic and monetary consequences. For the Ecuadorian government, its action by committing it self, led to a virtuous cycle of lower inflation, increased money demand, remonetization, and depolarization of the financial sector.

As of April 1998, the Indonesian government is in the process of formulating a FICORCA-type plan for corporate debt relief. Such a plan, if well executed with a credible, time-consistent, and sustainable exchange-rate agreement, may have the happy consequence of initiating a virtuous cycle of stabilization and remonetization as well as much needed debt relief. FICORCA may indeed function as Indonesia's preannounced "currency board "in disguise.[7]

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[7] Tsang (1998) recommends that Indonesia pre-announce a currency board for six months or one year in the future and use the transition period to engage in fundamental reforms with that exchange rate as the anchor of expectations.

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