

Economic Policy Uncertainty and Industrial Activity: An Evidence from Pakistan

Tunio, Mohsin Waheed

 $10~{\rm May}~2022$

Online at https://mpra.ub.uni-muenchen.de/113544/ MPRA Paper No. 113544, posted 30 Jun 2022 08:48 UTC "Economic Policy Uncertainty and Industrial Activity: An Evidence from

Pakistan"

Mohsin Waheed

Abstract

Economic Policy Uncertainty is defined as a state wherein the policymakers, or institutions are uncertain about the future course of economic policies owing to a myriad of factors ranging from economic conditions and political tensions to geo-politics. The pioneering work of Baker, Bloom and Davis (2016) brought-in a new way of thinking in economics; whereby, introducing newspaper-based uncertainty to reflect on economic policies and resulting impacts thereof on a whole lot of economic conditions including real sector activity. This paper follows Choudhary, Pasha and Waheed (2020) to check if uncertainty has negative implications for production in Pakistan. I use the VECM model to see if there exists a long-term relationship between economic policy uncertainty and real activity in Pakistan; alongside that, I also make use of a bivariate SVAR to further enrich analysis. My findings conform to this notion that uncertainty does affect production and real activity.

[SIPA MPA-EPM Empirical Econometric Project Paper]

May 2022

JEL codes: D80, E22, E66, G18

Keywords: economic policy uncertainty, large-scale manufacturing, automobiles production, real activity

Introduction

Economic Policy Uncertainty is generally defined as a state in which economic policymakers can not foresee a clear path down the road, and are thus unable to make predictions, or decide about the future course of action. Generally, economic policy uncertainty has remained heightened globally during the global financial crisis of 2008; Asian financial crisis of 1997; Mexican Tequila crisis of 1990s, and all other crises. In the US, the period during the global financial crisis was marked by 2nd highest amount of uncertainty since 1985; highest being aftermath the 9/11 attacks.

Moreover, not only is economic uncertainty driven by economic events such as currency devaluation, sudden stops, and recessions, but political developments such as coups, martial laws, wars, and other events are also seen to increase uncertainty manifolds and rapidly such as Gulf war and US elections; during such politically challenging times there remains high amount of economic uncertainty as things unfold sporadically thus triggering random spells of uncertainty. Russia - Ukraine crisis is a recent example. There are also some separate indices such as 'Geopolitical Risk Index' and 'Democracy Index' that attempt to capture regional conflicts and level of democracy in countries separately. Moreover, the enormous exogenous shocks such as pandemic created unprecedented amount of uncertainty that was not seen before. The onset of the pandemic was the only event in recorded human history that disrupted the entire planet at the same time and hence uncertainty remained unparalleled. This led economic policymakers to be innovative about policy formulation both in the developed countries as well as the developing ones.

The high amount of policy uncertainty badly affects economic agents' decisions about consumption and saving. There is a fear in heightened uncertainty whether banks would go insolvent, or is it safe to keep deposits in the local currency, or have them converted into hard currencies, or gold fearing depreciation. Additionally, uncertainty affects credit and investment too. During uncertain times, firms don't want to expand production thus they have little reliance on private sector credit; due to this, production is badly affected in the economy leading to higher unemployment.

This research builds on the premise that uncertainty affects production and manufacturing by looking at the interaction of policy uncertainty and the Large-Scale Manufacturing data of Pakistan. The monthly large-scale manufacturing index of Pakistan is the country's only high frequency data that well reflects the real sector activity; it is published and computed by the Pakistan Bureau of Statistics. Unlike many developed and some emerging market economies, the GDP data of Pakistan is only available annually, so that measure of real activity cannot be used for limited observations. Nevertheless, in two separate studies i.e., Tahir et al. (2018) and Hanif et al. (2013) have attempted to quarterize GDP for the country through statistical techniques, but these are the independent studies and hence may not be as reliable as the official source.

From the production point of view, according to the State Bank of Pakistan and the World Bank share of services, industry, and agriculture in country's GDP are 53.84%, 17.72%, and 23.3% respectively as of 2020. In addition, over 50% of the labor force is concentrated in the agriculture sector. Highest contributor to the index as shown below is the textile industry with an approximate share of 21%; its highest share indicates that this industry is the country's most salient industry which also contributes to country's approximately 60% of the total exports. The underlying reason

for the largest share of textile industry is that Pakistan is the world's 5th largest producer¹ of cotton according to the US Department of Agriculture.

Manufacturing Sector	Weight	(%) Change 2020-21		(%) Change 2021-22		YOY Growth Impact 2021-22	
		Dec	Jul-Dec	Dec	Jul-Dec	Monthly	Cumulative
Textile	20.9	3.3	2.6	2.6	1.1	0.6	0.3
Food, Beverages & Tobacco	12.4	18.2	20.7	5.8	3.1	1.7	0.6
Chemicals	1.7	16.5	10.9	-4.3	5.4	-0.1	0.1
Automobiles	4.6	43.8	11.1	41.5	35.7	2.0	1.9
Iron & Steel Products	5.4	11.8	-1.2	17.8	23.9	0.6	0.9
Leather Products	0.9	-40.5	-42.7	7.0	8.3	0.1	0.1
Paper & Board	2.3	-4.7	-2.7	7.7	8.3	0.3	0.3
Engineering Products	0.4	-23.9	-31.4	-0.9	1.1	0.0	0.0
Wood Products	0.6	-30.1	-60.1	478.4	292.4	0.0	0.0

 Table1: Pakistan Large Scale Manufacturing (LSM) Index

Source: Pakistan Bureau of Statistics

Literature Review

The notable paper of Baker, Bloom and Davis (2016) introduced a new method of looking at policy uncertainty i.e., uncertainty about economic conditions as reflected in the daily newspaper. This led to a new way of looking at uncertainty besides the other indicators that existed before such as VIX. Along these lines, Choudhary, Pasha and Waheed (2020) create a newspaper based economic policy index for Pakistan that seeks to explain periods of high uncertainty during the past a couple of decades.

Through this publication, the authors argue that, in Pakistan, spikes in uncertainty had been associated with political chaos and massive changes in government such as massive political demonstrations and also with the country's programs with the IMF. Besides, in Pakistan, uncertainty remained highest during the pandemic as suggested by the index which is also in resonance with the similar indices of several other countries.

¹ https://www.statista.com/statistics/263055/cotton-production-worldwide-by-top-countries/

The notable contribution of Bernanke (1983) sheds light on the negative impacts of economic policy uncertainty and investment and labor market. They document that the deleterious effects of uncertainty are passed down to firms over time leading to low production and high unemployment. In another study, Fernández-Villaverde et al. (2015) provide details of how uncertainty negatively impacts spending by providing details that high amount of uncertainty pushes people to precautionary savings. Their empirical analysis involves VAR and a New Keynesian model as Christiano, Eichenbaum and Evans (2005). Their VAR model is of quarterly frequency with four-lags and a linear time trend while identifying shocks recursively. Besides, their New Keynesian model is a representative agent model with the role of fiscal policy.

Furthermore, Jovanovic and Sai Ma (2020) empirically document different impacts of uncertainty on the real economic activity. They argue that, greater economic uncertainty is linked with lower growth. In addition, they also highlight, among other facts, that higher asset volatility increases the negative impact of uncertainty on the real activity. Their empirical model endogenizes growth and uncertainty. It has a collection of agents that can raise their productivity by embracing new technologies.

Data

The variables used in this research are the following monthly variables: interest rate i.e. call money rate; large-scale manufacturing index; count of automobiles production and sale; and economic policy uncertainty index. The sources of variables are State Bank of Pakistan, Pakistan Bureau of Statistics, and policyuncertainty.com respectively. Due to seasonality, as can be seen in the graphs at *Annexure-III*, two series namely large-scale manufacturing index and auto production have been seasonally adjusted with ARIMA 13 SEATS. The large-scale manufacturing follows a certain

pattern over the year; it is low during January to March and later accelerates until July. Moreover, all the variables are integrated of order 1 i.e. I (1); differencing them once makes all the variables stationary. The Dicky Fuller test of stationarity further provides evidence of stationarity suggesting that differencing the variables once makes them stationary; *Annexure-I* provide test results for stationarity.

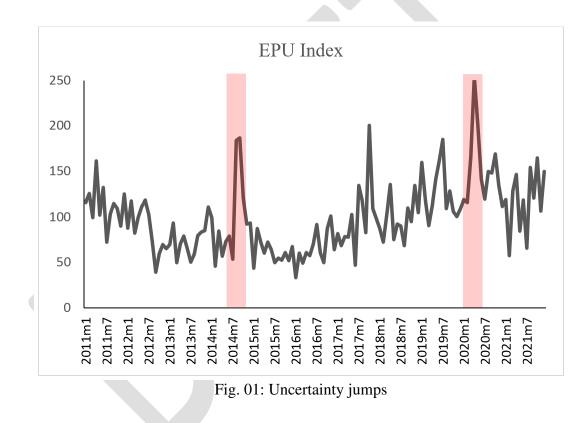
Tracing drastic surge in uncertainty through pulse dummies'

Although multiple up and down movements in uncertainty could be seen in the graph below, but there are two notable periods i.e., April 2020 and August 2014 where a drastic surge in uncertainty was seen. In the case of the former, uncertainty was due to the lockdowns that were imposed in the wake of COVID-19 and rising cases. In the month of April, an emergency Monetary Policy Committee meeting was convened and drastic measures were taken such as greater supply of credit and export refinance for purchase of priority healthcare equipment. Prior to that, in March 2020 alone, Monetary Policy Committee meet twice to beef up measures for the extraordinarily challenging times.

In usual circumstances, the monetary policy meetings are convened every two months. This reflects that, there was a reasonable amount of uncertainty regarding the central bank's likely steps to counter the devastating impacts on the economy. On the other hand, the uncertainty witnessed in the month of August 2014 was due to the sit-in of the opposition party in the country's capital which lasted for several days and badly affected country's logistics, transportation and supply chains. Both periods have been captured through pulse dummies for these two months. As shown below, the Autocorrelation and Partial Autocorrelation functions suggest that the likely data generating process of EPU is AR(2), so we run an ARIMA(2,0,0) model with two pulse dummies.

The coefficients of the pulse dummies are significant at 5% significance level. The increase in uncertainty in 2020 was much higher on scale than the one in the earlier episode of 2014; as we can see that there was a massive jump of 109 unit increase in April. Whereas, there had been an increase of 77 units in the month of August 2014.

The following index for Pakistan is updated every month and is available at *policyuncertainty.com*².



² http://www.policyuncertainty.com/pakistan_monthly.html

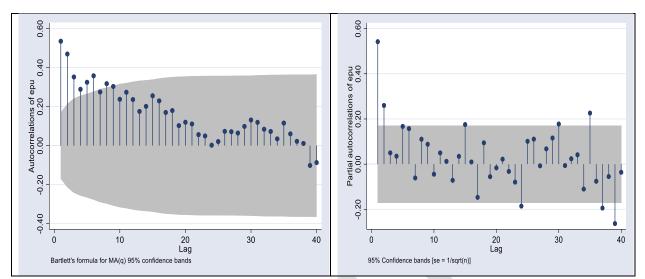


Fig. 02: Autocorrelation and Partial Autocorrelation

```
epu_{t} = \beta_{0} + \beta_{1}epu_{t-1} + \beta_{2}epu_{t-2} + \beta_{3}D_{t}^{2020} + \beta_{4}D_{t}^{2014} + \varepsilon_{t}
```

Log likelihood	= -631.7971			Number Wald cl Prob >	ni2(4)	= = =	132 70.73 0.0000
 epu	Coef.	OPG Std. Err.	z	P> z	[95% Co	nf.	Interval]
epu t20 t14 	109.2945 76.99194 99.29567	31.86307 22.45059 8.763737	3.43 3.43 11.33	0.001 0.001 0.000	46.8440 32.989 82.1190	6	171.745 120.9943 116.4723
ARMA ar L1. L2.	.3260107 .3512052	.0954983 .0812911	3.41 4.32		.138837 .191877		.5131839
/sigma 	28.94222	1.773787	16.32	0.000	25.4656	6	32.41878

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

Methodology

Part-I: Determining Long-run relationship through Vector Error Correction Model

The choice of VECM model comes from two fundamental factors; first one being that the variables show long-term co-movement; and the second reason is that for monthly frequency and 127 observations across time it's better to use this type of models when it is well established through empirical tests that there is co-integration amongst the variables. Since all the variables are I(1), so I can check whether there is a long-run relationship; this can be checked through co-integration tests. I check co-integration through two methods i) checking stationarity of residuals ii) Egranger test. Through the first method, after running OLS with the below specification, I obtain residuals and check whether they are stationary. The Dicky Fuller results suggest that these residuals are stationary that means there exists co-integration and hence a long-run relationship between the variables. The Null hypothesis H_0 of the Dicky Fuller test is that the series are non-stationary which implies that there is no co-integration. Rejecting the Null hypothesis gives us the reason that there is co-integration.

$$epu_t = \beta_0 + \beta_1 intrate_t + \beta_2 extrate_t + \beta_3 autoprod_t + \beta_4 lsm_t + \varepsilon_t$$

Or

$$\widehat{\varepsilon}_{t} = epu_{t} - \widehat{\beta_{0}} + \widehat{\beta_{1}}intrate_{t} + \widehat{\beta_{2}}extrate_{t} + \widehat{\beta_{3}}autoprod_{t} + \widehat{\beta_{4}}lsm_{t}$$

$$\widehat{\varepsilon}_t \sim I(0)$$

In order to double check, I use Egranger test for co-integration; which also shows that the variables are co-integrated. Once it's fairly established that all the five variables are co-integrated, I use the Vector Error Correction Model. Before using the VECM model, it is essential to specify the number of co-integrating relationships within the model; I have checked this through Johansen test. According to the test results, there are two co-integrating relationships. The results of this model are provided at *Annexure II*. The optimal lag length for the variables is determined to be 4

based on Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC), and Schwarz Bayesian Information Criterion (SBIC), so I run the VECM model with four optimal lags.

$$\begin{split} \Delta lsm_{t} &= \beta_{l0} + \beta_{l1} \sum_{i=1}^{4} lsm_{t-i} + \beta_{l2} \sum_{i=1}^{4} epu_{t-i} + \beta_{l3} \sum_{i=1}^{4} auto_{t-i} + \beta_{l4} \sum_{i=1}^{4} exrate_{t-i} + \\ &\beta_{l5} \sum_{i=1}^{4} irate_{t} + e_{t} - (1) \end{split}$$

$$\Delta epu_{t} &= \beta_{e0} + \beta_{e1} \sum_{i=1}^{4} lsm_{t-i} + \beta_{e2} \sum_{i=1}^{4} epu_{t-i} + \beta_{e3} \sum_{i=1}^{4} auto_{t-i} + \beta_{e4} \sum_{i=1}^{4} exrate_{t-i} + \\ &\beta_{e5} \sum_{i=1}^{4} irate_{t} + e_{t} - (2) \end{aligned}$$

$$\Delta auto_{t} &= \beta_{a0} + \beta_{a1} \sum_{i=1}^{4} lsm_{t-i} + \beta_{a2} \sum_{i=1}^{4} epu_{t-i} + \beta_{a3} \sum_{i=1}^{4} auto_{t-i} + \beta_{a4} \sum_{i=1}^{4} exrate_{t-i} + \\ &\beta_{a5} \sum_{i=1}^{4} irate_{t} + e_{t} - (3) \end{aligned}$$

$$\Delta exrate_{t} &= \beta_{e0} + \beta_{e1} \sum_{i=1}^{4} lsm_{t-i} + \beta_{e2} \sum_{i=1}^{4} epu_{t-i} + \beta_{e3} \sum_{i=1}^{4} auto_{t-i} + \\ &\beta_{e4} \sum_{i=1}^{4} exrate_{t-i} + \beta_{e5} \sum_{i=1}^{4} irate_{t} + e_{t} - (4) \end{aligned}$$

$$\Delta irate_{t} &= \beta_{r0} + \beta_{r1} \sum_{i=1}^{4} lsm_{t-i} + \beta_{r2} \sum_{i=1}^{4} epu_{t-i} + \beta_{r3} \sum_{i=1}^{4} auto_{t-i} + \\ &\beta_{r5} \sum_{i=1}^{4} irate_{t} + e_{t} - (5) \end{aligned}$$

Part-II: Determining Causal Relationship through Bi-variate Structural VAR

Structural VAR models are employed in a variety of econometric applications where measuring the causal impact of one variable on the other is of paramount importance. These models are different from simple VAR models in a sense that they allow causal interpretation, and the leeway to see the contemporaneous impact of one variable on the other. However, SVAR models require the use of restrictions as a method for Identification and these restrictions should come from the underlying economic rationale. For example, in my case, I am restricting the contemporaneous impact of Large Scale Manufacturing (LSM) on the uncertainty and not the vice versa; this is in resonance with the economic theory that a rise in production does not tend to impact uncertainty contemporaneously, but in a lagged fashion. In order to make the data more compelling, month-on-month percentage increase is computed first and then a structural model is fit-in on this data

with the following restriction i.e., large scale manufacturing is not contemporaneously impacting uncertainty, however, uncertainty does contemporaneously impact large-scale manufacturing. The matrix is defined as follows:

$$\begin{bmatrix} b_{21} & \mathbf{I} \end{bmatrix}$$

$$B = \begin{bmatrix} 1 & 0 \\ b_{21} & 1 \end{bmatrix}$$

Fig. 03: Month-on-month change

Selec Sampl	tion-order e: 2011m6	criteria - 2021m1				Number of	obs =	= 127
lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
+ 0 1 2 3 4	-873.295	13.432 57.774 17.756 43.914*	4 4 4 4	0.009 0.000 0.001 0.000	3692.95 3538.4 2391.24 2214.75 1669.64*	13.8899 13.8472 13.4552 13.3784 13.0956*	13.9081 13.9018 13.5462 13.5058 13.2594*	13.9347 13.9815 13.6792 13.692 13.4988*

Endogenous: epugrr lsmmgr Exogenous: _cons

$$epu_{t} = a_{0} - b_{11}lsm_{t} - (\sum_{i=1}^{4} b_{1i+1}lsm_{t-i}) + \sum_{i=1}^{4} b_{1i+5}epu_{t-i} + \varepsilon_{eput}$$
$$lsm_{t} = a_{1} - b_{21}epu_{t} + \sum_{i=1}^{4} b_{2i+1}lsm_{t-i} - (\sum_{i=1}^{4} b_{2i+5}epu_{t-i}) + \varepsilon_{lsmt}$$

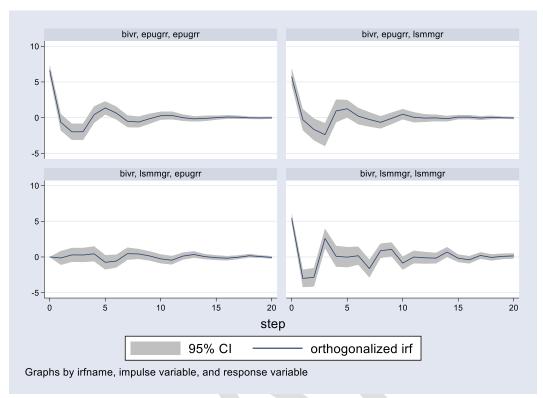


Fig. 04: Impulse responses

Interpreting Results

The VECM results give us the speed of adjustment of the co-efficient towards the long/short-run equilibrium. We started off with the assumption that the uncertainty negatively impacts the real sector activity and used two real sector variables namely auto-production and largescale manufacturing. Our results suggest uncertainty does have a negative relationship on the manufacturing, but a lagged one, this is in line with the economic rationale that firms require some time to adjust to the production processes hence an uncertain event happening today may impact production two months later as the firms have accumulated inventories and, in some cases, these are perishable, so they may want to keep production processes for some short interval. Therefore, it is plausible to assume that a surge in uncertainty will have negative repercussions after some time.

In addition, auto production and manufacturing index also seem to be having a positive relationship which is also pertinent because these both measure real-sector activity and their processes are intertwined. Furthermore, exchange rate does not play a role in the large-scale manufacturing index, however, it does explain auto-production because the auto-production in Pakistan relies on the imported parts, and hence an exchange rate depreciation does impact the production of automobiles that are reliant on imported parts. For the SVAR results in the Fig. 04, the first and fourth shocks are the shocks of the variable on itself, so we may keep them aside for a while a notice that one unit increase in uncertainty, as shown in the second shock tends to decrease production contemporaneously and also its impact lasts up to four periods, thereafter, the production sees an uptick. Hence, we can assert that the uncertainty does dampen production in the short-run. For the impact of largescale production shock on uncertainty, since the contemporaneous impact is assumed to be zero, however, in the later period we see a minor decrease, but not so significant which also conforms to our earlier stipulation that the impact translates from uncertainty to the real activity.

Conclusion

This research attempted to trace the impact of economic policy uncertainty on Pakistan's real economic activity. In doing so, I carried out the VECM analysis to ascertain if there existed any linkages between uncertainty and real activity measured in terms of large-scale manufacturing and automobiles production. Alongside that, I also used a bivariate SVAR model to see the causal relationship between uncertainty and manufacturing activity. My results for VECM suggest that there is a statistically significant long-term relationship between uncertainty and auto-production and largescale manufacturing, but more pronounced in the case of former. This could be due to the

fact that auto production decisions are relatively swift to be materialized compared with the largescale manufacturing where it is hard to cut back on the orders already placed. Additionally, as assembling of motor vehicles is done in Pakistan through imported parts, so these import orders are swiftly susceptible to an uptick in uncertainty. Moreover, since the large-scale manufacturing is a composite index comprising many different items including foods and beverages, therefore, this could be the probable reason for lesser impact than the auto-production. On the other hand, the SVAR results show that uncertainty has a short-term causal impact on the manufacturing activity which points to another valid direction. In the end, for the next iterations of this research, it would be interesting to see the impact with more observations as they become available; higher number of observations may serve to further enrich analysis. Besides, the impact of credit channel as a transmission channel of uncertainty may be looked at.

Annexure-I

. dfuller D.	r_dl, notrend					
Dickey-Fulle	r test for unit ro	ot		Number of obs	=	130
	Test Statistic		Critical Value	polated Dickey-Ful 5% Critical Value	10%	
Z(t)	-10.770		-3.500	-2.888		-2.578
MacKinnon ap	proximate p-value	for	Z(t) = 0.0000			
. dfuller D	.exrate, notrend					
Dickey-Fulle	r test for unit ro	ot		Number of obs	=	130
	Test Statistic	1%	Critical Value	polated Dickey-Ful 5% Critical Value	10%	
	-10.017		-3.500	-2.888		-2.578
MacKinnon ap	proximate p-value					
. dfuller D.	lsm_adjusted, notr	end				
Dickey-Fulle	r test for unit ro	ot		Number of obs	=	130
	Test Statistic	1%	Critical	polated Dickey-Ful 5% Critical Value		
Z(t)	-9.771		-3.500	-2.888		-2.578
MacKinnon ap	proximate p-value	for	Z(t) = 0.0000			
. dfuller D	.auto, notrend					
Dickey-Fulle	r test for unit ro	ot		Number of obs	=	130
	Test Statistic			polated Dickey-Ful 5% Critical Value	10%	
Z(t)	-10.422		-3.500	-2.888		-2.578
MacKinnon ap	proximate p-value	for	Z(t) = 0.0000			
. dfuller D	.epu, notrend					
Dickey-Fulle	r test for unit ro	ot		Number of obs	=	130
	Test		Inter Critical	polated Dickey-Ful. 5% Critical		Critical
	Statistic		Value	Value		Value

MacKinnon approximate p-value for Z(t) = 0.0000

Annexure-II

	esid, notrend er test for unit	root	Number of obs	= 131
		Inte	rpolated Dickey-Ful	ler
	Test	1% Critical	5% Critical	10% Critical
	Statistic	Value	Value	Value
Z(t)	-4.798	-3.500	-2.888	-2.578
MacKinnon a	pproximate p-valu	e for $Z(t) = 0.000$	1	

Engle-Granger test for cointegration			N (1st ste N (test)	p) =	132 131
	Test Statistic	1% Critical Value	5% Critical Value		ritical Value
Z(t)	-4.818	-5.127	-4.523		-4.214

Critical values from MacKinnon (1990, 2010)

. varsoc lsm_adjusted auto epu r_dl exrate

Sampl	ction-order Le: 2011m5	5 - 2021m1	2			Number of	obs =	= 128
lag		LR	df	p	FPE	AIC	HQIC	SBIC
0 1 2 3	-2644.61 -2028.54 -1974.42 -1934.78 -1882.84	1232.1 108.25 79.275	25 25 25 25 25	0.000 0.000 0.000 0.000	6.6e+11 6.4e+07 4.1e+07 3.3e+07 2.2e+07*	41.4002 32.1648 31.7096 31.4809 31.06*	41.4454 32.4363 32.2076 32.2052 32.0106*	41.5116 32.8332* 32.9351 33.2635 33.3996

```
Endogenous: lsm_adjusted auto epu r_dl exrate
Exogenous: _cons
```

. vec lsm_adjusted auto epu r_dl exrate, lag(4) rank(1)

Vector error-correction model

Sample: 2011m5 -	· 2021m12			Number of AIC	obs	=	128 31.16449
Log likelihood =				HQIC		=	31.97021
<pre>Det(Sigma_ml) =</pre>	5864803			SBIC		=	33.14754
Equation	Parms	RMSE	R-sq	chi2	P>chi2		
D lsm adjusted	17	8.97688	0.3610	62.69798	0.0000		
D_auto	17	11.1292	0.7238	290.9268	0.0000		
D_epu	17	28.1841	0.5016	111.7237	0.0000		
D_r_dl	17	.542148	0.2258	32.37576	0.0135		
D_exrate	17	2.39317	0.2951	46.47751	0.0001		
 	Coef.			z P> z	[95%	Conf	. Interval]
D_lsm_adjusted							

_cel	l					
L1.	0794664	.0340862	-2.33	0.020	1462742	0126586
	1					
lsm_adjusted						
LD.	.0220775	.1004202	0.22	0.826	1747423	.2188974
L2D.	4637702	.1074329	-4.32	0.000	6743348	2532057
L3D.	1948521	.1118807	-1.74	0.082	4141341	.02443
auto						
LD.	.1284691	.0591392	2.17	0.030	.0125584	.2443798
L2D.	.0367308	.0516505	0.71	0.477	0645023	.1379639
L3D.	.0407	.0513735	0.79	0.428	0599903	.1413903
epu						
LD.	0674974	.0375295	-1.80	0.072	1410538	.006059
L2D.	0846546	.036058	-2.35	0.019	1553269	0139823
L3D.	0500674	.0300155	-1.67	0.095	1088966	.0087618
r_dl						
LD.	4.165576	1.711721	2.43	0.015	.8106641	7.520487
L2D.	1.677553	1.628501	1.03	0.303	-1.51425	4.869356
L3D.	.0355016	1.58541	0.02	0.982	-3.071846	3.142849
exrate	I			_		
LD.	1792399	.326657	-0.55	0.583	8194758	.4609961
L2D.	.1381503	.3563269	0.39	0.698	5602377	.8365383
L3D.	4058688	.3667201	-1.11	0.268	-1.124627	.3128894
_cons	.5875335	.8969874	0.66	0.512	-1.170529	2.345596
	+					
D_auto						
_cel						
_cel L1.	1024046	.0422588	-2.42	0.015	1852303	019579
L1.	1024046	.0422588	-2.42	0.015	1852303	019579
_L1. lsm_adjusted						
_L1. lsm_adjusted LD.	.4716944	.1244969	3.79	0.000	.227685	.7157039
L1. lsm_adjusted LD. L2D.	.4716944 .2111599	.1244969 .133191	3.79 -1.59	0.000	.227685 4722094	.7157039 .0498897
_L1. lsm_adjusted LD.	.4716944	.1244969	3.79	0.000	.227685	.7157039
L1. lsm_adjusted LD. L2D. L3D.	.4716944 .2111599	.1244969 .133191	3.79 -1.59	0.000	.227685 4722094	.7157039 .0498897
L1. lsm_adjusted LD. L2D. L3D. auto	.4716944 2111599 7406905	.1244969 .133191 .1387052	3.79 -1.59 -5.34	0.000 0.113 0.000	.227685 4722094 -1.012548	.7157039 .0498897 4688333
L1. lsm_adjusted LD. L2D. L3D. auto LD.	.4716944 2111599 7406905	.1244969 .133191 .1387052 .0733184	3.79 -1.59 -5.34	0.000 0.113 0.000 0.494	.227685 4722094 -1.012548 1938638	.7157039 .0498897 4688333 .0935391
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D.	.4716944 2111599 7406905 0501624 1906722	.1244969 .133191 .1387052 .0733184 .0640342	3.79 -1.59 -5.34 -0.68 -2.98	0.000 0.113 0.000 0.494 0.003	.227685 4722094 -1.012548 1938638 316177	.7157039 .0498897 4688333 .0935391 0651674
L1. lsm_adjusted LD. L2D. L3D. auto LD.	.4716944 2111599 7406905	.1244969 .133191 .1387052 .0733184	3.79 -1.59 -5.34	0.000 0.113 0.000 0.494	.227685 4722094 -1.012548 1938638	.7157039 .0498897 4688333 .0935391
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D.	.4716944 2111599 7406905 0501624 1906722	.1244969 .133191 .1387052 .0733184 .0640342	3.79 -1.59 -5.34 -0.68 -2.98	0.000 0.113 0.000 0.494 0.003	.227685 4722094 -1.012548 1938638 316177	.7157039 .0498897 4688333 .0935391 0651674
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. L3D. epu	.4716944 2111599 7406905 0501624 1906722 .0388655	.1244969 .133191 .1387052 .0733184 .0640342 .0636909	3.79 -1.59 -5.34 -0.68 -2.98 0.61	0.000 0.113 0.000 0.494 0.003 0.542	.227685 4722094 -1.012548 1938638 316177 0859663	.7157039 .0498897 4688333 .0935391 0651674 .1636973
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. L3D. epu LD.	.4716944 2111599 7406905 0501624 1906722 .0388655	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98	0.000 0.113 0.000 0.494 0.003 0.542 0.003	.227685 4722094 -1.012548 1938638 316177 0859663 2297501	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. L3D. epu LD. L2D.	.4716944 2111599 7406905 7406905 1906722 .0388655 1385578 1085367	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. L3D. epu LD.	.4716944 2111599 7406905 0501624 1906722 .0388655	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98	0.000 0.113 0.000 0.494 0.003 0.542 0.003	.227685 4722094 -1.012548 1938638 316177 0859663 2297501	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. L3D.	.4716944 2111599 7406905 7406905 1906722 .0388655 1385578 1085367 0482452	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. L3D. epu LD. L2D. L3D. r_dl	.4716944 2111599 7406905 7406905 1906722 .0388655 1385578 1085367 0482452	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092 .0246889
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. r_dl LD.	.4716944 2111599 7406905 7406905 1906722 .0388655 1385578 1085367 0482452	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092 .0246889 4.852896
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. L2D. L3D. r_dl LD. L2D. L2D. L2D. L2D. L2D. L2D. L2D.	.4716944 2111599 7406905 7406905 7406905 1906722 .0388655 1385578 1085367 0482452 6936102 -2.538853	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.122124 2.018951	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092 .0246889 4.852896 1.418217
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. r_dl LD.	.4716944 2111599 7406905 7406905 1906722 .0388655 1385578 1085367 0482452	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092 .0246889 4.852896
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. r_dl LD. L2D. L3D. r_dl L2D. L3D.	.4716944 2111599 7406905 7406905 7406905 1906722 .0388655 1385578 1085367 0482452 6936102 -2.538853	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.122124 2.018951	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092 .0246889 4.852896 1.418217
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. L2D. L3D. r_dl LD. L2D. L3D. r_dl LD. L2D. L3D. r_dl L2D. L3D.	.4716944 2111599 7406905 7406905 7406905 1906722 .0388655 1385578 1085367 0482452 .6936102 -2.538853 -6.186562	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.122124 2.018951 1.965529	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26 -3.15	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209 0.002	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924 -10.03893	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092 .0246889 4.852896 1.418217 -2.334196
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. r_dl LD. L2D. L3D. r_dl LD. L2D. L3D. Exrate LD.	.4716944 2111599 7406905 7406905 7406905 1906722 .0388655 1385578 1085367 0482452 0482452 6936102 -2.538853 -6.186562 -1.0266	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.018951 1.965529 .4049763	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26 -3.15 -2.53	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209 0.002 0.011	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924 -10.03893 -1.82034	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092 .0246889 4.852896 1.418217 -2.334196 2328614
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. r_dl LD. L2D. L3D. r_dl LD. L2D. L3D. L2D. L3D.	.4716944 2111599 7406905 7406905 7406905 1906722 .0388655 1385578 1085367 0482452 0482452 6936102 -2.538853 -6.186562 -1.0266 -1.027633	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.018951 1.965529 .4049763 .4417599	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26 -3.15 -2.53 -2.33	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209 0.002 0.011 0.020	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924 -10.03893 -1.82034 -1.893467	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092 .0246889 4.852896 1.418217 -2.334196 2328614 1617999
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. r_dl LD. L2D. L3D. r_dl LD. L2D. L3D. Exrate LD.	.4716944 2111599 7406905 7406905 7406905 1906722 .0388655 1385578 1085367 0482452 0482452 6936102 -2.538853 -6.186562 -1.0266	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.018951 1.965529 .4049763	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26 -3.15 -2.53	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209 0.002 0.011	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924 -10.03893 -1.82034	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092 .0246889 4.852896 1.418217 -2.334196 2328614
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. r_dl LD. L2D. L3D. exrate LD. L2D. L3D.	.4716944 2111599 7406905 7406905 7406905 1906722 .0388655 1385578 1085367 0482452 0482452 6936102 -2.538853 -6.186562 -1.027633 2.033536	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.018951 1.965529 .4049763 .4417599 .454645	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26 -3.15 -2.53 -2.33 4.47	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209 0.002 0.011 0.020 0.000	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924 -10.03893 -1.82034 -1.893467 1.142448	.7157039 .0498897 4688333 .0935391 0651674 .1636973 02092 .0246889 4.852896 1.418217 -2.334196 2328614 1617999 2.924624
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. r_dl LD. L2D. L3D. r_dl LD. L2D. L3D. L2D. L3D.	.4716944 2111599 7406905 7406905 7406905 0501624 1906722 .0388655 1385578 1085367 0482452 0482452 6936102 -2.538853 -6.186562 -1.0266 -1.027633	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.018951 1.965529 .4049763 .4417599	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26 -3.15 -2.53 -2.33	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209 0.002 0.011 0.020	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924 -10.03893 -1.82034 -1.893467	.7157039 .0498897 4688333 .0935391 0651674 .1636973 0473655 02092 .0246889 4.852896 1.418217 -2.334196 2328614 1617999
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. r_dl LD. L2D. L3D. r_dl LD. L2D. L3D. cons	.4716944 2111599 7406905 7406905 7406905 1906722 .0388655 1385578 1085367 0482452 0482452 6936102 -2.538853 -6.186562 -1.027633 2.033536	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.018951 1.965529 .4049763 .4417599 .454645	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26 -3.15 -2.53 -2.33 4.47	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209 0.002 0.011 0.020 0.000	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924 -10.03893 -1.82034 -1.893467 1.142448	.7157039 .0498897 4688333 .0935391 0651674 .1636973 02092 .0246889 4.852896 1.418217 -2.334196 2328614 1617999 2.924624
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. L2D. L3D. r_dl LD. L2D. L3D. r_dl LD. L2D. L3D. exrate LD. L2D. L3D. cons D_epu	.4716944 2111599 7406905 7406905 7406905 1906722 .0388655 1385578 1085367 0482452 0482452 6936102 -2.538853 -6.186562 -1.027633 2.033536 .0515766	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.018951 1.965529 .4049763 .4417599 .454645	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26 -3.15 -2.53 -2.33 4.47	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209 0.002 0.011 0.020 0.000	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924 -10.03893 -1.82034 -1.893467 1.142448	.7157039 .0498897 4688333 .0935391 0651674 .1636973 02092 .0246889 4.852896 1.418217 -2.334196 2328614 1617999 2.924624
L1. lsm_adjusted LD. L2D. L3D. auto LD. L2D. L3D. epu LD. L2D. L3D. r_dl LD. L2D. L3D. r_dl LD. L2D. L3D. cons	.4716944 2111599 7406905 7406905 7406905 1906722 .0388655 1385578 1085367 0482452 .6936102 -2.538853 -6.186562 -1.027633 2.033536 .0515766	.1244969 .133191 .1387052 .0733184 .0640342 .0636909 .0465275 .0447032 .037212 2.122124 2.018951 1.965529 .4049763 .4417599 .454645	3.79 -1.59 -5.34 -0.68 -2.98 0.61 -2.98 -2.43 -1.30 0.33 -1.26 -3.15 -2.53 -2.33 4.47	0.000 0.113 0.000 0.494 0.003 0.542 0.003 0.015 0.195 0.744 0.209 0.002 0.011 0.020 0.000	.227685 4722094 -1.012548 1938638 316177 0859663 2297501 1961534 1211794 -3.465676 -6.495924 -10.03893 -1.82034 -1.893467 1.142448	.7157039 .0498897 4688333 .0935391 0651674 .1636973 02092 .0246889 4.852896 1.418217 -2.334196 2328614 1617999 2.924624

	I					
lsm adjusted						
LD.		.3152822	-2.10	0.036	-1.278508	0426244
L2D.	2350596	.3372995	-0.70	0.486	8961546	.4260353
L3D.	.6745039	.3512639	1.92	0.055	0139608	1.362969
auto						
LD.	2475354	.1856752	-1.33	0.182	6114521	.1163812
L2D.	.0412062	.1621635	0.25	0.799	2766284	.3590407
L3D.	.0432837 	.1612939	0.27	0.788	2728465	.359414
epu						
LD.		.1178286	-2.34	0.019 0.838	5062879	0444081
L2D. L3D.	0231159 .0921847	.1132086 .0942375	-0.20 0.98	0.838	2450008	.1987689 .2768868
LUU.	.0921047	.0942373	0.90	0.520	.0923173	.2700000
r_dl			1 00	0.017	5 150500	15 00706
LD. L2D.	5.374674 -12.93287	5.374171 5.112891	1.00 -2.53	0.317 0.011	-5.158509 -22.95395	15.90786 -2.911788
L2D. L3D.	-6.621417	4.977603	-2.33	0.183	-16.37734	3.134506
100.		1.977000	1.00	0.100	10.07701	3.131000
exrate		1 005500	2 1 1	0.001	1 51 6 4 1 0	5.536626
LD. L2D.	3.526522 4776017	1.025582 1.118735	3.44 -0.43	0.001	1.516418 -2.670282	1.715078
L3D.	.3012779	1.151366	0.45	0.794	-1.955357	2.557913
_cons	.0866191	2.816209	0.03	0.975	-5.433049	5.606287
D_r_dl	I					
_cel		0000505	0 51	0 455	0005.000	0055055
L1.	.0014709	.0020586	0.71	0.475	0025639	.0055057
lsm_adjusted	İ					
LD.	.0010805	.0060648	0.18	0.859	0108062	.0129672
L2D.	0149791	.0064883	-2.31	0.021	0276959	0022623
L3D.	0118202 	.0067569	-1.75	0.080	0250634	.0014231
auto						
LD.	.00085	.0035716	0.24	0.812	0061503 0013825	.0078503
L2D. L3D.	.0047313 .0067784	.0031194 .0031026	2.18	0.129	.0006974	.0108452 .0128595
		.0031020	2.10	0.025	.0000074	.0120393
epu		0000665	0 50	0 605	0000704	0056140
LD. L2D.	.001172 .0006038	.0022665	0.52 -0.28	0.605 0.782	0032704 004872	.0056143 .0036644
L2D. L3D.		.0018127	0.04	0.971	0034878	.003618
2021	1		0.01	0.072		
r_dl						
LD.		.1033774	0.11	0.911	1910686 .0576565	.2141633
L2D. L3D.	.2504217 0539882	.0983514 .095749	2.55 -0.56	0.011 0.573	2416528	.4431869 .1336764
	i					
exrate		.0197281	1 00	0.282	0174436	.059889
LD. L2D.	.0212227 .0467727	.0215199	1.08 2.17	0.282	.0045944	.088951
L3D.		.02210199	1.31	0.191	0144239	.0723932
		0 = 44 = 0 =	1 0 0			0001.004
	0680138 +	.0541725	-1.26	0.209	1741899	.0381624
D_exrate	I					
-						
_cel		0000075	0 50	0 005	0000000	0 4 0 4 4 0 5
_cel L1.	 .0253334	.0090872	2.79	0.005	.0075229	.0431439
_	.0253334	.0090872	2.79	0.005	.0075229	.0431439

LD. L2D. L3D.	0217193 .0079354 1154866	.0267713 .0286409 .0298266	-0.81 0.28 -3.87	0.417 0.782 0.000	0741901 0481996 1739456	.0307515 .0640705 0570275
auto LD. L2D. L3D.	004918 .0122886 0087447	.0157661 .0137697 .0136958	-0.31 0.89 -0.64	0.755 0.372 0.523	035819 0146994 035588	.025983 .0392766 .0180986
epu LD. L2D. L3D.	.0323094 .0173283 .0029584	.0100051 .0096128 .0080019	3.23 1.80 0.37	0.001 0.071 0.712	.0126998 0015125 012725	.0519191 .036169 .0186419
 r_dl LD. L2D. L3D.	0384577 5919011 1201787	.4563328 .4341469 .4226593	-0.08 -1.36 -0.28	0.933 0.173 0.776	9328536 -1.442813 9485758	.8559382 .2590112 .7082183
 exrate LD. L2D. L3D.	.1128628 0443227 .2496275	.0870845 .0949943 .097765	1.30 -0.47 2.55	0.195 0.641 0.011	0578197 230508 .0580116	.2835452 .1418627 .4412434
_cons	.6905483	.2391305	2.89	0.004	.2218611	1.159236

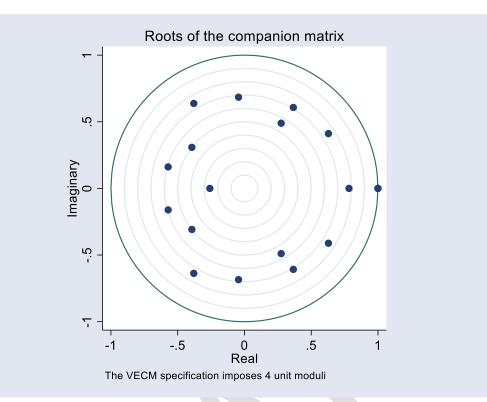
Cointegrating equations

Equation	Parms	chi2	P>chi2
ce1	4	46.2414	0.0000

Identification: beta is exactly identified

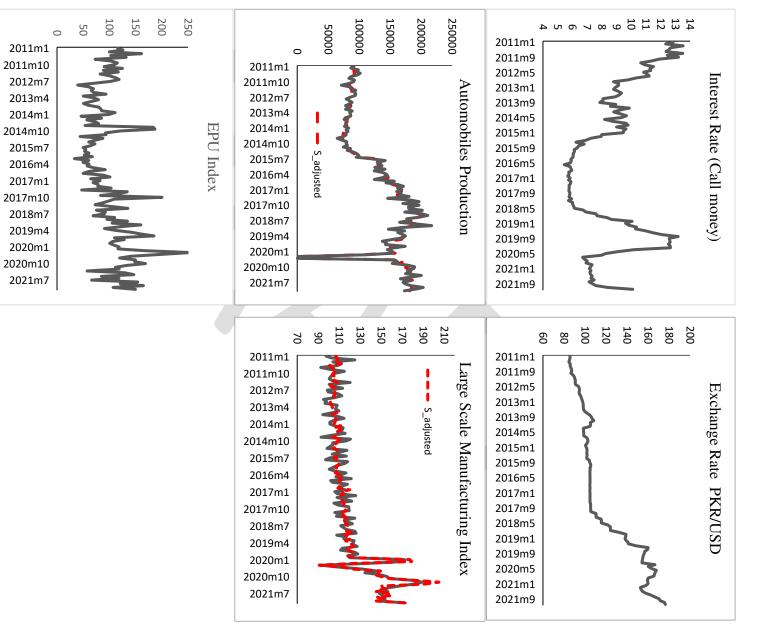
Johansen normalization restriction imposed

beta	Coef.	Std. Err.	Z	P> z	[95% Conf.	. Interval]
_cel lsm_adjusted auto epu r_dl exrate _cons	1 . 4638984 -1.045444 11.09078 2627707 -145.5386	.1708767 .2046175 2.832929 .2426413	2.71 -5.11 3.91 -1.08	0.007 0.000 0.000 0.279	.1289863 -1.446487 5.538345 7383389	.7988105 6444005 16.64322 .2127976









References:

[1] Baker, Bloom and Davis (2016), "Measuring Economic Policy Uncertainty," The Quarterly Journal of Economics, 2016, 131 (4), 1593–1636.

[2] Bernanke, Ben S., "Irreversibility, Uncertainty and Cyclical Investment," The Quarterly Journal of Economics, 97 (1983), 85–106.

[3] Boyan, Jovanovic and Sai Ma (2020). "Uncertainty and Growth Disasters. International Finance Discussion Papers 1279.

[4] Choudhary, Pasha and Waheed, "Measuring Economic Policy Uncertainty in Pakistan," State Bank of Pakistan Staff Notes, 2020.

[5] Christiano, Eichenbaum and Evans (2005), "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy", Journal of Political Economy, Vol. 113, No. 1

[6] Fernandez-Villaverde, Jesus, Pablo Guerron-Quintana, Keith Kuester, and Juan Rubio-Ramirez, "Fiscal Volatility Shocks and Economic Activity," American Economic Review, 105 (2015), 3352–3384.

[7] Hanif et al. (2013), "Quarterization of National Income Accounts of Pakistan", State Bank of Pakistan Working Paper Series WP No. 54

[8] Tahir et al. (2018), "Robust quarterization of GDP and determination of business cycle dates for IGC partner countries", International Growth Centre Working Paper-I-37400-PAK-1