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Time Series Analysis

Interest rate pass-through in Armenia

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Term Paper

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Abstract

A central bank's policy rate can influence lending rates in the economy, as changes in the policy rate can affect the cost of borrowing for banks and other financial institutions. When the central bank raises or lowers its policy rate, this can influence the rates that banks charge their customers for loans and other types of credit. The results suggest that there is imperfect pass-through from interbank rate to lending rate for more than one year, interbank rate has no significant impact on it and also we find that there is significant relationship between retail rates

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1 Introduction

Interest rate pass-through refers to the degree to which changes in central bank policy rates are transmitted to various interest rates in the economy. While central banks use policy rates to influence the economy, the transmission mechanism is imperfect, meaning that not all changes in policy rates are fully reflected in market interest rates.

There are several reasons why interest rate pass-through can be imperfect:

Financial system structure: The structure of the financial system can affect the degree of interest rate pass-through. For example, if banks have a large market share and are less competitive, they may not fully pass on changes in policy rates to borrowers or depositors.

Information asymmetry: Borrowers and lenders may have different levels of information about market conditions, creditworthiness, and other factors that affect interest rates. This can lead to imperfect pass-through, as lenders may not adjust their rates to reflect changes in policy rates if they perceive that borrowers are less likely to shop around for better rates.

Market segmentation: Different markets for borrowing and lending may have different characteristics and pricing structures, leading to imperfect pass-through. For example, some borrowers may have limited access to credit markets or may be subject to different regulatory requirements, which can affect their borrowing costs.

Time lag: It takes time for changes in policy rates to be fully reflected in market interest rates. This time lag can be due to factors such as the frequency of interest rate adjustments or the timing of the transmission channels.

Overall, the imperfect pass-through of interest rates is a complex phenomenon that reflects the interaction of many factors in the financial system. While central banks can influence interest rates through their policy actions, the degree of pass-through depends on the broader economic and financial context in which these actions occur.

The interest rate channel is one of the transmission mechanisms through which changes in a central bank's policy rate can affect the broader economy. When the central bank adjusts its policy rate, this can lead to changes in other interest rates in the economy, such as those on loans, mortgages, and bonds. These changes in turn can affect the behavior of households, businesses, and financial markets, with potential impacts on consumption, investment, and inflation.

The interest rate channel works in several ways. First, changes in the central bank's policy rate can affect short-term interest rates, such as the rate at which banks lend to one another overnight. This can influence the cost of borrowing for households and businesses, and can affect the demand for credit and investment. For example, when the central bank lowers its policy rate, banks may pass on these lower rates to borrowers, making borrowing cheaper and potentially boosting consumption and investment.

Second, changes in the policy rate can also affect long-term interest rates, such as those on mortgages and bonds. This can influence the cost of borrowing

for longer-term investments and affect the behavior of investors in financial markets. For example, if the central bank raises its policy rate, this may lead to higher bond yields, which can attract more investment and potentially lead to a stronger currency.

Overall, the interest rate channel is an important mechanism through which changes in central bank policy can affect the broader economy. However, the extent and timing of these effects can vary depending on a range of factors, including the structure of the financial system, the behavior of market participants, and the overall economic environment.

In general, when a central bank raises its policy rate, this can lead to an increase in lending rates in the economy. This is because banks and other financial institutions must pay higher interest rates to borrow money from the central bank, and this higher cost of funding can be passed on to their customers in the form of higher lending rates. Conversely, when the central bank lowers its policy rate, this can lead to a decrease in lending rates in the economy, as banks and other financial institutions can borrow money at lower rates and pass on these savings to their customers.

However, the extent to which changes in the central bank's policy rate affect lending rates can vary depending on a range of factors, including the structure of the financial system, the behavior of market participants, and the overall economic environment. For example, if the banking system is highly competitive and interest rates are already low, a central bank's rate cut may not lead to lower borrowing costs for consumers and businesses. On the other hand, if the banking system is dominated by a few large players or interest rates are already high, a central bank's rate hike may lead to a more pronounced increase in borrowing costs.

Overall, the relationship between a central bank's policy rate and lending rates in the economy is complex and can be influenced by a range of factors. Understanding this relationship is important for central banks, as it can help them to anticipate the likely impact of changes in monetary policy on the broader economy.

2 Literature Review

There are various studies and academic papers on interest rate pass-through by different authors. Here are a few examples:

A paper by Bernanke and Gertler (1995) found that the degree of interest rate pass-through to bank lending rates can vary across countries and over time, depending on factors such as the nature of the banking system, the competitive environment, and the stance of monetary policy.

A study by Clarida et al. (2002) analyzed the degree of pass-through of policy rates to retail interest rates in the United States and other industrialized countries. They found that pass-through rates were generally incomplete and varied across types of loans and financial institutions.

A paper by De Bondt and Mojon (2012) examined the pass-through of policy rates to lending rates in the euro area. They found that the pass-through was generally incomplete, with smaller and slower adjustments for retail lending rates than for wholesale market rates.

A study by Gambacorta and Mistrulli (2004) analyzed the pass-through of policy rates to bank lending rates in Italy. They found that the degree of pass-through was higher for large banks than for small banks, suggesting that market power may play a role in interest rate pass-through. Gertler and Gilchrist (1994) studied the pass-through of monetary policy to bank lending rates in the United States. They found that pass-through rates were incomplete, with less than one-for-one adjustment of bank lending rates to changes in policy rates. They attributed this to factors such as imperfect competition in the banking sector and the presence of asymmetric information.

Carlstrom and Fuerst (1997) analyzed the pass-through of monetary policy to bank lending rates in a dynamic general equilibrium model. They found that incomplete pass-through could arise due to factors such as credit market frictions and differences in the maturity structure of assets and liabilities.

Peek and Rosengren (1997) studied the pass-through of monetary policy to commercial and industrial loan rates in the United States. They found that pass-through rates were incomplete and varied across types of loans and financial institutions. They attributed this to factors such as information asymmetry and market segmentation.

Jimenez et al. (2008) examined the pass-through of monetary policy to lending rates in the euro area. They found that pass-through rates were generally incomplete, with smaller and slower adjustments for retail lending rates than for wholesale market rates. They attributed this to factors such as market power, the use of reference rates, and heterogeneity in bank lending behavior.

Overall, the literature suggests that interest rate pass-through is complex and can vary depending on a variety of factors, including the structure of the banking system, the regulatory environment, the competitive landscape, and the broader economic context.

Figure 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
A	268	18855.72	2359.17	14792	22919
interbank	266	8.061015	4.427477	2.8	27.9
uptoone_dom	268	17.16704	4.021905	10.41164	33.54569
uptoone_for	268	13.4525	5.804745	6.569844	33.61
fifteend_dom	268	15.68541	5.244078	4.640236	42.93502
fifteend_for	268	12.40973	5.592462	1.842201	34.93796
month_dom	268	17.90699	3.720594	9.846412	34.01209
month_for	268	14.5461	5.669405	5.359101	39.29391
twomonth_dom	268	15.85726	5.525131	8.771974	44.58399
twomonth_for	268	13.19718	6.47289	3.730284	41.49239
threem_dom	268	17.8407	5.696154	4.116899	39.88717
threem_for	268	14.38407	7.584148	3.416978	39.4513
sixm_dom	268	18.55101	4.759936	9.560068	36.03216
sixm_for	268	13.96821	6.164768	5.784531	33.71715
year_dom	268	17.34238	3.691295	10.22849	32.39734
year_for	268	13.56049	5.385699	6.629199	32.66729
plus_dom	268	16.92699	2.739887	11.64192	24.88569
plus_for	268	13.59351	3.992168	7.84053	23.68257
date	268	619.5	77.50914	486	753
ehat	266	1.59e-10	2.602021	-4.946802	6.847766

3 Data

We have monthly data of lending interest rates for different time period. In the table we can see the coefficients and its explanation. The series begin in July of 2000 and go through October 2022, for a total of 268 observations. The following graph depicts our data.

Variable	Definition	Source
<i>uptoone_dom</i>	Lending interest rates for domestic currency for up to one year	CBA Statistics
<i>interbankrate</i>	Interbank rate	CBA Statistics
<i>year_dom</i>	Lending interest rates for domestic currency for 180days to one year	CBA Statistics
<i>plus_dom</i>	Lending interest rates for domestic currency for more than one year	CBA Statistics

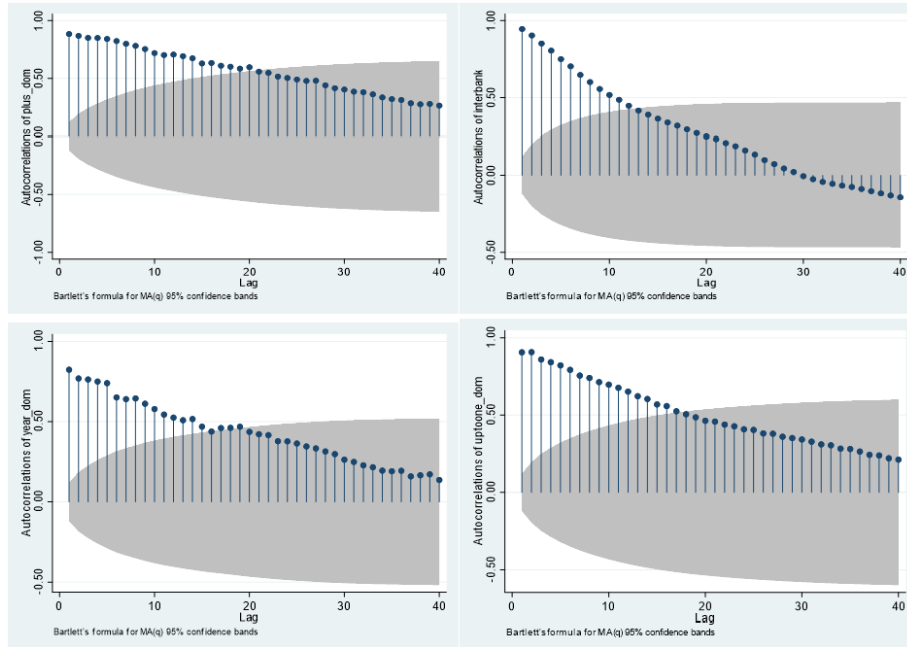
Table 1: Variables and definitions

In Table 1 we have names and definitions for our regression analysis.

In Figure 1 we can see summary statistics of the data. As we see we have 268 observations.

In Figure 2 we can see correlograms of our variables. A correlogram, also known as Auto Correlation Function (ACF) plot, is a graphic way to demonstrate serial correlation in data that doesn't remain constant with time. A correlogram gives

Figure 2: Correlograms



a fair idea of auto-correlation between data pairs at different time periods. It's used as a tool to check randomness in a data set which is done by computing auto-correlations for data values at different time lags.

The auto-correlations are near zero for any time lag separation if it is random but if not, one or more of the auto-correlations will be non-zero.

From the graph we can see that there is serial correlation in our data.

4 Methodology

In our analysis we use VECM model to estimate interest rate pass through. As we know a vector error correction model (VECM) is a statistical model used to analyze the relationship between multiple time series variables, particularly those that exhibit long-term co-movements or cointegration. VECM is a type of vector autoregression (VAR) model that is based on the concept of error correction. The basic idea is that deviations from the long-run equilibrium relationship between the variables are corrected over time through a process of gradual adjustment. The methodology for estimating a VECM involves several steps:

Data collection: The first step is to collect data on the variables of interest. These variables should be stationary or made stationary through differencing.

Model specification: The second step is to specify the appropriate lag order for the model and determine whether the variables are cointegrated. This can be done using statistical tests such as the Johansen test or the Engle-Granger test.

Estimation: The third step is to estimate the parameters of the VECM using maximum likelihood or other estimation methods.

Model evaluation: The fourth step is to evaluate the goodness of fit of the model and check for any model misspecification or violation of assumptions.

The general formula for a VECM with p lags can be expressed as:

$$\Delta y_t = \alpha + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \dots + \Gamma_p \Delta y_{t-p} + \epsilon_t \quad (4.0.1)$$

where:

Δy_t is a K -dimensional vector of differenced variables.

α is a K -dimensional vector of constants.

y_{t-1} is a K -dimensional vector of lagged levels of the variables.

Π is a $K \times K$ matrix of coefficients that captures the long-run equilibrium relationships between the variables.

$\Gamma_1, \Gamma_2, \dots, \Gamma_p$ are $K \times K$ matrices of coefficients that capture the short-run dynamics of the variables.

ϵ_t is a K -dimensional vector of error terms.

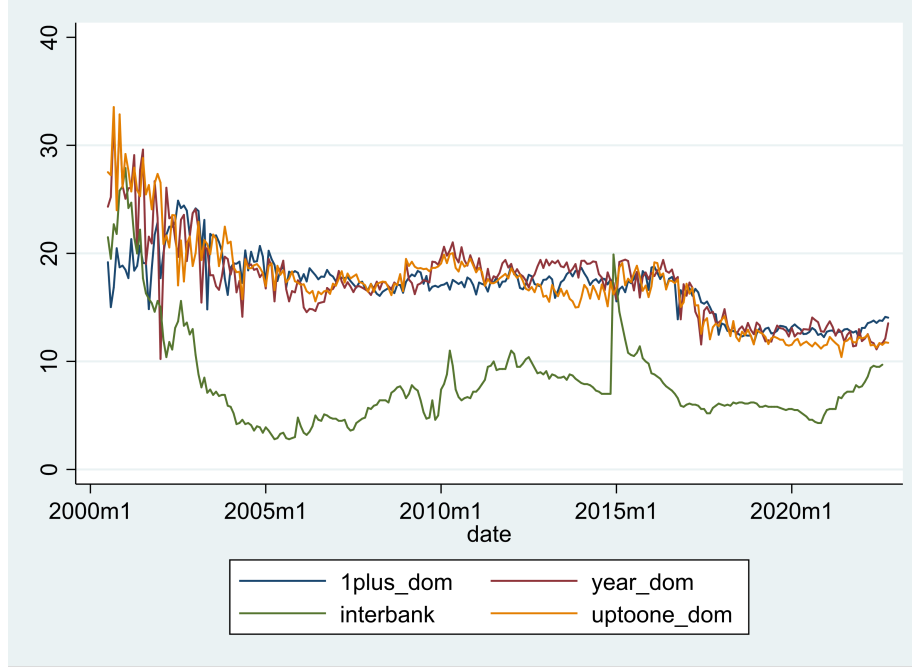
The error correction term in the VECM is captured by the coefficient matrix Π . This term reflects the adjustment process that occurs in response to deviations from the long-run equilibrium relationship between the variables. The VECM specification includes lagged differences of the variables ($\Delta y_{t-1}, \Delta y_{t-2}, \dots, \Delta y_{t-p}$) to capture the short-run dynamics of the system.

Fitting a VECM

vec estimates the parameters of cointegrating VECMs. There are four types of parameters of interest:

1. The parameters in the cointegrating equations β
2. The adjustment coefficients α
3. The short-run coefficients
4. Some standard functions of β and α that have useful interpretations.

Figure 3: Used data, 2000M7-2022M10



To begin our analysis first of all we need to check stationarity of our series. We have all $I(1)$ variables in this model. The plots on the graph also indicate that all the series are potential $I(1)$ processes. We thought that there may also be a link between the retail rates and we have lending rate up to one year and lending rate for a year as explanatory variables.

Selecting the number of lags

To test for cointegration or fit cointegrating VECMs, we must specify how many lags to include. The order of the corresponding VECM is always one less than the VAR. The optimal number of lags in a VECM is determined using the same criteria as in a VAR model, such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). One reason why a VECM may have fewer optimal lags than a VAR model is that the inclusion of the error correction term can help to capture some of the long-run relationships between the variables. This means that the VECM may be able to capture the same amount of information as a VAR model with fewer lags.

In addition, the error correction term in a VECM helps to reduce the impact of spurious correlations that may arise in a VAR model due to the presence of non-stationary variables. By including the error correction term, the VECM ensures that the long-run relationships between the variables are properly accounted for, which can help to improve the accuracy of the model and reduce

Figure 4: Finding optimal lag

```
. varsoc plus_dom interbank uptoone_dom year_dom
```

Selection-order criteria
Sample: 2000m11 - 2022m8 Number of obs = 262

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2428.03				1357.75	18.5651	18.587	18.6196
1	-1741.01	1374	16	0.000	8.09567	13.4428	13.5523	13.7152
2	-1640.41	201.19	16	0.000	4.2446	12.797	12.9941	13.2874*
3	-1601.82	77.188	16	0.000	3.57295	12.6246	12.9092	13.3328
4	-1569.41	64.815*	16	0.000	3.15361*	12.4993*	12.8716*	13.4255

Endogenous: plus_dom interbank uptoone_dom year_dom
Exogenous: cons

Figure 5: Johansen Cointegration Test 1

```
. vecrank plus_dom interbank uptoone_dom year_dom, trend(trend) lags(4)
```

Johansen tests for cointegration
Trend: trend Number of obs = 262
Sample: 2000m11 - 2022m8 Lags = 4

maximum				5%	
rank	parms	LL	eigenvalue	trace statistic	critical value
0	56	-1602.0316	.	78.1408	54.64
1	63	-1585.1666	0.12080	44.4107	34.55
2	68	-1573.9973	0.08173	22.0723	18.17
3	71	-1566.0988	0.05851	6.2752	3.74
4	72	-1562.9612	0.02367		

the number of lags required.

So the order of the corresponding VECM is always one less than the VAR. VEC makes this adjustment automatically, so we will always refer to the order of the underlying VAR. As can be seen from the graph retail rates seem to have downwards trend we will choose an option trend for finding the cointegrating relationship. We find optimal lag which is equal to 4.

Testing for cointegration: Cointegration refers to the long-term relationship between two or more non-stationary time series variables. In econometrics, cointegration is important because it implies that the variables are not independent, but rather that they share a common stochastic trend.

The tests for cointegration are based on Johansen's method. If the log likelihood of the unconstrained model that includes the cointegrating equations is significantly different from the log likelihood of the constrained model that does not include the cointegrating equations, we reject the null hypothesis of no cointegration.

Estimates for deposit and lending rates and lending rates are in Appendix.

Figure 6: Johansen Cointegration Test 2

```
. vecrank plus_dom interbank uptoone_dom year_dom, trend(trend) lags(8)
```

Johansen tests for cointegration

Trend: trend Number of obs = 258
Sample: 2001m3 - 2022m8 Lags = 8

maximum					5%
rank	parms	LL	eigenvalue	trace statistic	critical value
0	120	-1478.7447	.	82.8707	54.64
1	127	-1460.9788	0.12866	47.3387	34.55
2	132	-1445.8405	0.11073	17.0622*	18.17
3	135	-1440.0671	0.04377	5.5155	3.74
4	136	-1437.3094	0.02115		

tegration. The body of the table presents test statistics and their critical values of the null hypotheses of no cointegration (line 1) and one or fewer cointegrating equations (line 2). The eigenvalue shown on the last line is used to compute the trace statistic in the line above it. Johansen's testing procedure starts with the test for zero cointegrating equations (a maximum rank of zero) and then accepts the first null hypothesis that is not rejected. There are results of cointegration test for 4 lag in figure 5.

But for removing serial correlation we did the same test for 8 and more lags, and we find that there is cointegration. In the output above, we strongly reject the null hypothesis of no cointegration and fail to reject the null hypothesis of at most two cointegrating equation. Thus we accept the null hypothesis that there is two cointegrating equation in the model(Figure 6).

5 Empirical findings

The interpretation of the results of a VECM model depends on the specific output generated by the model. Here we have forms of error correction term and VECM equation for lending rate for more than one year.

Here we have results of our VEC model(Figure 7). The sign of results are reverse in the long-run. In the long-run interbank rate has a negative impact on lending rate for more than one year, lending rate up to one year has no impact and lending rate for a year has a positive impact.

Coefficient estimates: These represent the relationship between the variables in the model. Positive coefficients indicate a positive relationship, while negative coefficients indicate an inverse relationship. The magnitude of the coefficient indicates the strength of the relationship. We find that only the second lag of interbank rate and lending rate for up to one year is statistically significant at 10 percent significance level, which means that change in interbank rate has a lagged and positive effect on change in lending rate for more than 1 year period(Figure 8). So, if interbank rate changes by 1 unit in January, lending rate for more than 1 year period will increase by 11 percent in March. Up to one year lending rate is significant up to 3-rd lag and has negative impact on more than 1 year lending rate and lending rate for a year has a significant impact with its 4-th lag on more than 1 year lending rate. But in this case trend coefficient is not significant.

Error correction term: This term represents the speed at which the variables in the model adjust to long-term equilibrium after a shock or disturbance. If the error correction term is negative and statistically significant, it indicates that there is a long-term relationship between the variables in the model. In our model error term is also negative and significant.

The adjustment term is statistically significant at the 1 percent level, suggesting that previous year's error or deviation from long-run equilibrium are corrected within the current year at a convergence speed of 15 percent(Figure 8).

After all we check for autocorrelation, check for normally distributed disturbances and apply other diagnostic tests.

In figure 9 we can see Lagrange-multiplier test for residuals. Results show us that there is autocorrelation only in the 3-th, 5-th and 8-th lag.

6 Conclusion

Imperfect interest rate pass-through refers to a situation in which changes in the policy interest rate set by the central bank are not fully transmitted to the lending and deposit rates offered by commercial banks to their customers. In other words, changes in the policy interest rate do not lead to a proportionate change in lending and deposit rates.

VECM model is used to study the relationship between the policy interest rate and lending rates for different time period, and the results suggest that

there is imperfect pass-through from interbank rate to lending rate for more than one year but interbank rate is not significant in our model and also we find that there is significant relationship between retail rates, then we can draw several conclusions:

Monetary policy transmission is incomplete: Imperfect pass-through indicates that the central bank's monetary policy decisions have a weaker impact on the lending and deposit rates set by commercial banks. This means that the effectiveness of monetary policy in achieving its objectives, such as controlling inflation or promoting economic growth, may be limited.

The degree of pass-through may vary: The degree of interest rate pass-through may vary depending on factors such as the competitive environment in the banking sector, the level of market concentration, and the regulatory environment. This suggests that policy interventions aimed at improving pass-through may need to take into account these factors.

The impact on the economy may be ambiguous: The incomplete transmission of monetary policy may have different effects on different sectors of the economy. For example, if lending rates do not respond fully to changes in the policy interest rate, this may limit the ability of firms to invest and expand.

7 Appendix

Figure 7: Long-run equations

Cointegrating equations						
Equation	Parms	chi2	P>chi2			
_ce1	2	25.63168	0.0000			
_ce2	2	35.61581	0.0000			
Identification: beta is exactly identified						
Johansen normalization restrictions imposed						
beta	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
_ce1						
plus_dom	1
interbank	0 (omitted)					
uptoone_dom	-8.217902	1.664715	-4.94	0.000	-11.48068	-4.955121
year_dom	5.253318	1.447889	3.63	0.000	2.415507	8.09113
_trend	-.1058292
_cons	44.02723
_ce2						
plus_dom	2.22e-16
interbank	1
uptoone_dom	-9.233789	1.583095	-5.83	0.000	-12.3366	-6.13098
year_dom	5.949118	1.3769	4.32	0.000	3.250442	8.647793
_trend	-.1593076
_cons	66.25479

Figure 8: Short-run equations

```
. vec plus_dom interbank uptoone_dom year_dom, trend(trend) lags(8) rank(2)
```

Vector error-correction model

Sample: 2001m3 - 2022m8

Number of obs	=	258
AIC	=	12.23132
Log likelihood = -1445.84	HQIC	= 12.96226
Det(Sigma_ml) = .8663705	SBIC	= 14.04911

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_plus_dom	32	1.01024	0.4400	176.7723	0.0000
D_interbank	32	1.08506	0.1947	54.39958	0.0080
D_uptoone_dom	32	.947329	0.5033	228.0171	0.0000
D_year_dom	32	1.37642	0.5869	319.6558	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
D_plus_dom						
_ce1						
L1.	-.0542788	.0227118	-2.39	0.017	-.0987932	-.0097645
_ce2						
L1.	.0401446	.0235589	1.70	0.088	-.00603	.0863193
plus_dom						
L1D.	-.5577744	.067634	-8.25	0.000	-.6903346	-.4252141
L2D.	-.3545207	.0779239	-4.55	0.000	-.5072488	-.2017926
L3D.	-.3379194	.0819734	-4.12	0.000	-.4985842	-.1772545
L4D.	-.2264313	.0827811	-2.74	0.006	-.3886794	-.0641833
L5D.	-.0924266	.0842823	-1.10	0.273	-.2576168	.0727636
L6D.	.0786264	.0831869	0.95	0.345	-.0844169	.2416697
L7D.	.1039498	.0672774	1.55	0.122	-.0279115	.235811

interbank						
LD.	-.0635554	.060107	-1.06	0.290	-.1813629	.0542522
L2D.	.1140421	.0604394	1.89	0.059	-.004417	.2325013
L3D.	-.0075738	.0598841	-0.13	0.899	-.1249444	.1097968
L4D.	-.0206919	.0583803	-0.35	0.723	-.1351151	.0937313
L5D.	-.0133381	.0596922	-0.22	0.823	-.1303326	.1036565
L6D.	.0632346	.0594995	1.06	0.288	-.0533823	.1798514
L7D.	-.0220635	.0591198	-0.37	0.709	-.1379362	.0938093
uptoone_dom						
LD.	-.2886161	.0901755	-3.20	0.001	-.4653569	-.1118753
L2D.	-.2041064	.0944724	-2.16	0.031	-.3892689	-.0189439
L3D.	-.216143	.0953502	-2.27	0.023	-.403026	-.02926
L4D.	-.1047299	.0942032	-1.11	0.266	-.2893647	.0799049
L5D.	-.0492756	.0863238	-0.57	0.568	-.2184671	.1199159
L6D.	-.0370889	.080846	-0.46	0.646	-.1955441	.1213663
L7D.	-.0937768	.0670002	-1.40	0.162	-.2250948	.0375411
year_dom						
LD.	.0521522	.0692588	0.75	0.451	-.0835926	.1878969
L2D.	.0950249	.0728984	1.30	0.192	-.0478533	.2379032
L3D.	.0304188	.0769069	0.40	0.692	-.1203161	.1811536
L4D.	.1877529	.0727153	2.58	0.010	.0452336	.3302722
L5D.	.1018671	.0701863	1.45	0.147	-.0356954	.2394296
L6D.	-.027002	.0587849	-0.46	0.646	-.1422183	.0882142
L7D.	-.0214144	.048381	-0.44	0.658	-.1162395	.0734106
_trend	.0009908	.0009712	1.02	0.308	-.0009128	.0028943
_cons	-.265256	.1538542	-1.72	0.085	-.5668046	.0362927

Figure 9: LM Test for Residuals

```
. veclmar, mlag(8)
```

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	17.9825	16	0.32492
2	24.5144	16	0.07886
3	26.8411	16	0.04328
4	15.4495	16	0.49199
5	36.5070	16	0.00246
6	17.9671	16	0.32583
7	17.4088	16	0.35963
8	34.3188	16	0.00492

H0: no autocorrelation at lag order

Figure 10: Cointegrating relationship with a trend

```
. reg plus_dom interbank date
```

Source	SS	df	MS	Number of obs	=	266
Model	1279.08199	2	639.540997	F(2, 263)	=	237.21
Residual	709.058387	263	2.69603949	Prob > F	=	0.0000
				R-squared	=	0.6434
				Adj R-squared	=	0.6406
Total	1988.14038	265	7.50241653	Root MSE	=	1.642

plus_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
interbank	.0342665	.0241202	1.42	0.157	-.0132267	.0817597
date	-.0278489	.0013881	-20.06	0.000	-.0305822	-.0251156
_cons	33.89663	.9459058	35.84	0.000	32.03412	35.75914


```
. predict ehat2, residuals
(2 missing values generated)

. dfuller ehat2, noconstant regress lag(1)
```

Augmented Dickey-Fuller test for unit root

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.201	-2.580	-1.620

D.ehat2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ehat2						
L1.	-.2353508	.0452478	-5.20	0.000	-.3244465	-.1462551
LD.	-.3032489	.0567938	-5.34	0.000	-.4150792	-.1914185

Results for deposit rates and lending rates without additional explanatory variables.

Lending rates

1. Cointegrating relationship with a trend for more than a year lending rate.

With a trendour tau statistics is lower than critical value, we reject null hypothesis, which says that error term is random walk and conclude that there is a cointegration(Figure 10). In this case we will run ECM with kagged residuals which is shown in Figure 11.

2. Cointegrating relationship with a trend for up to one year lending rate.

Figure 11

```

. ***there is cointegration
. ***estimating ECM
. reg D.plus_dom L.ehat L.D.interbank D.interbank

```

Source	SS	df	MS	Number of obs	=	264
Model	84.7054749	3	28.2351583	F(3, 260)	=	21.12
Residual	347.550049	260	1.33673096	Prob > F	=	0.0000
				R-squared	=	0.1960
				Adj R-squared	=	0.1867
Total	432.255524	263	1.64355713	Root MSE	=	1.1562

D.plus_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ehat						
Ll.	-.3304521	.0435789	-7.58	0.000	-.4162646	-.2446397
interbank						
LD.	-.1276369	.0597713	-2.14	0.034	-.2453344	-.0099394
Dl.	.0364443	.0601287	0.61	0.545	-.081957	.1548455
_cons	-.0074145	.0712524	-0.10	0.917	-.1477198	.1328908

We don't reject the Null(Figure 12) , and conclude that there is no cointegration and our error term follows random walk. In this case we will estimate ARDL in first differences(Figure 13).

3. Cointegrating relationship with a trend for one year lending rate. We reject the Null of random walk residuals(Figure 14), and conclude that there is cointegration. In this case we will estimate ECM model with lagged residuals(Figure 15).

Figure 12

```
. reg uptoone_dom interbank
```

Source	SS	df	MS	Number of obs	=	266
Model	1817.89627	1	1817.89627	F(1, 264)	=	196.54
Residual	2441.88072	264	9.24954817	Prob > F	=	0.0000
				R-squared	=	0.4268
				Adj R-squared	=	0.4246
Total	4259.77699	265	16.0746301	Root MSE	=	3.0413

uptoone_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
interbank	.5915688	.0421969	14.02	0.000	.5084835	.6746542
_cons	12.43913	.3879109	32.07	0.000	11.67534	13.20292

```
.
```

```
. dfuller ehat1, noconstant regress lag(1)
```

Augmented Dickey-Fuller test for unit root Number of obs = 264

		Interpolated Dickey-Fuller		
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z (t)	-2.361	-2.580	-1.950	-1.620

D.ehat1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ehat1						
L1.	-.0723581	.0306416	-2.36	0.019	-.1326932	-.012023
LD.	-.4577163	.0554358	-8.26	0.000	-.5668727	-.34856

Figure 13

```
. reg D.uptoone_dom L.D.uptoone_dom D.interbank L.D.interbank
```

Source	SS	df	MS	Number of obs	=	264
Model	252.414662	3	84.1382207	F(3, 260)	=	51.84
Residual	421.977638	260	1.62299092	Prob > F	=	0.0000
				R-squared	=	0.3743
				Adj R-squared	=	0.3671
Total	674.3923	263	2.56422928	Root MSE	=	1.274

D. uptoone_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
uptoone_dom						
LD.	-.5969398	.0496076	-12.03	0.000	-.6946235	-.499256
interbank						
DL.	.0959248	.0663932	1.44	0.150	-.034812	.2266616
LD.	-.0364189	.066339	-0.55	0.583	-.1670489	.0942112
_cons	-.0933543	.0785618	-1.19	0.236	-.2480527	.061344

```
.
end of do-file
```

Figure 14

```
. reg year_dom interbank date
```

Source	SS	df	MS	Number of obs	=	266
Model	2526.04753	2	1263.02376	F(2, 263)	=	310.49
Residual	1069.85411	263	4.06788634	Prob > F	=	0.0000
				R-squared	=	0.7025
				Adj R-squared	=	0.7002
Total	3595.90163	265	13.5694401	Root MSE	=	2.0169

year_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
interbank	.3877687	.0296279	13.09	0.000	.3294305	.4461068
date	-.0268204	.0017051	-15.73	0.000	-.0301777	-.023463
_cons	30.83893	1.161901	26.54	0.000	28.55112	33.12674

```
. dfuller ehat1, noconstant regress lag(1)
```

Augmented Dickey-Fuller test for unit root

Figure 15

```
***there is cointegration
***estimating ECM
reg D.year_dom L.ehat1 L.D.interbank D.interbank
```

Source	SS	df	MS	Number of obs	=	264
Model	359.122404	3	119.707468	F(3, 260)	=	36.23
Residual	859.041184	260	3.30400455	Prob > F	=	0.0000
Total	1218.16359	263	4.63180072	R-squared	=	0.2948
				Adj R-squared	=	0.2867
				Root MSE	=	1.8177

D.year_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ehat1						
L1.	-.5805971	.0561897	-10.33	0.000	-.691242	-.4699523
interbank						
LD.	-.1339128	.0943193	-1.42	0.157	-.3196398	.0518143
DL.	.1713637	.094598	1.81	0.071	-.0149121	.3576396
_cons	-.0408966	.1120233	-0.37	0.715	-.2614851	.1796919

Deposit rates

1. Cointegrating relationship with a trend for more than one year deposit rate.

As -5.005 is less than -3.7(critical value) so we reject the Null of random walk of residuals(Figure 16) and conclude that there is cointegration. In this case we will run ECM model(Figure 17).

2. Cointegrating relationship with a trend for up to one year deposit rate.

We reject the Null of random walk residuals(Figure 18), and conclude that there is cointegration. In this case we will estimate ECM model with lagged residuals(Figure 19).

3. Cointegrating relationship with a trend for more than one year deposit rate.

And here also we reject the Null of random walk residuals(Figure 20), and conclude that there is cointegration. We will estimate ECM model with lagged residuals(Figure 21).

We can conclude that in both cases(for lending rates and deposit rates) adjustment speeds are negative and significant. And in some cases interbank rate is significant, other cases not.

Figure 16

```

. * cointegration relationship with a trend
. reg plus_dom interbank date

```

Source	SS	df	MS	Number of obs	=	266
				F(2, 263)	=	34.42
Model	276.297354	2	138.148677	Prob > F	=	0.0000
Residual	1055.69711	263	4.01405745	R-squared	=	0.2074
				Adj R-squared	=	0.2014
Total	1331.99446	265	5.02639421	Root MSE	=	2.0035

plus_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
interbank	.1027092	.0294312	3.49	0.001	.0447583	.16066
date	.0139832	.0016938	8.26	0.000	.0106481	.0173183
_cons	.5649429	1.154188	0.49	0.625	-1.707682	2.837568


```

. predict ehat, residuals
(2 missing values generated)

. dfuller ehat, noconstant regress lag(1)

```

Augmented Dickey-Fuller test for unit root

			Number of obs	=	264
--	--	--	---------------	---	-----

Test Statistic	Interpolated Dickey-Fuller		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.005	-2.580	-1.950
			-1.620

D.ehat	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ehat						
L1.	-.1993423	.0398288	-5.00	0.000	-.2777676	-.1209171
LD.	-.237855	.0585825	-4.06	0.000	-.3532075	-.1225026

Figure 17

```
. ***there is cointegration
. ***estimating ECM
. reg D.plus_dom L.ehat L.D.interbank D.interbank
```

Source	SS	df	MS	Number of obs	=	264
Model	72.1886735	3	24.0628912	F(3, 260)	=	15.99
Residual	391.387784	260	1.50533763	Prob > F	=	0.0000
				R-squared	=	0.1557
				Adj R-squared	=	0.1460
Total	463.576457	263	1.76264813	Root MSE	=	1.2269

D.plus_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ehat						
L1.	-.2494155	.0387384	-6.44	0.000	-.3256965	-.1731345
interbank						
LD.	.1141847	.0638517	1.79	0.075	-.0115476	.2399169
D1.	-.0256541	.0639301	-0.40	0.689	-.1515408	.1002326
_cons	.0395957	.0756152	0.52	0.601	-.1093005	.1884919

Figure 18

```
. reg year_dom interbank date
```

Source	SS	df	MS	Number of obs	=	266
Model	1713.72685	2	856.863425	F(2, 263)	=	267.11
Residual	843.676035	263	3.20789367	Prob > F	=	0.0000
Total	2557.40289	265	9.65057693	R-squared	=	0.6701
				Adj R-squared	=	0.6676
				Root MSE	=	1.7911

year_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
interbank	.6007491	.0263104	22.83	0.000	.5489433	.6525549
date	.0062271	.0015142	4.11	0.000	.0032457	.0092086
_cons	1.796372	1.031798	1.74	0.083	-.2352642	3.828009

```
. predict ehat1, residuals
(2 missing values generated)
```

```
. dfuller ehat1, noconstant regress lag(1)
```

Augmented Dickey-Fuller test for unit root Number of obs = 264

Test Statistic	Interpolated Dickey-Fuller		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-8.603	-2.580	-1.950

D.ehat1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ehat1						
L1.	-.5184507	.0602637	-8.60	0.000	-.6371136	-.3997879
LD.	-.043331	.0590878	-0.73	0.464	-.1596783	.0730164

Figure 19

```
. reg D.year_dom L.ehatl L(0/3).D.interbank D.interbank
note: D.interbank omitted because of collinearity
```

Source	SS	df	MS	Number of obs	=	262
Model	138.078665	5	27.6157329	F(5, 256)	=	16.86
Residual	419.271061	256	1.63777758	Prob > F	=	0.0000
				R-squared	=	0.2477
				Adj R-squared	=	0.2330
Total	557.349725	261	2.13543956	Root MSE	=	1.2798

D.year_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ehatl						
L1.	-.4415745	.0523716	-8.43	0.000	-.5447085	-.3384406
interbank						
D1.	.0878991	.0679771	1.29	0.197	-.0459665	.2217647
LD.	-.0772312	.070781	-1.09	0.276	-.2166184	.0621559
L2D.	-.1911043	.068753	-2.78	0.006	-.3264978	-.0557109
L3D.	.0525107	.0686412	0.77	0.445	-.0826626	.187684
D1.	0	(omitted)				
_cons	-.0431632	.0793973	-0.54	0.587	-.1995182	.1131917

Figure 20

. reg year_dom interbank date						
Source	SS	df	MS	Number of obs	=	266
Model	1713.72685	2	856.863425	F(2, 263)	=	267.11
Residual	843.676035	263	3.20789367	Prob > F	=	0.0000
				R-squared	=	0.6701
				Adj R-squared	=	0.6676
Total	2557.40289	265	9.65057693	Root MSE	=	1.7911
year_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
interbank	.6007491	.0263104	22.83	0.000	.5489433	.6525549
date	.0062271	.0015142	4.11	0.000	.0032457	.0092086
_cons	1.796372	1.031798	1.74	0.083	-.2352642	3.828009
. predict ehat2, residuals						
(2 missing values generated)						
. dfuller ehat2, noconstant regress lag(1)						
Augmented Dickey-Fuller test for unit root				Number of obs	=	264
Test Statistic		1% Critical Value	5% Critical Value	10% Critical Value		
Z(t)	-8.603	-2.580	-1.950	-1.620		
D.ehat2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
ehat2						
LL.	-.5184507	.0602637	-8.60	0.000	-.6371136	-.3997879
LD.	-.043331	.0590878	-0.73	0.464	-.1596783	.0730164

Figure 21

```
. reg D.uptoone_dom L.ehat2 L(0/5).D.interbank D.interbank
note: D.interbank omitted because of collinearity
```

Source	SS	df	MS	Number of obs	=	260
Model	39.85216	7	5.69316572	F(7, 252)	=	8.44
Residual	169.909427	252	.674243757	Prob > F	=	0.0000
				R-squared	=	0.1900
				Adj R-squared	=	0.1675
Total	209.761587	259	.809890297	Root MSE	=	.82112

D. uptoone_dom	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ehat2					
L1.	-.0420647	.034437	-1.22	0.223	-.1098857 .0257564
interbank					
D1.	.1063895	.0450181	2.36	0.019	.0177297 .1950492
LD.	.1409217	.0470569	2.99	0.003	.0482468 .2335966
L2D.	-.0450903	.0446869	-1.01	0.314	-.1330977 .0429172
L3D.	.1897254	.0453588	4.18	0.000	.1003947 .2790561
L4D.	-.0761926	.0431283	-1.77	0.078	-.1611305 .0087453
L5D.	.1466114	.0433807	3.38	0.001	.0611764 .2320463
D1.	0	(omitted)			
_cons	-.0010015	.0514058	-0.02	0.984	-.1022412 .1002381

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```