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Animal Spirits, the Stock Market, and the Unemployment Rate: Some Evidence for German Data

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Abstract

Models recently studied by Farmer (2012, 2013, 2015) predict that, due to labor-market frictions and "animal spirits", stock-market fluctuations should Granger cause fluctuations of the unemployment rate. We performed several Granger-causality tests on more than half a century of data of German data to test this hypothesis. Confirming findings documented by Farmer (2015) for U.S. data, we found that the stock market Granger causes unemployment in the short run and the long run when we control for a deterministic trend in the unemployment rate. Results of a frequency-domain test show that, in the short run, feedback cannot be rejected, whereas the causality clearly runs from the stock market to the unemployment rate in the medium to long run.

JEL-Classification: E12, E44, C32
Keywords: Cointegration, Granger causality, frequency domain, animal spirits, stock market, unemployment rate

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1 Introduction

In a series of recent papers, Farmer (2012, 2013, 2015) develops models that formalise key elements of the famous Chapter 12 of Keynes (1936) "General Theory", where Keynes emphasised the fundamental role of "animal spirits" as a determinant of the steady-state equilibrium of an economy. The model laid out by Farmer (2013) feature a search friction in the labor market and a macroeconomic "belief function" that determines the steady-state employment/unemployment levels in a causal sense. The macroeconomic "belief function" is modelled in terms of the log ratio of asset prices to money wages. Farmer (2012, 2013) argues that a transformed unemployment rate should be cointegrated with such a "belief function" and that the "belief function" should Granger-cause the unemployment rate. For U.S. data, Farmer (2015) reports empirical evidence supporting that the "belief function" predicts the unemployment rate using cointegration techniques (Johansen, 1991, 1995) and tests for Granger noncausality (Toda and Yamamoto, 1995).

We reconstructed, for the long time span from 1960 to 2014, quarterly time series for Germany that are comparable to the U.S. data used by Farmer (2015). We then applied several econometric methods to test the predictions of Farmer's models, where we extended the methodological apparatus by testing for short- and long-run causality using both a vector error-correction framework (Lütkepohl, 2005) and a frequency-domain test (Breitung and Candelon, 2006). We found that (i) the "belief function" as proxied by the log ratio of a stock-market index to money wages and the transformed unemployment rate are cointegrated, and, (ii) the log ratio of asset prices to money wages Granger causes the unemployment rate. Our findings imply that the predictions of the Farmer (2012, 2013) model cannot be rejected for long-term German data.

We structure the remainder of this research note as follows. In Section 2, we describe our data. In Section 3, we briefly describe the empirical methods. In Section 4, we lay out our results. In Section 5, we conclude.

2 Data

Like Farmer (2015), we analysed the following transformed data:

$$p_t = \log\left(\frac{\text{Stock market index}_\text{t}}{\text{Money wage series}_\text{t}}\right), \qquad u_t = \log\left(\frac{100 \times \text{Unemployment rate}_\text{t}}{100 - \text{Unemployment rate}_\text{t}}\right). \tag{1}$$

The model outlined in Farmer (2013) implies that p and u should be cointegrated and that it should be possible to reject Granger non-causality from p to u. In order to test for noncointegration and Granger non-causality, we reconstructed time series of p and u for Germany in four steps:

1. We retrieved data on the stock market index from the OECD Main Economic Indicators database. The data was available at a monthly index. We transformed the data into quarterly data using quarterly averages of the monthly data.

2. We reconstructed the money wage series from two different data sources. First, for the sample period 1960:Q1−1990:Q4, we collected data on the compensation of employees per employee from the quarterly national account and employment data for West Germany as published by the German Institute of Economic Research (DIW) in its weekly

report (“Wochenbericht des DIW”) until 1998 (Müller-Krumholz, 2000). Specifically, we used data on the sum of gross wages (“Bruttolohn- und -gehaltssumme, Mrd. DM, Inlandskonzept)” and number of employees (“Beschäftigte Arbeitnehmer, 1000 Personen, Inlandskonzept”). Second, for the sample period 1991:Q1−2014:Q4 (that is, after German reunification), we retrieved data on gross wages per employee from the SNA framework from the website of the German Statistical Office. We saisonally adjusted the data for both sample periods using the Census X-12-ARIMA method and converted all historical data that were expressed in units of Deutsche mark into euros using the official Deutsche mark/euro exchange rate at the introduction of the euro. We concatenated the seasonally adjusted data for both sample periods using the ratio of the data for the overlapping period to account for the effect of German reunification.

3. We collected historical data on the monthly West German unemployment rate from the periodical “Arbeitsmarkt in Zahlen, Arbeitslosigkeit im Zeitverlauf” published by the German Unemployment Agency (BfA). We chained the West German data with data for the sample period from 1991:M1 onwards for reunified Germany from the same periodical, where we again used overlapping observations to construct a chaining factor. We saisonally adjusted the data and transformed the monthly data into quarterly data using quarterly averages of the monthly data.

4. Finally, we calculated the time series, p and u, using the formulas given in Eq. (1), resulting in the time series shown in Figure 1.

– Please include Figure 1 and Table 1 about here. –

We tested for the presence of a unit root in p and u using the methods of Elliott et al. (1996) (H_0 : series contains a unit root) and Kwiatkowski et al. (1992) (H_0 : stationarity).[1] Whereas p seems to be trend-stationary, the test results suggest that u contains a unit root even after controlling for a deterministic trend (Table 1). Because unit-root tests have limited power in small samples, we used (i) methods appropriate for the analysis of non-stationary data with the same degree of integration (Johansen, 1991, 1995), and, (ii) methods appropriate for the analysis of data with different degrees of integration (Toda and Yamamoto, 1995). Furthermore, we added a deterministic trend to our model and tested for structural breaks in different settings.[2]

3 Methods

Like Farmer (2015), we tested for cointegration and Granger non-causality using different methods. We started with a test for cointegration developed by Johansen (1991, 1995). To

[1] Most estimations and tests were calculated using the open-source software *gretl* (version 1.10.1) (Cottrell and Lucchetti, 2015). The seasonal adjustment of the data was conducted using the program EViews (version 8.1) (using the default settings implemented therein). The frequency-domain test for Granger noncausality (see Section 3) was implemented using the *gretl* package “BreitungCandelonTest 1.5.1” written by Schreiber (2015). For the cointegration analysis, we used the *gretl* package coint2rec (Jensen and Schreiber, 2015).

[2] Further analyses using tests for a unit root in the presence of breakpoints Perron (2006) revealed that potential breakpoints vary from 1973 to 1982. Accounting for a structural break did not change our result qualitatively. Detailed test results are available from the authors on request.

this end, we considered a bivariate VAR(n) model with the variables, $p = y_1$ and $u = y_2$, in the vector $y = (y_1, y_2)^T$ being $I(1)$. We have

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{n-1} \Gamma_i \Delta y_{t-i} + Bx_t + \varepsilon_t. \tag{2}$$

The Johansen (1991) test is based on the rank of the matrix Π. If Π has reduced rank, $r < k$, then there exist $k \times r$ matrices, α and β, such that $\alpha\beta' = \Pi$ and $\beta' y_t$ is stationary (Granger's representation theorem, Engle and Granger, 1987). The rank r, the cointegrating rank, gives the number of cointegrating relationships and each column of β contains a cointegrating vector. Given the results of the unit-root tests, we studied a scenario in which the level data and the cointegrating equations have linear trends (Johansen, 1995, p.80-84), i.e.:

$$\Pi y_{t-1} + Bx_t = \alpha\left(\beta' y_{t-1} + \rho_0 + \rho_1 t\right) + \alpha\bot\gamma_0. \tag{3}$$

The test procedure is sequential and two statistics are usually employed. The trace statistic tests the null hypothesis of r cointegrating vectors against the alternative of $k \geq r + 1$ cointegrating vectors. The maximum-eigenvalue statistic tests the null hypothesis of r cointegrating vectors against the alternative of $r + 1$ cointegrating vectors.

Furthermore, we tested for Granger-causality (Granger, 1969). Assuming that both series are $I(1)$ and that the one cointegrating vector features a deterministic trend, a vector-error-correction model (VECM) representation of the VAR(n) model is given by:

$$\begin{aligned}\Delta y_{1,t} &= \alpha_1\left(y_{2,t-1} - \beta y_{1,t-1} - \rho_0 - \rho_1 t\right) + \sum_{i=1}^{n-1} \delta_{1,i}\Delta y_{1,t-i} + \sum_{i=1}^{n-1} \delta_{2,i}\Delta y_{2,t-i} + \alpha_1\bot\gamma_{1,0} + \varepsilon_{1,t},\\ \Delta y_{2,t} &= \alpha_2\left(y_{2,t-1} - \beta y_{1,t-1} - \rho_0 - \rho_1 t\right) + \sum_{i=1}^{n-1} \phi_{1,i}\Delta y_{1,t-i} + \sum_{i=1}^{n-1} \phi_{2,i}\Delta y_{2,t-i} + \alpha_2\bot\gamma_{2,0} + \varepsilon_{2,t}.\end{aligned} \tag{4}$$

We used the VECM representation to test for both long-run and short-run Granger non-causality (Lütkepohl, 2006). *Long-run causality* implies cointegration and exogeneity of one variable with respect to the other variable. This in turn implies a significant loading coefficient, α, in the VECM representation, where a necessary condition is that the sign of the loading coefficient implies a stable adjustment ("error correction"). For example, if α_1 is significantly different from zero and negative and α_2 is not significantly different from zero, y_2 is said to be weakly exogenous to the system and (long-run) Granger-causes y_1. If both loading coefficients are different from zero, there is a long-run Granger-causal feedback relationship between y_1 and y_2 as long as the loading coefficients have the correct sign (that is, as long as there is a cointegration relationship).

A test for *short-run causality* can be set up by performing a Wald test of the hypotheses

$$H_0 : \delta_{2,1} = \delta_{2,2} = \ldots = \delta_{2,i} = 0,$$
$$H_0 : \phi_{1,1} = \phi_{1,2} = \ldots = \phi_{1,i} = 0.$$

If both series are $I(1)$ and the hypothesis of no cointegration cannot be rejected, one can reformulate the level VAR(n) model under the restrictions $\alpha_1 = \alpha_2 = 0$ (and allowing for a now uniquely defined constant in each equation) such that:

$$\begin{aligned}\Delta y_{1,t} &= \sum_{i=1}^{n-1} \delta_{1,i}\Delta y_{1,t-i} + \sum_{i=1}^{n-1} \delta_{2,i}\Delta y_{2,t-i} + \gamma_1 + \varepsilon_{1,t} \\ \Delta y_{2,t} &= \sum_{i=1}^{n-1} \phi_{1,i}\Delta y_{1,t-i} + \sum_{i=1}^{n-1} \phi_{2,i}\Delta y_{2,t-i} + \gamma_2 + \varepsilon_{2,t}\end{aligned} \tag{5}$$

A test for Granger non-causality is then equivalent to a test for short-run causality, that is, $\phi_{2,i} = 0$ or $\delta_{1,i} = 0$ for $i = 1., ...n$.

If both series are either $I(1)$ or $I(0)$ or if they have different stationarity properties, a test for Granger non-causality can be set up as proposed by Toda and Yamamoto (1995).

1. Test the two time series to determine their order of integration and denote the maximum order of integration for the group of time-series as m, that is, if one of the time series is $I(0)$ and the other is $I(1)$, then $m = 1$. If the two time series have the same order of integration then $m = 0$.

2. Estimate a VAR model on the levels of the time series regardless of their orders of integration. Determine the order, n, of the VAR model using standard techniques (that is, information criteria) and make sure that the VAR model is well-specified.

3. Add m lags to the preferred VAR model as exogenous variables and perform a test for Granger noncausality by performing a Wald test only to the lags of the endogenous variables. The Wald test has asymptotically a chi-squared distribution with n degrees of freedom under the null hypothesis.

We also used a test suggested by Breitung and Candelon (2006) to test for Granger non-causality in the frequency domain at specific frequencies (see also Geweke, 1982). The test makes use of the implicit restrictions imposed on the parameters of a VAR model by the concept of Granger non-causality in a frequency domain setting. Geweke (1982) argues that causal effects can be different at different frequencies, ω. Starting with a VMA representation of a bi-variate VAR model given by

$$y_t = \Psi(L)\,\eta_t, \tag{6}$$

with $y_t = (y_1, y_2))'$, η_t denoting a white noise disturbance, and L denoting the lag operator, the lag polynomial, $\Psi(L)$ can be partioned as follows:

$$\Psi(L) = \begin{pmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{pmatrix}. \tag{7}$$

Geweke (1982) then uses the frequency domain representation and proceeds by showing that to set up a test for Granger non-causality at a specific frequency, ω, a measure $M_{y_1 \to y_2}(\omega)$ can be calculated in the following way:

$$M_{y_1 \to y_2}(\omega) = \log\left(1 + \frac{|\Psi_{12}(\exp(-i\omega))|^2}{|\Psi_{11}(\exp(-i\omega))|^2}\right), \tag{8}$$

with i denoting the imaginary number. Breitung and Candelon (2006) show that for a given frequency ω_0, $M_{y_1 \to y_2}(\omega_0) = 0 \Leftrightarrow \Psi_{12}(\exp(-i\omega_0)) = 0$, which, in turn, implies (two) linear restrictions on the VMA representation.

We studied graphical representations of the test applied on differenced data for a grid of 50 frequency points dividing the intervall $(0, \pi)$ equidistantly, where we performed the test for every frequency individually. For indicators that exhibit Granger causality at business-cycle frequencies, we expect a hump-shape behavior of the test results at the very left side of the x-axis (frequencies), with the hump attaining a maximum above the critical value of the test.

4 Results

We started our empirical analysis assuming that the variables are I(1). We then tested for cointegration allowing for a deterministic trend in the data, and we tested for the structural stability of a possible cointegration vector.

The BIC crition indicated that two lags should be included in the VECM for the Johansen (1995) test. For a VECM specified in this way, the cointegration analysis revealed cointegration at the 10% level according to the trace statistic (Table 2). We then used the *Recursive Eigenvalue test* and the *Recursive β test* of Hansen and Johansen (1999) to test for the stability of the cointegration vector. At the usual 5% level, we found no evidence of a structural break (Figure 2).

– Please include Table 2 and Figure 2 about here. –

Under the assumption of cointegration, we tested for long-run and short-run causality in the VECM as described in Section 3. The results for the Wald tests are clear (Table 2). We found strong evidence of causality running from p to u, but no evidence of causality running the other way round.

– Please include Table 3 about here. –

As a further check, we used a forecast-error-variance decomposition, based on a standard Cholesky decomposition, to analyse the relative importance of the two random innovations for the dynamics of the variables in the VECM. The results for the forecast-error-variance decomposition support the results of the causality tests (Tables 4 and 5). Shocks to the variable p explain about 10% of the variation of the variable u in the short run, but about 60% of the variation of u in the long run. In contrast, the explanatory power of shocks to the variable u for the variation of the variable p is small in both the short run and the long run.[3]

– Please include Table 4 and Table 5 about here. –

Because unit-root test results have low power and the null of no cointegration can only be rejected at the 10% level, we furthermore implemented the test advocated by Toda and Yamamoto (1995). The results of the test given in Table 6 are in line with our other findings. We can reject that p does not cause u, but we cannot reject non-causality from u from to p.

– Please include Table 6 about here. –

[3]Results remain the same qualitatively reverse the order of the Cholesky identification. Results are available from the authors on request.

Finally, we applied the frequency-domain test developed by Breitung and Candelon (2006) on the differenced data. Figure 3 summarizes the test results. As for the interpretation of the figure, it should be noted that a shorter frequency corresponds to longer a time span. For example, a frequency of 0.166 translates into 12 periods (for quarterly data: 3 years), a frequency of 0.10 translates into 18 periods (that is, 4.5 years), and a frequency of 0.02 translates into 96 periods (24 years). Hence, the test results revealed a feedback relationship starting in both cases at short frequencies of about 1 to 1.15 (about two quarters or half a year) up to a frequency of 0.2 (10 quarters or 2.5 years), but a clear one-directional causality from p to u for frequencies smaller than approximately 0.2 (2.5 years to the very long run).

– Please include Figure 3 about here. –

5 Conclusion

The results we have documented in this research note lend support to the prediction of the models studied by Farmer (2012, 2013) that a macroeconomic "belief function", proxied in our research by stock-market fluctuations, causes fluctuations of the unemployment rate. Using reconstructed data on p and u for Germany covering more than half a century, we have derived our results using cointegration tests, tests for noncausality in the short run and the long run, and a frequency-domain test for noncausality. Taken together, the test results show that, in line with results documented by Farmer (2015) for U.S. data, p causes u, while there is only limited evidence of causality running the other way round.

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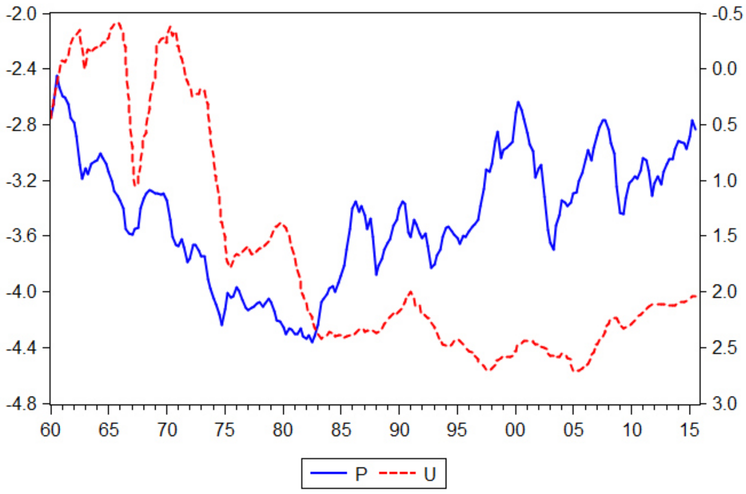
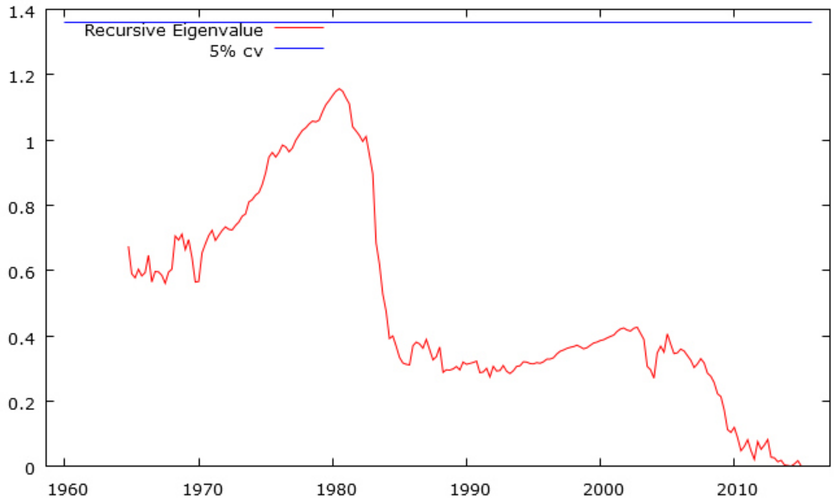
Figures and Tables

Figure 1: p and u for Germany: 1960-2014

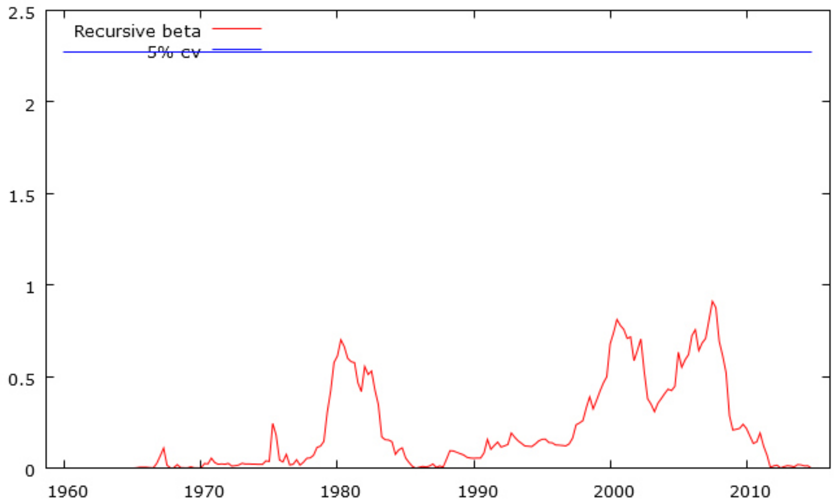


Note: p on the left scale, u on the right scale (inverted).

Figure 2: Results of the Hansen and Johansen (1999) stability tests

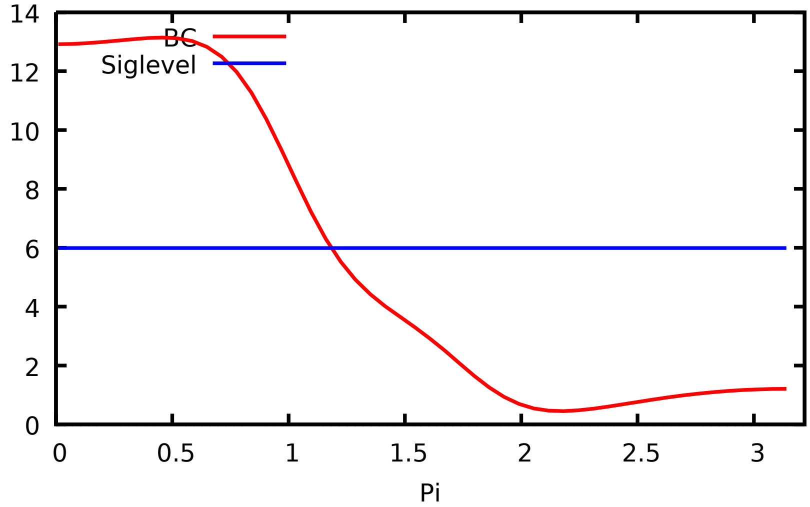


(a) Recursive Eigenvalue test

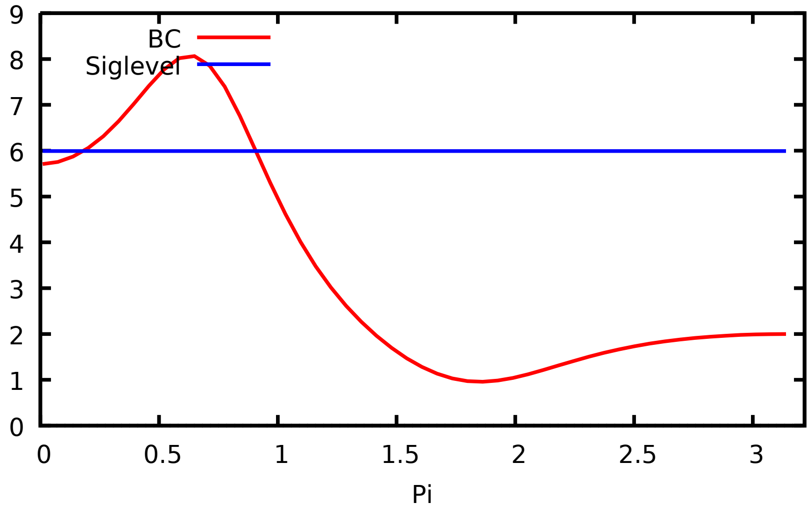


(b) Recursive β test

Figure 3: Results of the Breitung and Candelon (2006) test



(a) Null hypothesis: p does not cause u



(b) Null hypothesis: u does not cause p

Table 1: Results of unit-root tests

Test	ADF-GLS		KPSS	
Specification	constant, trend	constant	constant, trend	constant
		(a) Full Sample		
u	-2.171	-1.443	0.257***	1.237***
p	-3.171**	-0.291	0.084	1.819***
$\Delta(u)$		-2.758***		0.182
$\Delta(p)$		-2.132**		0.062
		(b) Sample 1960-1979		
u	-2.233	-1.340	0.244***	1.384***
p	-3.324**	-0.003	0.112	1.931***
$\Delta(u)$		-2.794***		0.149
$\Delta(p)$		-2.127**		0.043
		(b) Sample 1980-2014		
u	-1.480	-1.000	0.482***	0.694**
p	-2.737*	-0.939	0.281***	2.379***
$\Delta(u)$		-2.997***		0.736**
$\Delta(p)$		-4.907***		0.055

***, ** denotes significance at the 1%, 5% level.

Table 2: Results of the Johansen (1991) tests (p-values)

Null: 0 CI vector		Null: at most 1 CI vector	
Trace test	Max. Eigenvalue test	Trace test	Max. Eigenvalue test
0.069	0.201	0.146	0.146

Table 3: Causality tests within the VECM framework (p-values)

Null:	p does not cause u	u does not cause p
Long-run	0.046	0.261
Short-run	0.000	0.673

Table 4: Decomposition of the variance of u

period	standard error	u	p
4	0.216	92.374	7.626
8	0.369	80.793	19.207
20	0.685	58.478	41.522
40	1.064	42.842	57.158

Table 5: Decomposition of the variance of p

period	standard error	u	p
4	0.205	0.349	99.651
8	0.296	0.931	99.069
20	0.423	4.022	95.978
40	0.533	9.408	90.592

Table 6: Results of the Toda and Yamamoto (1995) causality test (p-values)

dependent:	u	dependent	p
excluded	p-value	excluded	p-value
p	0.000	u	0.106