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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 German data to test this hypothesis. Our findings show 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.

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1 Introduction

In a series of recent papers, Farmer (2012, 2013, 2015) develops models that formalise key elements of the Chapter 12 of Keynes (1936) "General Theory", where Keynes emphasised the fundamental role of "animal spirits" as a determinant of the macroeconomic equilibrium of an economy. The model laid out by Farmer (2013) features a search friction in the labor market and a macroeconomic "belief function" that determines the steady-state unemployment rate 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 that Farmer (2015) studies. 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 tranformed unemployment rate. Our findings imply that the predictions of the model in Farmer (2012, 2013) cannot be rejected for long-term German data.

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:

$$p_t = \log\left(\frac{\mathrm{Stock\ market\ index_t}}{\mathrm{Money\ wage\ series_t}}\right), \qquad u_t = \log\left(\frac{100 \times \mathrm{Unemployment\ rate_t}}{100 - \mathrm{Unemployment\ rate_t}}\right). \quad (1)$$

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. 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 as a monthly index. We transformed the data into quarterly data using quarterly averages of the monthly data.

2. We reconstructed the money wage series. First, for the 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 Ger-

man Institute of Economic Research (DIW) in its weekly report ("Wochenbericht des DIW") until 1998 (Müller-Krumholz, 2000). We used data on the sum of gross wages ("Bruttolohn- und -gehaltssumme, Mrd. DM, Inlandskonzept)" and the number of employees ("Beschäftigte Arbeitnehmer, 1000 Personen, Inlandskonzept"). Second, for the period 1991:Q1−2014:Q4 (after German reunification), we retrieved data on gross wages per employee from the system of national accounts from the website of the German Statistical Office. We saisonally adjusted the data for both periods (Census X-12-ARIMA) 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 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 period from 1991:M1 onwards for reunified Germany from the same periodical, where we 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. We calculated p and u using the formulas given in Eq. (1). Figure 1 shows both time series.

3 Methods

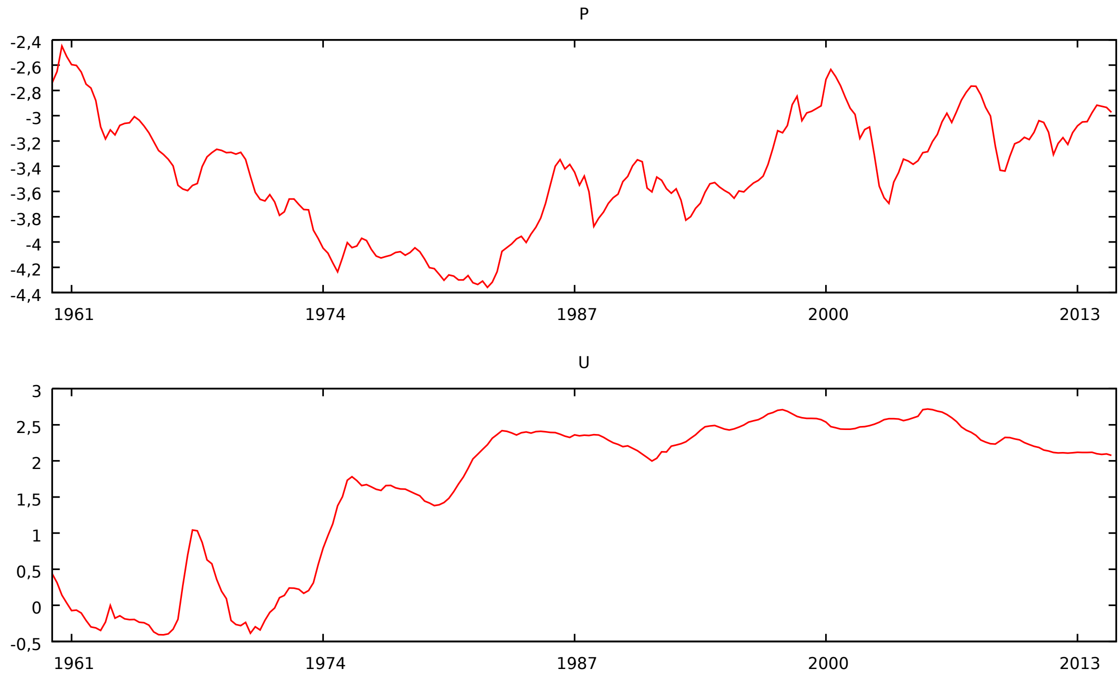
Like Farmer (2015), we tested for cointegration and Granger non-causality using different methods. We started with a test for cointegration developed by Johansen (1991, 1995). We considered a bivariate VAR(n) model with the variables, $p = y_1$ and $u = y_2$, in the vector $y = (y_1, y_2)^T$ being $I(1)$. We have

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

The Johansen (1991) test is based on the rank of the matrix Π. If (in the general case) 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 cointegration rank, r, gives the number of cointegrating relationships and each column of β contains a cointegrating vector. Based on results of unit-root tests, we studied a scenario in which the level data and the cointegrating equations have linear trends (Johansen, 1995, p.80-84):

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

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



We used the trace statistic to test the null hypothesis that there are at most r 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 cointegrating vector features a deterministic trend, a VECM representation of the VAR(n) model is given by:

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

We used the VECM representation to test for both long-run and short-run Granger non-causality (Lütkepohl, 2005). *Long-run causality* implies cointegration and exogeneity of one variable with respect to the other variable. This implies a significant loading coefficient, where a necessary condition is that its sign 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 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 there is a cointegration relationship.

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

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

If both series are $I(1)$ and the hypothesis of no cointegration cannot be rejected, one can reformulate the VAR(n) model using 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 ($\phi_{1,i} = 0$ or $\delta_{2,i} = 0$ for $i = 1., ...n - 1$).

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. Denote the maximum order of integration for a group of time-series as m. 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. Make sure that the VAR model is well-specified.

3. Add m lags to the VAR model and perform a test for Granger noncausality by performing a Wald test only to the first $n - m$ lags of the endogenous variables (Dolado and Lütkepohl, 1996).

We further used a test suggested by Breitung and Candelon (2006) to test for Granger non-causality in the frequency domain at specific frequencies. The test makes use of the 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 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, in order 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.

4 Results

We started our empirical analysis by testing 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 a mix of methods (Johansen, 1991, 1995; Toda and Yamamoto, 1995) to analyse the data. Furthermore, we added a deterministic trend to our model and tested for structural breaks in different settings.[2]

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 reveals cointegration at the 10% level according to the trace but not the maximum-eigenvalue statistic (Table 2).

We 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 5% level, there is no evidence of a structural break (Figure 2).

[1]Most estimations and tests were calculated using the program *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 default settings). 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]Tests for a unit root in the presence of breakpoints (Perron, 2006) reveals that potential breakpoints vary from 1973 to 1982. Accounting for a structural break did not change our results qualitatively.

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

Under the assumption of cointegration, we tested for long-run and short-run causality in the VECM (Wald tests). The results summarized in Table 3 provide strong evidence of causality running from p to u, but no evidence of causality running the other way round.

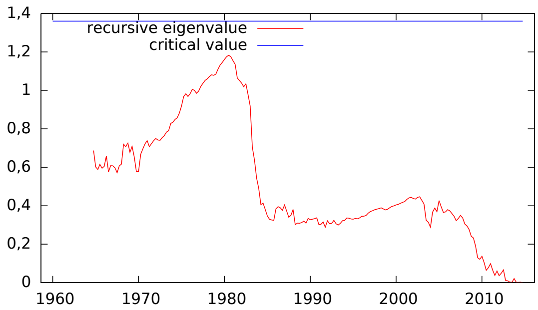
Table 3: Causality tests within the VECM framework (p-values)

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

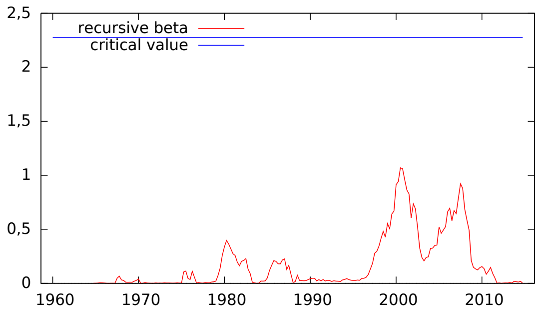
Next, we used a forecast-error-variance decomposition, based on a Cholesky decomposition, to analyse the relative importance of the two random innovations for the dynamics of the variables in the VECM. The results for the forecast-error-variance decomposition support the results of the causality tests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

[3]Results (not reported) remain the same qualitatively if we reverse the order of the Cholesky decomposition.

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



(a) Recursive Eigenvalue test



(b) Recursive β test

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

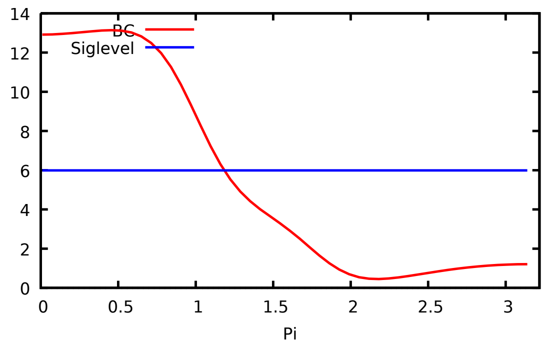
Because unit-root test results have low power and only the trace statistic rejects the null of no cointegration (at the 10% level), we implemented the test proposed by Toda and Yamamoto (1995). The results of the test (Table 6) show that we can reject that p does not cause u. We cannot reject non-causality from u to p at conventional significance levels.

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

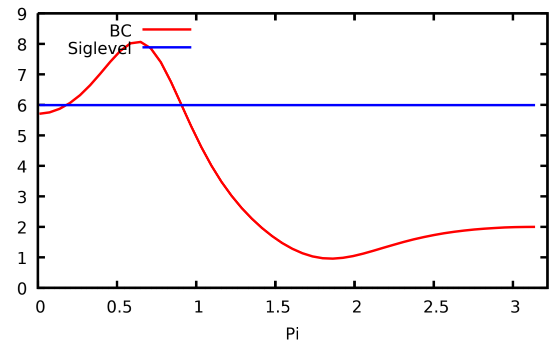
dependent:	u	dependent	p
excluded	p-value	excluded	p-value
p	0.000	u	0.106

Figure 3 plots the results of the Breitung and Candelon (2006) test. A shorter frequency corresponds to a longer time span. A frequency of 0.166 translates into 12 periods (for quarterly data: 3 years), a frequency of 0.10 translates into 18 periods (4.5 years), and a frequency of 0.02 translates into 96 periods (24 years). The test results reveals a feedback relationship starting at short frequencies of about 1 to 1.15 (about half a year) up to a frequency of 0.2 (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).

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



(a) H_0: p does not cause u



(b) H_0: u does not cause p

5 Conclusion

The results we have documented in this research lend support to the prediction of the models studied by Farmer (2012, 2013) that a macroeconomic "belief function", proxied 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 short-run and long-run noncausality, 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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