School of Economics

Working Paper 2005-13

A Heliocentric Journey into Germany's Great Depression

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ISSN 1444 8866

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October 20, 2005

Abstract

The paper finds empirical evidence on the ripple effect of sunspots on the interwar German economy. It identifies a sequence of negative shocks to expectations for the 1927 to 1932 period. The artificial economy predicts the 1928-1932 depression and a long boom from 1933 onwards. Overall, a tangible fraction of interwar output volatility is attributed to sunspots.

*I would like to thank Stephen Broadberry, Michael Burda, Jagjit Chadha, Jang-Ting Guo, Sharon Harrison, Karl Christian Kuhlo, Albrecht Ritschl, seminar participants at Dresden (Verein für Socialpolitik), Münster, Paris (Coordination Failures: Theories and Economic Policies), St. Andrews and especially two anonymous referees of this Journal for helpful comments. Special thanks go to Albrecht Ritschl for making his data available and to the UCLA Economics Department for its hospitality. Remaining errors are, of course, my own. Support in the form of a *DFG Heisenbergstipendium* is gratefully acknowledged. *Keywords*: Sunspots, Great Depression, Germany, Temin (1971). *JEL Classifications*: **E32, N14**.

1 Introduction

Over the past decade the literature on indeterminacy in macroeconomics has moved from slight obscurity into the spotlight by demonstrating that otherwise standard models can exhibit multiple equilibria, and, moreover, that nonfundamental shocks (a.k.a. *sunspots* or *animal spirits*) can generate dynamics that resemble observed aggregate fluctuations.[1] For sunspots to be an accepted explanation for business cycles, however, it is vital that the implications be supported by empirical evidence. The present paper offers such evidence and it does so by looking at one of the most troubling of cyclical episodes: the Great Depression in Germany.

1.1 Map of the paper

This paper unfolds in four parts. The first part assigns theory. Sunspot models are distinguished from other models in that their original source of economic fluctuations is found in shocks to expectations. The chosen theoretical model here is a non-monetary, fully specified dynamic general equilibrium model with increasing returns of a magnitude consistent with empirical evidence. The size of scale economies is significant enough to give rise to equilibria which are indeterminate; hence non-fundamental expectations matter.

The artificial economy is exploited to derive the sunspot shocks in the second part of the paper. The model will be calibrated to German long-run averages. Then data will be filtered through the model to ferret out residuals. Specifically, sunspots are uncovered by sifting out the part of the calibrated model that is not explained by fundamentals so as to reflect changes in extrinsic uncertainty. The paper finds a sequence of pernicious sunspot shocks that seeped into the German economy from 1927:IV to 1932:III. This roughly coincides with the economic cycle: the German business cycle peaked in the first quarter of 1928 and passed its trough in the third quarter of 1932 (see Figure 1).

The effects of the estimated sunspot innovations will be traced in the third part of the paper. I check the forecasting ability of sunspots and test the predictive power of the model, i.e. the empirical shocks will be fed back into the model. I find that sunspot impulses can account for a significant portion of the interwar cycle in Germany. The fourth part probes various dimensions of the results' robustness.

The paper thus provides new support to Temin's (1971) interpretation of the German Depression. Temin stresses a fall in domestic demand, however, he leaves unexplained the ultimate cause of the plunge:

> "Sales, unfilled orders, expectations; these are the items we

[1] Benhabib and Farmer (1999) provides a lucid review of sunspot models.

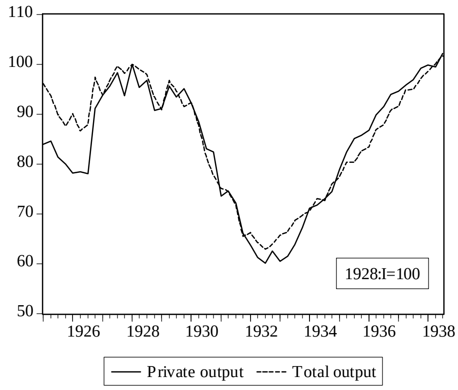

Figure 1: Per capita outputs (deviations from linear 1925-1938 trends). Total output is GNP (*Bruttosozialprodukt zu Marktpreisen von 1913*). Private output is sum of the private sector's consumption and investment expenditures (*Konsum der privaten Haushalte* and *Investitionen des Untermehmensektors*; in 1913-prices). Original source of data: Ritschl (2002b); 1925:I - 1938:III.

> are told influence investment. [...] To elucidate the nature of this change, attention must be shifted from the international economy to the domestic and from supply considerations to demand." [Temin, 1971, p. 248]

The findings here suggest that it was sunspots which had a ripple effect on aggregate demand and, consequently, on the German economy.

1.2 Methodology and related work

The paper is related to recent attempts that employ theoretical models to trace the sources of economic fluctuations (most notably Chari, Kehoe and McGrattan's, 2002, accounting framework). It also resembles work that computes historical sunspots (for example Harrison and Weder, 2005). More specifically, within a dynamic general equilibrium framework, the current paper builds on and modifies a method originally developed by Sheffrin and Salyer (1998) for post-war U.S. data. In a nutshell, Sheffrin and Salyer uncover sunspots from a version of the Farmer and Guo (1994) model. This economy is driven by both fundamental technology shocks and by sunspot shocks. Sunspot expectations matter since the model accommodates increasing returns which result in an indeterminacy: the well-specified dynamic general equilibrium model includes an expectational-error term which stands for the non-fundamental changes in expectations. Using financial markets in conjunction with this error term, Sheffrin and Salyer (1998) send U.S. data through the model. It then becomes possible to extract period-by-period error terms, i.e. sunspots. The use of the error-term parallels the methodology promoted by Chari, Kehoe and McGrattan (2002, 2004). Chari, Kehoe and McGrattan advocate a business cycle accounting approach as the only fruitful technique for guiding the development of business cycle models. Given the availability of useful theoretical models, there is no reason to employ methods that use only a minimal amount of theory such as structural vector autoregressions (SVAR). In particular, Chari, Kehoe and McGrattan claim that SVARs are no reliable technique for pointing to the sources of economic fluctuations.

Several important differences distinguish Sheffrin and Salyer's (1998) work from mine: (i) the underlying theoretical model is different – the Farmer and Guo (1994) economy requires unrealistically large increasing returns to scale – (ii) I do not employ financial markets, (iii) sunspots are sifted out from the model equation's residuals in different ways, and (iv) the forecasting power of shocks to expectations is determined.

To my knowledge, Fisher and Hornstein (2002) and Weder (2003) are the only other approaches which attempt to explain the Great Depression in Germany using dynamic general equilibrium theory. Both find a deterioration in total factor productivity which accounts for a substantial decline in economic activity – yet both claim that a complete explanation requires many more inputs such as fiscal shocks and labor market distortions (in the case of Fisher and Hornstein) or taste shocks (in Weder's case). These mentioned papers rely on theoretical inclusiveness in the hope of drawing together varying approaches to show how these contribute to a more complete explanation. The paper here neglects other shocks. This does not rule out other factors such as the above mentioned. However, the monocausal strategy applied here allows the effects of expectations to be analyzed in isolation.

Another conceptual issue pertains to the notion of equilibrium economics. Equilibrium business cycle models – such as the one advocated here – banish the notion of involuntary unemployment essentially because of its unsound distinction and as an intricate concept. Business cycles are not interpreted as deviations from equilibrium but decoded as fluctuations of the equilibrium itself: the out-of-work must have chosen rest over employment, however, the equilibrium concept does not presume that the non-employed relish depressions:

> "Of course, the hypothesis of a cleared labor market carries with it no such suggestion, any more than the observation that people go hungry in cleared food markets suggest that people enjoy hunger." [Lucas, 1977, p. 226].

More importantly, equilibria do not necessitate Pareto-efficiency: the artificial economy that will be outlined shortly is interspersed with imperfect product markets and any realized equilibrium represents a flaw in the economy that a rearrangement of resources could correct at no cost to anyone. In short, the labor market is modelled as if in equilibrium, therefore, the controversy is not whether unemployment is involuntary but instead whether the level of employment is efficient. It clearly isn't.

2 The artificial economy

This Section presents the theoretical model, discusses the calibration and reports on qualitative dynamics. The economy builds on the standard dynamic general equilibrium model. There are several departures from the plain-vanilla real business cycles model: the pace of capital utilization rate is endogenously set, technology displays internal economies to scale and markets for intermediate products are monopolistic competitive.[2] Taken together, these departures lead to equilibria that are not uniquely determined by preferences and technology: the artificial economy may be driven by non-fundamental shocks to expectations.

The economy consists of two sectors. The final goods sector is perfectly competitive. Final goods production assembles distinct intermediate inputs $y_{i,t}$ with the constant returns to scale production function

$$y_t = \left(\int_0^1 y_{i,t}^{\upsilon} di \right)^{1/\upsilon} \qquad 0 < \upsilon < 1 \tag{1}$$

where $i \in [0,1]$. Any final goods firm will potentially make profits

$$\pi_t = p_t y_t - \int_0^1 p_{i,t} y_{i,t} di$$

where p_t denotes the good's competitive price. Assuming free entry in the market for final goods, the profits will be zero. The conditional demand for $y_{i,t}$ can be derived as

$$y_{i,t} = \left(\frac{p_{i,t}}{\mathbf{p}_t} \right)^{\frac{1}{\upsilon-1}} y_t, \qquad \mathbf{p}_t \equiv \left(\int_0^1 p_{i,t}^{\frac{\upsilon}{\upsilon-1}} di \right)^{\frac{\upsilon-1}{\upsilon}}. \tag{2}$$

Here, $p_{i,t}$ is intermediate good i's price and $\mathbf{p}_t$ is the exact price index. Monopolistic competitors produce intermediate products and have access to an increasing returns to scale technology given by

$$y_{i,t} = z_t (u_t k_{i,t})^{\alpha} l_{i,t}^{\beta} \qquad \alpha + \beta > 1. \tag{3}$$

Firms rent the services from labor, $l_{i,t}$, and capital, $k_{i,t}$, from the household at the competitive rental rates w_t and r_t. The households decide on the

[2] The models by Greenwood, Hercowitz and Huffman (1988), Farmer and Guo (1994) and Wen (1998) – to which my model is related – feature similar attributes.

index of the use of capital, u_t. It is taken as a given by the firms. z_t is the state of technological knowledge which is determined outside the model. It follows the first-order autoregressive process

$$\ln z_t = (1-\zeta)\ln z + \zeta \ln z_{t-1} + \varepsilon_t \qquad 0 < \zeta < 1. \tag{4}$$

The shocks to technology, ε_t, are uncorrelated at all leads and lags and uncorrelated with z_{t-j} $\nabla j > 0$. They are the part of z_t that cannot be predicted based on past values of the variables of the model. Each monopolistic competitor's profit maximization is given by the static problem

$$\max_{l_{i,t}, u_t k_{i,t}} p_{i,t} y_{i,t} - w_t l_{i,t} - r_t u_t k_{i,t} \qquad \text{s.t. (2) and (3)}$$

where the maximand is concave in inputs whenever $(\alpha+\beta)\upsilon$ is less or equal to one. In fact, I will restrict $(\alpha+\beta)\upsilon = 1$ which implies zero average pure profits. The assumption is on congenial terms with data reported by Sweezy (1940).[3] The factor demands of firm i are

$$w_t = \beta\upsilon p_{i,t} z_t (u_t k_{i,t})^{\alpha} l_{i,t}^{\beta-1} \qquad \text{and} \qquad r_t = \alpha\upsilon p_{i,t} z_t (u_t k_{i,t})^{\alpha-1} l_{i,t}^{\beta} \tag{5}$$

that is, firms are renting effective capital units, i.e. $u_t k_{i,t}$. The reason is the following. Technology displays a nonconvexity if the usual commodity point is employed: an alternative commodity is needed. My approach is to assume that firms demand effective capital units. Phrased alternatively, from the firm's point of view, output can be increased by running existing machines more intensely or by putting into operation additional machines. The firms do not care how the increase is realized; the decision is made by the households who own the capital stock and who can decide on the utilization rate.

All intertemporal decisions are administered by the household sector. Households supply labor to and purchase output from the firms. The *stand-in* household's preferences are ordered by

$$U = E_0 \sum_{t=0}^{\infty} \rho^t u(c_t, 1-l_t) \qquad 0 < \rho < 1 \tag{6}$$

where c_t and ρ stand for consumption and the discount factor. The period utility function is assumed to have the form

$$u(c_t, 1-l_t) = \eta \log c_t - (1-\eta) l_t \qquad 0 < \eta < 1.$$

The fact that labor enters linearly into the utility function follows the assumption that labor is indivisible, utility is separable in consumption and

[3]Splitting up the capital income into rental and pure profit income, for example, would change the model insofar as to make it even easier to obtain indeterminacy.

in leisure and agents trade employment lotteries. E_t is the expectations operator, conditional on all information available in periods t and earlier. The capital accumulation equation

$$k_{t+1} = (1-\delta_t)k_t + w_t l_t + r_t u_t k_t + \Pi_t - c_t \tag{7}$$

is a standard one except for the variable depreciation rate, δ_t. Depreciation is an increasing convex function of utilization

$$\delta_t = \frac{1}{\theta} u_t^\theta \qquad\qquad \theta > 1.$$

Higher utilization causes faster depreciation because of wear and tear on the capital stock. Π_t represents pure profit income arising from the presence of market power. Factor prices (and profit income) are taken as given by the household. The maximization of (6) subject to (7) yields the first-order conditions

$$\frac{\eta}{1-\eta} = \frac{w_t}{c_t} \tag{8}$$

$$\frac{1}{c_t} = E_t \frac{\rho}{c_{t+1}} \left(r_{t+1} u_{t+1} + 1 - \frac{1}{\theta} u_{t+1}^\theta \right) \tag{9}$$

$$u_t^{\theta-1} = r_t. \tag{10}$$

In addition, the budget constraint

$$k_{t+1} = (1-\delta_t)k_t + y_t - c_t$$

and the usual transversality condition – given the initial stock of capital, $k(0) > 0$ – must hold. Equation (8) describes the consumption-leisure trade-off, (9) is the intertemporal Euler equation. (10) characterizes the efficient level of capital utilization. It states that capital should be utilized at a rate which sets the marginal user costs equal to the marginal benefit of capital services.

In symmetric equilibrium, we have $k_{i,t} = k_t$, $l_{i,t} = l_t$, $y_{i,t} = y_t$, and $p_{i,t} = p_t = 1$. The last equality comes from the zero profits condition in the final goods sector with final goods being the numeraire. The first-order conditions with respect to capital utilization and investment become

$$u_t^\theta = \alpha v \frac{y_t}{k_t} \qquad \text{and} \qquad \frac{1}{c_t} = E_t \frac{\rho}{c_{t+1}} \left(\alpha v \frac{y_{t+t}}{k_{t+1}} + 1 - \frac{1}{\theta} u_{t+1}^\theta \right)$$

and, consequently, the commodity point selection does not change the usual forms of these Euler equations.[4]

Next, I calibrate the model using parameter values that mimic certain ratios of the actual German economy that are more or less constant (Table

[4] See for example Greenwood et al. (1998) or Wen (1998).

1). Time evolves in discrete units and periods are specified to be one quarter long. Significant market power is widely reported for interwar Germany. For example, Kellenbenz (1981) estimates the rise of cartels from 233 to 1539 in the period from 1905 to 1925. To offer an idea of the extent of market power, Bloch (1932) compares price indices of raw material and semifinished products arranged by commodities for domestic (i.e. German) and foreign consumption. Over the 1929 to 1932 period, the domestic price level was about 30 percent above the world price level. A high degree of *de facto* cartelization was also widespread in the agricultural sector due to the political influence of East Elbian Junkers. In this respect, Kindleberger (1986) notes that the market power combined with import restrictions

> "[...] raised German agricultural prices to Rm 2 billion above the level of world prices in 1932." [Kindleberger, 1986, p. 132]

The capital share is 25 percent. No reliable estimate of markups for interwar Germany is available, however. I assume that the average markup is 20 percent. This implies that $\upsilon = 0.83$ so that the elasticity of substitution between varieties of intermediate goods is about 6. Consequently, the zero-profit condition implies that returns to scale amount to $1/\upsilon = 1.20$. This is substantially lower than in Farmer and Guo (1994). It is also smaller than the value that is reported by Gehrig and Kuhlo (1961). Gehrig and Kuhlo estimate a macroeconomic production function for Germany 1925-1938 and 1950-1957. They find substantial increasing returns ranging from 1.31 to 1.4. My parameter selection for υ allows me to err on the conservative side. The choice is within the span reported by Basu and Fernald (1997) who conclude that increasing returns fall within the 1.02 to 1.26 orbit. The steady state rate of depreciation is 3 percent per annum. The discount factor, ρ, is set such that the steady state capital-output ratio is 4.18 which is the empirical observed value (information on great ratios, income shares and depreciation rates draws on Ritschl, 2002b). The utility weight η has no influence on equilibrium dynamics and is therefore not needed to be calibrated.

Denoting steady state values with no time subscripts, the unique steady state is described by the following three equations

$$\begin{aligned} \frac{1}{\rho} &= \alpha\upsilon\frac{y}{k} + 1 - \delta \\ \frac{1}{\rho} &= 1 - \delta(1-\theta) \\ \delta &= \frac{x}{k} = \frac{x}{y}\frac{y}{k}. \end{aligned}$$

These conditions imply a value of 1.99 for the elasticity of depreciation with respect to utilization, θ. The steady state investment share on output, x/y, is 17 percent.

I take a log-linear approximation to the equilibrium conditions to obtain the following dynamical system that describes the economy (see Appendix):

$$\begin{pmatrix} \widehat{c}_{t+1} \\ \widehat{k}_{t+1} \\ \widehat{z}_{t+1} \end{pmatrix} = \mathbf{M} \begin{pmatrix} \widehat{c}_{t} \\ \widehat{k}_{t} \\ \widehat{z}_{t} \end{pmatrix} + \mathbf{W} \begin{pmatrix} \omega_{t+1} \\ 0 \\ \varepsilon_{t+1} \end{pmatrix} \tag{11}$$

Hatted variables denote percent deviations from their steady-state values. $\mathbf{M}$ is the 3×3 Jacobian matrix of partial derivatives. The term $\omega_{t+1} \equiv E_t\widehat{c}_{t+1} - \widehat{c}_{t+1}$ denotes the expectational error. Its role is as follows. Consumption is a non-predetermined variable whereas capital is predetermined. If exactly one eigenvalue of $\mathbf{M}$ is outside the unit circle, the model is unique (i.e. saddle-path stable); unless the extraneous random variable ω_{t+1} is removed, the economy would eventually violate the transversality conditions. With the presence of market power, however, we do not have the guarantee that the equilibrium is unique. Indeterminacy of rational expectations requires that both eigenvalues of $\mathbf{M}$ are inside the unit circle. This situation implies that equilibria are possible in which fluctuations in economic activity may be driven by arbitrary and self-fulfilling changes in people's expectations. Rational expectations require that expectational errors be essentially random errors which are uncorrelated with the information obtained and processed: in a word, people make no systematic mistakes.

Sunspot cycles are generated in the model in the following manner. Let there be a pessimistic shock to expectations unrelated to any available fundamental data – the first step in a harmful sequence of events. In particular, people believe that the future income stream dwindles. The households respond by reducing today's consumption expenditures and by increasing the supply of labor. To understand the effect of the change in expectations on employment, one must regard that labor demand is unconventionally sloped given departures from constant returns. This can be seen by combining the symmetric equilibrium conditions

$$u_t^{\theta} = \alpha v \frac{y_t}{k_t} \qquad \text{and} \qquad y_t = z_t (u_t k_t)^{\alpha} l_t^{\beta}$$

which yield

$$y_t = (\alpha v)^{\frac{\alpha}{\theta-\alpha}} z_t^{\frac{\theta}{\theta-\alpha}} k_t^{\frac{\alpha(\theta-1)}{\theta-\alpha}} l_t^{\frac{\beta\theta}{\theta-\alpha}}.$$

Given Table 1's calibration, the effective labor-output elasticity $\beta\theta/(\theta - \alpha)$ exceeds unity for markups (or, equivalently, increasing returns to scale) larger than 1.16: the reduced-form labor demand curve is upward sloping. Now, the sunspot-driven shift in labor supply reduces employment and investment today. Therefore, the future capital stock and output will be low and the initially pessimistic undercurrent about future income is self-fulfilled. This completes the circuit.

3 Unearthing sunspots

This Section checks whether nonfundamental changes in expectations can explain the fluctuations that occurred in Germany during the interwar period. In the context of the model, in other words, among the infinite number of possible sequences of the expectational errors in (11), I seek the one that I believe best describes the behavior of peoples' extrinsic uncertainty during the 1920s and 1930s period. Then, the effects of the estimated sunspot innovations will be traced and the predictive power of the model will be inspected.

Technology shocks are customarily estimated as residuals from a Solow decomposition. In other words, these shocks are not directly observable; measurement takes place within a particular model – a production function. Taking the theoretical model as a starting point, the current paper derives sunspots directly from model equations as well.

A note on the observational equivalence between sunspot models and Real Business Cycles (RBC) is compulsory. Cole and Ohanian (1999) and Kamihigashi (1996) show that if the exogenous technology shock process is not restricted, then the following correspondence exists: one will always be able to find a series of sunspot shocks paired with increasing returns to scale that will replicate a technology shock driven RBC model and *vice versa*. Phrased alternatively, the economic modeler needs additional information otherwise it is not possible to identify sunspots. One way the equivalence can be broken is to impose a restriction on the exogenous process (see Cole and Ohanian, 1999). In the current model, exogenous technology follows a first-order process. Of course, this assumption might not be altogether satisfactory. To lesser the quandary, the estimation of technology shocks will take place along two competing strategies: a Solow decomposition that yields the efficiency wedge and an atheoretical model. The latter follows the SVAR-based approach promoted by Gali (1999) and others. I will show that both methods deliver very similar sequences (this may come to some surprise given the critique on SVARs put fourth by Chari, Kehoe and McGrattan, 2004). Once the technology shocks are pinned down, the model structure allows the identification of sunspot noise.

Now, sunspots are unearthed as follows. Let us recall equation (11). In the absence of any other form of uncertainty, the term ω_{t+1} is a belief shock. By filtering data on *per capita* consumption, capital and total factor productivity through the model, an empirical sequence of residuals $\{\omega_t\}$ can be computed.

There is no *a priori* reasoning to expect that the belief shocks are uncorrelated to fundamental disturbances. For example, Pigou (1929) took a somewhat lenient stance on sunspots and has put forth an agnostic interpretation of sunspots as overreactions to fundamental shocks. Here, I define sunspots as the changes to expectations that are not connected to fundamentals. This, then, conforms to a definition of sunspots that is much stricter than Pigou's.

All this is done as follows. The consumption equation residual can be decomposed into a part which is related to technology shocks and into sunspots. The natural way of orthogonalization is to regress technology shocks on the consumption equation residual. If both shocks are found to be uncorrelated, this would indicate that $\{\omega_t\}$ does not simply capture disturbances on the supply side.

To begin with, German total factor productivity, z_t^d, is tallied by carrying out a Solow decomposition (the superscript d denotes data). The efficiency wedge is calculated from

$$z_t^d = \frac{y_t^d}{(u_t^d k_t^d)^\alpha (l_t^d)^\beta}.$$

Here capital utilization is variable and the production function is increasing returns to render the total factor productivity (TFP) estimation compatible with the theoretical model. Utilization, u_t^d, is instrumented by the HP-deviations of output so as to account for the cyclical intensity that capital is working. The instrument was transformed such that 25 percent of capital was idled at the business cycle trough – consistent with evidence by Bresnahan and Raff (1991); Meester (1961) suggests an even larger fall. The Solow-based technology shocks can then be computed from the first-order autoregressive process (4).

Of course, the efficiency wedge itself may be a noisy measure of true supply shocks (see Hall, 1990). To check for the appropriateness of the Solow decomposition, I alternatively apply Gali's (1999) method: SVAR-measurement of technology shocks with the key identifying assumption that it is only technology shocks that can generate permanent effects on productivity. This long-run identifying restriction translates into estimating the productivity equation

$$\Delta q_t^d = c_x + \sum_{j=1}^{b} \alpha_{xj} \Delta q_{t-j}^d + \sum_{j=0}^{b-1} \alpha_{nj} \Delta^2 l_{t-j}^d + \varepsilon_t^x.$$

Here, as in Shapiro and Watson (1988), Francis and Ramey (2002) or Francis, Owyang and Theodorou (2003), I confine hours to appear in double differenced form, i.e. non-technology disturbances cannot generate permanent effects on labor productivity, q_t^d. The equation's residuals can be interpreted as technology shocks. I employ an instrumental variables regression. As in Francis and Ramey (2002), I use $b = 4$ lags of Δq_t^d and Δl_t^d as instruments. Figure 2 plots the theoretical versus the atheoretical shocks. The calculated shocks are remarkably similar: the correlation of the shock-series is 0.89; 1927 is the single year in which the shocks impart any significant disparity.

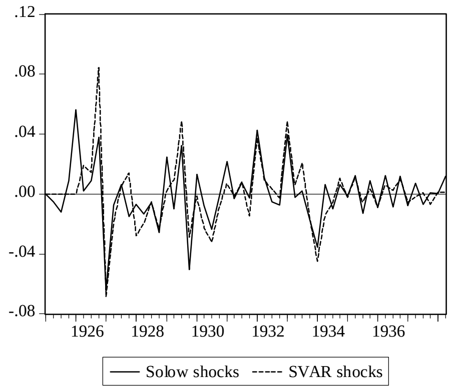

Figure 2: Theoretical and atheoretical supply shocks

Thus, at the stage at which sunspot shocks will be calculated, I can rely on technology shocks being reliably identified. I will continue using Solow's method to keep matters consistent with the theoretical model.

Since the variables in equation (11) are measured as deviations from the steady state, an estimation of the steady state values is necessary. Accordingly, I linearly detrend series individually. All data are taken from Ritschl (2002b). The sunspot orthogonalization yields (absolute t-value in parentheses)

$$\begin{aligned} \omega_t &= \underset{(0.61)}{-0.125152}\varepsilon_t + sun_t \\ \overline{R}^2 &= 0.008 \quad SER = 0.0306. \end{aligned}$$

Of note is the small explanatory power of the regression as measured by $\overline{R}^2$ and the insignificance of the regressor. It does not matter for the interpretation of the error terms if one follows Pigou or not: technology shocks do not cause the identified belief shocks. Moreover, for serial correlation up to fourth-order, the Breusch-Godfrey test statistics do not reject the null of zero serial correlation (Table 2). Therefore, the sequence of sunspots appears to be in line with the assumption of rational expectations.

Figure 3 shows that pessimism started to engulf the German economy during 1927.[5] In fact I am able to unearth an unfavorable sequence of sunspots from 1927:IV to 1932:II. This sequence roughly coincides with the economic cycle. The business cycle peak occurred in 1928:I and the economy went through its trough in 1932:III. Likewise, confidence reaches a plateau in 1926, it does not recover before 1932:II and it rises on average throughout

[5] Weder (2004) shows that this method delivers essentially the same result as Sheffrin and Salyer's (1998).

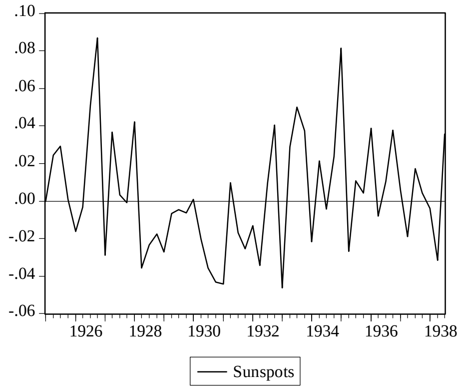

Figure 3: German sunspots as identified from artificial economy

the 1930s. Only by 1936 does the upsurge come to a pause.[6] The findings imply that German expectations changed direction well before the U.S. cycle peaked. This is in line with the hypothesis originally promoted by Temin (1971) and recently picked up again by Ritschl (1999, 2002a).[7]

Next, I address a potential pitfall of the sunspot extracting procedure and ask whether calculated sunspots are caused by other fundamental variables. Here I apply Geweke, Meese and Dent's (1983) small samples causality tests.[8] I evaluate whether possible fundamentals decrease the forecast variance of sunspots. Table 3 finds no evidence that the calculated sunspots are caused by considered fundamentals (inflation, government spending, deficit, wage bill, interest rates, and a monetary aggregate). The exception is the first-differenced deficit to output ratio at 4 lags: the implied p-value is 0.062. However, this result does not carry over for shorter or longer lags and it also does not carry over when the non-differenced deficit ratio is considered: the p-value rises to 0.142.

By way of showing this non-causality, it is palpable that the use of a

[6] The above sunspot-series is by no means dependent on the way capital utilization is measured in z_t^d. In slight model-inconsistency, I find that the correlation of the above series of sunspots and one that arises when utilization is constant is 0.995 (when both utilization and returns to scale are constant, the correlation is 0.987).

[7] In particular Ritschl suggests a worsening of the business climate.

[8] Let the residual variance of sunspots be σ^2 and φ^2 when a fudamental is included as explanatory variable in the aautoregression. Let the number of observations be N and the number of lags τ. Then Geweke, Meese and Dent (1983) show that

$$\varrho(\tau) = N(\frac{\sigma^2 - \varphi^2}{\sigma^2}) \sim \chi^2_\tau$$

asymptotically under the null of no Granger causality. See also Matsusaka and Sbodorne (1995). A previous version of the paper apllied a standard Granger test: the results were identical.

model with only two shocks does not create a bias in the estimation of the sunspots: the calculated sunspots do not pick up any influence that perhaps could operate through the considered fundamental variables.

4 Do sunspots matter?

Up to this point, I have found indications of pessimistic sunspots that began to surface sometime during 1927. The current Section will trace the economic effects of the estimated swings of expectations. First I will present results of an empirical investigation to determine how well sunspots predict economic activity. The second part addresses the role of sunspots within a fully specified dynamic general equilibrium. That is, the identified historical sunspots will be fed into the model; data and artificial output series will be confronted.

4.1 The (forecasting) power of sunspots

This Subsection determines how well sunspots predict output. It relays the outcome of forecasting regressions for output growth and discusses the findings of a vector autoregression analysis.[9]

Do sunspots help predict output growth? I examine the predictive power of sunspots by regressing movements on lagged sunspot innovations on output growth:

$$\Delta \ln y_t^d = \alpha + \beta Z_t + \sum_{t=i}^{4} \gamma_i sun_{t-i} + \epsilon_t. \tag{12}$$

The reduced-form forecasting model (12) attempts to isolate the independent contribution of sunspots. Here $\Delta \ln y_t^d$ is the growth rate of *per capita* output (data) and Z_t is a vector of control variables which is comprised of a number of fundamental variables. The control variables included in Z_t are the four lags of the growth in the real wage bill and four lags of first-differences of the interest rate (*Privatdiskont in Berlin*). Of course, the choice of controls is somewhat arbitrary. The role of the controls is to affect the path of aggregate output for other reasons than animal spirits. The choice of the interest rate and wage income can be thought of in attempting to capture the effects of monetary policy and credit-rationing.[10] Again, data are quarterly and cover 1925:I through 1938:IV.

The top panel of Table 4 shows estimations of equation (12) without control variables. The measure of economic significance is the increase of $\overline{R}^2$. Lagged values of sunspots, taken on their own, explain a substantial

[9] Bram and Ludvigson (1997) conduct a similar exercise to examine the role of confidence on consumption.

[10] Adding variables will surely involve econometric risk given the small sample.

portion of output. Specifically, sunspots explain between 11 and 16 percent of the variation in output one quarter hence. While this finding shows that sunspots by themselves help to predict the future path of output, a more important question is whether sunspots contain information not captured by economic fundamentals. Do sunspots still forecast output to a significant degree once the control variables are included in equation (12)?

The information content of sunspots can be assessed by recording the increase to $\overline{R}^2$: the fraction of the variance of output growth explained by adding sunspot lags to the baseline regression. The lower part of Table 4 shows statistical results from running the regression (12) on both the sunspot lags and the control variables; no doubt at econometric risk given that 13 coefficients are being estimated in a sample of 52 observations. In the case of private GNP, the significance of nonfundamental confidence stays put: $\overline{R}^2$ rises substantially by 10 percent when sunspots are added to the set of control variables and the coefficients on the four lags of sunspots are estimated to be statistically significant at better than the 1 percent level. As for total GNP, the margin is narrower and the evidence more murky. Sunspots contribute about 8 percent to the $\overline{R}^2$ and, more importantly, the four lags are only jointly significant at only the 6 percent level. For the purpose of the current paper, private output may constitute the more pertinent variable to check against since by definition sunspots affect predominantly the private sector.

For an alternative way to gauge whether sunspots have had much of a role in accounting for movements in output, Table 5 reports variance decompositions for various time horizons based on the 1925 to 1938 estimation period.[11] Underlying the analysis is a bivariate, unrestricted vector autoregression (VAR) containing sunspots and output. Sunspots are ordered first in the VAR. This is consistent with the assumption that sunspots influence output contemporaneously, but output influences expectations only with a one period lag. The VARs suggest that sunspots account for between 25 to 75 percent of the output forecast variance at a three year horizon.

Figure 4 summarizes the dynamic relationship between sunspots and output. The chart shows the responses of log private output to an innovation in confidence. The lines above and below the impulse response are the probability bands which are generated by taking 1000 Monte Carlo draws from the posterior distribution of the VAR coefficients. Sunspot shocks have a very persistent effect on output. The strongest response is about one-and-

[11] In a sense, variance decompositions of this sort are a harder test than simply comparing the output amplitudes of data and of the sunspot driven model as is normally done in the RBC literature. In fact, when the sequence of sunspots is fed into the model, the model variance exceeds data's by factor three. The reasoning for this is that in the presence of variable capital utilization, consumption becomes extremely smooth. There is a solution to this puzzle by departing from logarithmic utility (see Weder, 2002). Since I am only engaged in regressions in the following, the scaling (as in Figure 5) is not important.

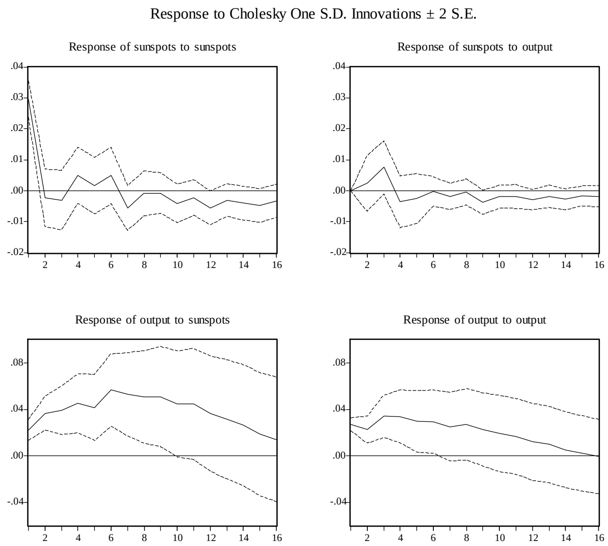

Figure 4: Impulse responses. VAR as in Table 5.

a-half years after the impact.[12]

Overall, I interpret these results as an indication of sunspots' pertinent role during the Great Depression. Granted the analysis up to this point has not considered the model and – at this point of the discussion – it is not clear whether theory would in fact produce a sequence of artificial economic activity that resembles that of the actual economy. This is will be shown in the following Sections.

4.2 Injecting sunspots – a visual clue

The following Subsections will provide clues of how sunspot theory tracks the German interwar cycle. To that avail, an artificial output series is derived by feeding the empirical sunspot series back into the model (11). The procedure encompasses tautology and unlike Chari, Kehoe and McGrattan's (2002) accounting scheme, there is nothing to expect that every facet of the business cycle can be explained by the sunspots shocks. First of all, sunspots have been derived from a subset of equations that constitute the general equilibrium of the economy and therefore the procedure is not an accounting exercise. Second, the sequence of estimated shocks is dependent on the specific theoretical model. Two scenarios are possible that would question my claim that sunspots matter. (i) the model is a poor description of the German economy: the shocks are significant in the sense of adjusting

[12]The respective charts for total output are very similar, however, the (initial) output response is cut by 30 percent and the pattern is somewhat less persistent.

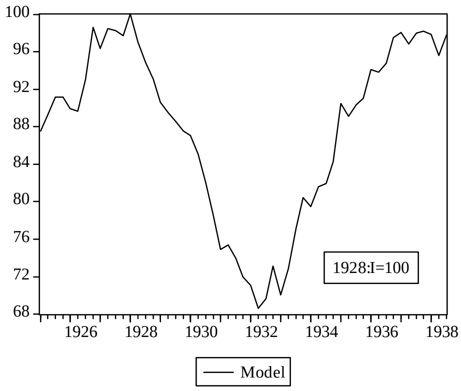

Figure 5: Artificial output. Scaled to match 75 percent of data volatility.

the model's prediction such to pick up alternative sources of fluctuations. This, however, is not the case. The causality tests suggest that the considered fundamental forces do not drive the calculated sunspots. (ii) the model is correct and able to pick up the true sunspots, but sunspots are not an important source of the German cycle. As a consequence, artificial and German output differ substantially. The following Subsections attempt to monitor any such differences.

Before conducting quantitative tests, Figure 5 graphically presents the behavior of artificial output. The putative impulses are fluctuations in sunspot expectations. The model economy does extremely well in capturing the general pattern of output. That is, the model correctly reaches a plateau in 1927, it predicts the upper turning point, the slide into the Depression as well as the beginning of the recovery more than four years later.

4.3 Sunspot theory in action

Figure 5's graphical characterization remains uninformative unless a quantitative test of the sunspot theory of the Great Depression is provided. This will be done next.

A natural starting point is to regress model output, y_t^m, on linearly detrended total output, $y_t^{t,d}$. This yields (t-values in parentheses)

$$\begin{aligned} \ln y_t^{t,d} &= \underset{(4.27)}{0.824} + \underset{(18.86)}{0.825} \ln y_t^m \\ \overline{R}^2 &= 0.868 \qquad SER = 0.0518 \end{aligned}$$

and

$$\begin{aligned}\ln y_t^{t,d} &= \underset{(4.41)}{0.715} + \underset{(23.10)}{0.850} \ln y_{t-1}^m \\ \overline{R}^2 &= 0.909 \qquad SER = 0.0432.\end{aligned}$$

The coefficients are highly significant and a substantial fraction of the sample variance is explained. At first glance, this finding evokes that the sunspot model mimics fairly closely the actual behavior of output. Moreover, when the artificial economy appears in lagged form, the regressions improve which indicates that model output leads the German cycle. Nevertheless, the above regressions cannot be seen as a logical affirmation in favor of or against a sunspot-based interpretation of the German Depression: the ability to mimic the economy's cyclical pattern is a necessary but not a sufficient condition that any theory should be able pass. Stronger evidence would be to show that sunspots provide added apprehension over rival modelling structures (see also Salyer and Sheffrin, 1998, which I follow here).

Time series econometrics allows data to be distinguished in atheoretical ways. For example, modelling aggregate output as a low-order autoregressive or moving-average process generates reasonable fits. If the sunspot approach to business cycles conveys anything unique about the German economy it must provide some advantage relative to atheoretical time series models. I implement this investigation by estimating equations of the following form

$$\ln y_t^d = \alpha + \sum_{i=1}^{n} \beta_i \ln y_{t-i}^d + \gamma \ln y_t^{\mathrm{m}} + \epsilon_t.$$

The idea behind conducting these tests is that by adding output from the sunspot model to the regression, one obtains a measure of to what extent sunspots provide additional informational content.

Let us begin with the autoregressive model. A lag length of $n = 3$ (4) was determined to remove fourth-order serial correlation for private (total) GNP. The time series model's predictive power is large – it explains over 93 percent of the variation in output one quarter hence (Lines 1 and 3 in Table 6). The Table also shows that the sunspot model contains incremental explanatory power on private and total output (Lines 2 and 4). The standard errors of the regressions fall by 15 (11) percent and the probability that the explanatory power is produced by pure chance is essentially nil.[13]

A natural alternative is to check the forecasting ability of the sunspot model since sunspots represent forward-looking expectations. This alternative hypothesis is represented in the following equation

$$\ln y_t^d = \alpha + \sum_{i=1}^{n} \beta_i \ln y_{t-i}^d + \sum_{i=1}^{m} \gamma_i \ln y_{t-i}^{\mathrm{m}} + \epsilon_t. \tag{13}$$

[13] It can furthermore be shown that adding the sunspots model to the regression does not create serial correlations.

Table 7 reports. In the first row, the dependent variable is data output (private) alone. The next line adds one period lagged model output which is followed by the case $m = 4$. The sunspot model, again, has explanatory power. For example, there is a 16 to 18 percent reduction of the standard errors in the regression relative to Line 1. The results for total output are somewhat worse. The one-period lagged artificial output is endowed with incremental predictive power, however, the distributed lag of artificial output is not jointly significant at reasonable probability values (Lines 5 and 6 of Table 7).

5 Robustness and extensions

This Section discusses the robustness and first looks at the explanatory power of technology shocks. This is followed by considering a model version in which technology is constant and I show that variable factor utilization and increasing returns to scale provide an endogenous mechanism for explaining movements in the naive Solow residual. Finally, I check for robustness by employing an alternative labor series and by considering a different representation of the model from which sunspots are extracted.

5.1 The role of technology shocks

At the stage of sunspot estimation, technology was assumed to be stochastic. It would therefore be logical to move to a model that contains TFP shocks. Let us begin by shutting down the sunspot channel and shock the model (11) only by the identified shocks to efficiency, z_t. Table 8 reports. A real business cycle version of the model contains valuable information. However, the informational content is abruptly lost for lagged realizations which indicates that the supply driven economy is lagging.[14] It should, of course, be emphasized that the result is dependent on the current model and, thus, the results are to some extent unfair to the RBC approach. Taken together, however, the Subsection finds that sunspots models are certainly not inferior to a supply-based explanation and furthermore, it points to the possibility that factors other than the broadly defined shock to efficiency may be responsible for the interwar cycle. This being said, it appears that shutting down the channel of intertemporal substitutions of TFP shocks may be an adequate strategy to divulge the riddle of the Great Depression. This will be done next.

[14] For total output, the real business cycle model always has insignificant, negative coefficients.

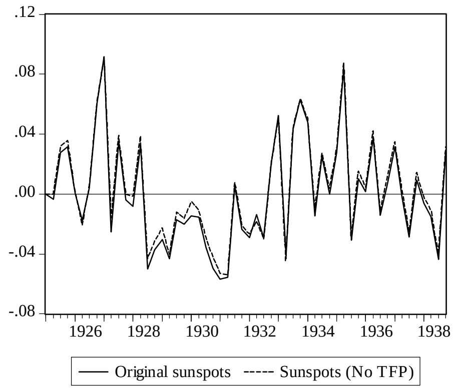

Figure 6: Sunspots when TFP is not in model

5.2 No role for technology shocks?

Shutting down TFP shocks completely might create a puzzle of its own: how can this be feasible after the variations in TFP are a fact? I conduct the following experiment. TFP can be computed as the residual from a naive Solow-residual accounting in which all TFP-movements are attributed to technology

$$z_t^{crs} = \frac{y_t}{k_t^{0.25} l_t^{0.75}}. \tag{14}$$

In (14) I now ignore both variable capital utilization and increasing returns as do Fisher and Hornstein (2002). I then ask, is the artificial sunspots economy able to endogenously replicate the z_t^{crs}-pattern? Let us assume that technology is deterministic. Thus, the economy is best described by

$$\begin{pmatrix} \widehat{c}_{t+1} \\ \widehat{k}_{t+1} \end{pmatrix} = \mathbf{F} \begin{pmatrix} \widehat{c}_t \\ \widehat{k}_t \end{pmatrix} + \mathbf{G} \begin{pmatrix} \omega_{t+1} \\ 0 \end{pmatrix}$$

and sunspots are elicited accordingly. The matrix $\mathbf{F}$ is 2×2. The economic structure parallels the approach taken in Farmer and Guo (1994).

Figure 6 plots the original shock sequence and the new series. Quite remarkably, the sequences are just about identical – their correlation is 0.988. Figure 7 plots the computed naive model TFP *vis-a-vis* data-z_t^{crs}. Because of the presence of increasing returns and of variable capacity utilization in the model, sunspot shocks lead to a procyclical series of naive TFP. The correlation of artificial and data TFP is quite large; even when Lölhöffel's data is used it is 0.94.

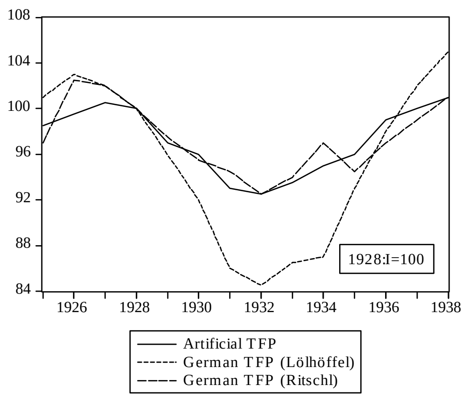

Figure 7: Artificial TFP. Data TFP constructed by using Lölhöffel's and Ritschl's employment series. German TFP detrended by sample trend to make both series comparable to model (trend for the series is 2 percent and 1.76 percent resp.).

5.3 Robustness with respect to employment data

Given the discussion on TFP and Fisher and Hornstein's (2002) use of Lölhöffel's employment series, it should be checked if my results can be replicated when TFP is computed based on Lölhöffel's employment data. Lölhöffel's and Ritschl's series differ in the way the employment in the government sector is accounted for. Ritschl's data is a better representation for non-government employment than Lölhöffel's and it is more volatile.

I use a cubic spline method to transform Lölhöffel's annual data into quarterly frequency. Once again, I find that belief shocks and technology shocks are not correlated as the orthogonalization evinces (t-values in parentheses):

$$\begin{aligned}\omega_t &= \underset{(1.34)}{0.23282}\varepsilon_t + sun_t \\ \overline{R}^2 &= 0.029 \quad SER = 0.0322.\end{aligned}$$

The coefficient of technology shocks now has the expected positive sign, however, it is still not significant. Table 9 shows the significant predictive power of sunspots. I then add output from the sunspot model to the regression as in (13) to obtain a measure of to what extent sunspots provide informational content. The specific model is driven by expectational shocks only. Table 10 reports; the analysis is analog to Table 4 to which it should be compared. Artificial output again possesses significant explanatory power. I conclude that my results are robust with respect to the specific employment series.

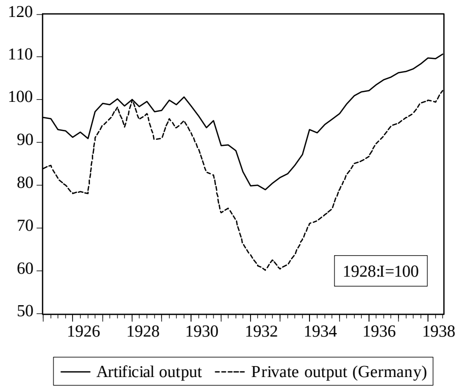

Figure 8: Artificial output.

5.4 A different model reduction

Next, I will demonstrate the non-importance of reducing the dynamic system to (11). In the case of the German Depression, Temin's (1971) story concerns an early fall in investment. Thus, the natural question arises if there is any gain from identifying the sunspots with a residual from the investment equation (i.e. *animal spirits*) rather than from the consumption equation in (11)?[15] To address this, I will consider a rearranged reduced-form version of the model that includes investment instead of consumption:

$$\begin{pmatrix} \widehat{x}_{t+1} \\ \widehat{k}_{t+1} \end{pmatrix} = \mathbf{S} \begin{pmatrix} \widehat{x}_{t} \\ \widehat{k}_{t} \end{pmatrix} + \mathbf{B} \begin{pmatrix} \widetilde{\omega}_{t+1} \\ 0 \end{pmatrix}.$$

As before, $\mathbf{S}$ denotes the 2×2 Jacobian and $\widetilde{\omega}_{t+1} \equiv E_t \widehat{x}_{t+1} - \widehat{x}_{t+1}$. I use this equation again to extract sunspots. Figure 8 shows that the sunspot-driven economy tracks real data quite well. The artificial economy peaks in 1928:I, turns around in 1932:III and predicts a long boom after that. Moreover, the sunspot driven economy accounts for 45 percent of German output standard deviation (see also footnote 11 on this issue). Table 11 shows that explanatory model power endures. The economic reason for the equivalence of both modelling structures is that consumption and investment share one important characteristic: they are both forward-looking, thus, changes in expectations are captured in the behavior of both variables.

6 Concluding comments

There are many speculations when it comes to solving the riddle of the Great Depression in Germany. Existing theories often stress fundamental

[15] I would like to thank Stephen Broadberry for suggesting this to me.

imbalances and distortions, like TFP deteriorations, inept fiscal policy, reparations, taxes *et cetera* and all have put forth plausible but certainly not fully convincing accounts. The present paper challenges the view that matters were purely fundamental. I find that nonfundamental factors, in and of itself, played a prominent role. In particular, my analysis has tracked down historical sunspots that had a ripple effect on the German economy. The paper shows that sunspots contain important information on economic activity and it points to a tangible fraction of output volatility that is directly attributable to nonfundamental expectations. Most notable is that the detrimental shocks began to hit the economy well before other disturbances (such as the rise in real interest rates, Gold exports or financial panics) entered the picture. Sunspots therefore offer a reason for the early beginning of the Depression in Germany. In a sense, the paper provides the theoretical backbone to Temin's (1971) interpretation of the German Depression. Temin stresses a fall in domestic investment demand, however, he leaves unexplained what caused the plunge. The current paper makes a case for a dramatic swing towards pessimistic expectations that developed during 1927 which depressed aggregate demand and persisted until the later half of 1932.

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7 Appendix 1: The linearized model and the tables

Let us denote $\widehat{y}_t \equiv (y_t - y)/y$ *et cetera*, then the linear model is given by

$$\widehat{y}_t = \alpha\widehat{u}_t + \alpha\widehat{k}_t + \beta\widehat{l}_t \tag{A1}$$

$$\widehat{l}_t = \widehat{y}_t - \widehat{c}_t \tag{A2}$$

$$\widehat{\delta}_t = \widehat{y}_t - \widehat{k}_t \tag{A3}$$

$$\widehat{\delta}_t = \theta\widehat{u}_t \tag{A4}$$

$$\frac{c}{y}\widehat{c}_t + \frac{x}{y}\widehat{x}_t = \widehat{y}_t \tag{A5}$$

$$-\widehat{c}_t = -E_t\widehat{c}_{t+1} + \alpha\upsilon\rho\frac{y}{k}\left(E_t\widehat{y}_{t+1} - \widehat{k}_{t+1}\right) - \rho\delta E_t\widehat{\delta}_{t+1} \tag{A6}$$

$$\widehat{k}_{t+1} = (1-\delta)\widehat{k}_t - \delta\widehat{\delta}_t + \frac{x}{k}\widehat{x}_t \tag{A7}$$

and

$$\widehat{z}_{t+1} = \zeta\widehat{z}_t + \varepsilon_{t+1}. \tag{A8}$$

The static equations (A1) through (A5) yield

$$\Pi_1 \begin{bmatrix} \widehat{y}_t \\ \widehat{x}_t \\ \widehat{l}_t \\ \widehat{u}_t \\ \widehat{\delta}_t \end{bmatrix} = \Pi_2 \begin{bmatrix} \widehat{c}_t \\ \widehat{k}_t \\ \widehat{z}_t \end{bmatrix}.$$

The dynamic equations (A6) through (A8) give

$$\mathbf{J}_1 \begin{bmatrix} E_t\widehat{c}_{t+1} \\ \widehat{k}_{t+1} \\ E_t\widehat{z}_{t+1} \end{bmatrix} + \mathbf{J}_2 \begin{bmatrix} E_t\widehat{y}_{t+1} \\ E_t\widehat{x}_{t+1} \\ E_t\widehat{l}_{t+1} \\ E_t\widehat{u}_{t+1} \\ E_t\widehat{\delta}_{t+1} \end{bmatrix} = \mathbf{J}_3 \begin{bmatrix} \widehat{c}_t \\ \widehat{k}_t \\ \widehat{z}_t \end{bmatrix} + \mathbf{J}_4 \begin{bmatrix} \widehat{y}_t \\ \widehat{x}_t \\ \widehat{l}_t \\ \widehat{u}_t \\ \widehat{\delta}_t \end{bmatrix}.$$

The model reduces to

$$\mathbf{J}_1 \begin{bmatrix} E_t\widehat{c}_{t+1} \\ \widehat{k}_{t+1} \\ E_t\widehat{z}_{t+1} \end{bmatrix} + \mathbf{J}_2\Pi_1^{-1}\Pi_2 \begin{bmatrix} E_t\widehat{c}_{t+1} \\ \widehat{k}_{t+1} \\ E_t\widehat{z}_{t+1} \end{bmatrix} = \mathbf{J}_3 \begin{bmatrix} \widehat{c}_t \\ \widehat{k}_t \\ \widehat{z}_t \end{bmatrix} + \mathbf{J}_4\Pi_1^{-1}\Pi_2 \begin{bmatrix} \widehat{c}_t \\ \widehat{k}_t \\ \widehat{z}_t \end{bmatrix}$$

or

$$\begin{bmatrix} E_t\widehat{c}_{t+1} \\ \widehat{k}_{t+1} \\ E_t\widehat{z}_{t+1} \end{bmatrix} = \left(\mathbf{J}_1 + \mathbf{J}_2\Pi_1^{-1}\Pi_2\right)^{-1} \left(\mathbf{J}_3 + \mathbf{J}_4\Pi_1^{-1}\Pi_2\right) \begin{bmatrix} \widehat{c}_t \\ \widehat{k}_t \\ \widehat{z}_t \end{bmatrix} \equiv \mathbf{M} \begin{bmatrix} \widehat{c}_t \\ \widehat{k}_t \\ \widehat{z}_t \end{bmatrix}$$

which is equation (11) in the text.

Table 1					
Quarterly model calibration					
$\alpha \upsilon$	$\beta \upsilon$	ρ	δ	υ	ζ
0.25	0.75	$1.03^{-1/4}$	0.0075	0.83	0.95

Table 2	
Serial correlation of shocks	
Lags	Probability
1	0.60
2	0.86
3	0.55
4	0.62

Table 2 – Serial correlation LM test: Breusch-Godfrey tests (various orders) for autocorrelated disturbances (probability values).

Table 3				
Causality tests (ϱ-values)				
Variable	Lags (τ)			
	1	2	3	4
D	0.049	1.456	1.954	4.168
ΔD	2.058	1.943	4.372	6.791
D/Y	0.002	1.640	1.952	5.230
$\Delta D/Y$	2.077	1.925	5.734	8.977*
G	0.182	0.275	0.470	0.660
G/Y	0.684	0.632	0.391	1.742
ΔG	0.035	0.082	0.238	1.079
$\Delta G/Y$	0.705	0.567	0.823	1.556
W	0.004	0.842	2.059	2.616
M/P	0.035	0.082	0.238	1.079
$\Delta M/P$	0.765	0.567	0.823	1.556
Interest rate	0.201	0.823	0.875	1.526
P	0.008	0.041	0.236	0.230
π	0.785	0.849	0.105	0.912

Table 3 – Table reports test results whether fundamentals reduce forecast variance of calculated sunspots. The null is that fundamentals do not help to forecast sunspots. The ϱ-statistics indicate no rejection at least at the 13 percent level (exception denoted by *). Variables: D = real deficit, D/Y = real deficit as fraction of output, G = real government expenditures, G/Y = government share, M/P

= real money (base), W = real wage bill, Interest = Privatdiskont in Berlin, P = CPI, π = growth rate of CPI. Δ denotes change in variable.

Table 4
Predictive power of sunspots

Dependent	$\overline{R}^2$ or $\Delta\overline{R}^2$	Significance (p-value)
$GNP^{private}$	0.161	0.010
GNP^{total}	0.117	0.032
$GNP^{private}$	0.107	0.006
GNP^{total}	0.079	0.051

Table 4 – The upper part reports $\overline{R}^2$ and the lower one changes in $\overline{R}^2$ after sunspots are added to the baseline regression that only included the controls on the right hand side. The third column displays probability values of the null that the sunspot variable is zero (log likelihood ratio).

Table 5
Sunspot shocks: variance decomposition

Period	$\Delta \ln y^T$	$\ln y^T$	$\Delta \ln y^P$	$\ln y^P$
0	23.3	24.1	41.4	40.0
4	26.6	24.4	49.2	61.8
8	27.0	28.2	49.8	71.9
12	27.1	30.4	49.8	75.3

Table 5 – Cholesky ordering: sunspots, output. VAR containing total output growth ($\Delta \ln y^T$) and private output growth ($\Delta \ln y^P$) has lag length 3. VAR containing total output growth ($\Delta \ln y^T$) and private output growth ($\Delta \ln y^P$) has lag length 5 (detrended); lags determined by Akaike info criteria and Schwarz criteria.

Table 6 Regression results I (Sunspot shocks)						
Line	Variable	Coefficient (t-value)	$\overline{R}^2$	S.E.R.	F-statistic (variable)	Log likelihood ratio
1	-	-	0.938	0.0399	-	-
2	y^m	0.342 (6.56)	0.967	0.0291	0.000	0.000
3	-	-	0.955	0.0311	-	-
4	y^m	0.321 (4.94)	0.970	0.0253	0.000	0.000

Table 6 – Each line reports regression statistics of German linearly detrended per capita output on a constant and on own lags using quarterly data 1925:I to 1938:III. Dependent variable: Lines 1 & 2 private output, Lines 3 & 4 total output. Coefficient = estimate when variable is added to regression, SER = standard errors of regression, F-statistic = probability value of the null that the variable is zero, Log-likelihood-ratio = probability value of the null that the variable is zero.

Table 7 Regression results II (Sunspot shocks)						
Line	Variable	Coefficient (t-value)	$\overline{R}^2$	S.E.R.	F-statistic (variable)	Log likelihood ratio
1	-	-	0.938	0.0399	-	-
2	y^m_{-1}	0.363 (4.59)	0.957	0.0334	0.000	0.000
3	$y^m_{-1 \text{ to } -4}$		0.960	0.0324	0.000	0.000
4	-	-	0.955	0.0311	-	-
5	y^m	0.253 (2.98)	0.962	0.0288	0.005	0.002
6	$y^m_{-1 \text{ to } -4}$	–	0.990	0.0294	0.071	0.037

Table 7 – Each line reports regression statistics of German linearly detrended per capita output on a constant and on own lags using quarterly data 1925:I to 1938:III. Dependent variable: Lines 1 to 3 private output, Lines 4 to 6 total output.

Table 8 Regression results (Supply shocks)						
Line	Variable	Coefficient (t-value)	$\overline{R}^2$	S.E.R.	F-statistic (variable)	Log likelihood ratio
1	-	-	0.938	0.0399	-	-
2	y^m	0.145 (2.87)	0.946	0.0372	0.009	0.006
3	y^m_{-1}	0.084 (1.49)	0.940	0.0394	0.143	0.121
4	$y^m_{-1\text{ to }-4}$	-	0.941	0.0394	0.219	0.155

Table 8 – Each line reports regression statistics of German linearly detrended per capita private output on a constant and on own lags using quarterly data 1925:I to 1938:III.

Table 9 Predictive power of sunspots (Alternative employment series)		
Dependent	$\overline{R}^2$ or $\Delta\overline{R}^2$	Significance (p-value)
$GNP^{private}$	0.127	0.031
GNP^{total}	0.185	0.008
$GNP^{private}$	0.104	0.030
GNP^{total}	0.143	0.004

Table 9 – The upper part reports $\overline{R}^2$ and the lower one changes in $\overline{R}^2$ after sunspots are added to regression. The third column displays probability values of the null that the sunspot variable is zero (log likelihood ratio).

Table 10: Regression results (Alternative employment series)						
Line	Variable	Coefficient (t-value)	$\overline{R}^2$	S.E.R.	F-statistic (variable)	Log likelihood ratio
1	-	-	0.938	0.0311	-	-
2	y^m	0.495 (2.87)	0.963	0.0286	0.006	0.003
3	-	-	0.955	0.0399	-	-
4	y^m	0.165 (1.53)	0.957	0.0307	0.133	0.108

Table 10 – Reports regression statistics of German linearly detrended per capita output on a constant and own lags using quarterly data 1925:I to 1938:III. Dependent variable: Lines 1 to 3 private output, Lines 4 to 6 total output.

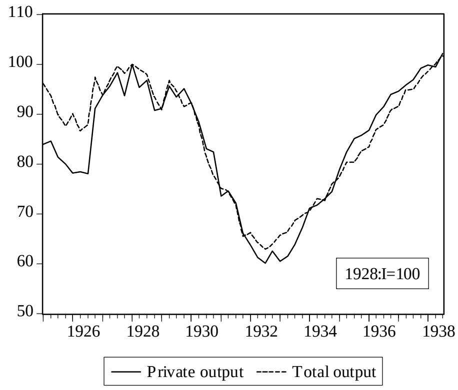

Figure 9: Per capita outputs (deviations from linear 1925-1938 trends). Total output is GNP (*Bruttosozialprodukt zu Marktpreisen von 1913*). Private output is sum of the private sector's consumption and investment expenditures (*Konsum der privaten Haushalte* and *Investitionen des Untermehmensektors*; in 1913-prices). Original source of data: Ritschl (2002b); 1925:I - 1938:III.

Table 11
Regression results (Alternative reduced form)

Line	Variable	Coefficient (t-value)	$\overline{R}^2$	S.E.R.	F-statistic (variable)	Log likelihood ratio
1	-	-	0.938	0.0399	-	-
2	y^m	0.605 (5.48)	0.962	0.0315	0.000	0.000
3	-	-	0.955	0.0311	-	-
4	y^m	0.328 (2.44)	0.960	0.0296	0.019	0.012

Table 11 – Each line reports regression statistics of German linearly detrended per capita output on a constant and on own lags using quarterly data 1925:I to 1938:III. Dependent variable: Lines 1 & 2 private output, Lines 3 & 4 total output.