Stock Markets and the Business Cycle in Germany before World War I: Evidence from Spectral Analysis

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Abstract

We want to find a new business cycle dating scheme for pre-World War I Germany. For this purpose we employ multivariate spectral analysis to compare national product estimates to stock market indices. Then we choose the one being closest to the stock market benchmark to date the business cycle. We find that business cycles obtained from deflated national product series are severely distorted by the implicit price deflator provided by Hoffmann
(1965). However, of the nominal series, Hoffmann’s income estimate correlates best with the stock market, while the one by Hoffmann and Mueller (1959) is too smooth especially before 1890. We find impressive congruency between the stock market and nominal wages, a subseries of Hoffmann’s income estimate. We can show that a substantial part of these series, although containing prices, are driven by real movements. Our findings confirm the traditional business cycle chronology for Germany of Burns and Mitchell (1946) and Spiethoff (1955), and lead us to discard later attempts to date the business cycle.
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1 Introduction

Among the industrialized countries, Germany compares relatively favorably regarding the knowledge about national income and output in the 19th century. For Germany, four different estimates exist that go back to the early 1850s. However, there are major differences between these series regarding both trends and business cycle characteristics.

All these estimates rest on the seminal work of Hoffmann (1965) and earlier work of Hoffmann and Mueller (1959). Hoffmann and his collaborators collected and aggregated a vast amount of data to produce independent estimates of output, expenditure, factor income-cum-employment, and the income tax base. The inevitable inconsistencies and deviations generated a literature that called for improvements and corrections of the most obvious problems. Recent work by Burhop and Wolff (forthcoming) provides a systematic attempt to apply these corrections and obtain revisions of all four data series for the pre-1913 period. They also present a compromise estimate, which is an unweighted average of the existing data. Their ambitious contribution is intended to put an end to the debate about the main trends of German economic growth in the 19th century and the implied business cycle chronology.

The work by Burhop and Wolff (forthcoming) is without doubt an important improvement to the various series. However, we regard their compromise estimate and its implications for the pre-war business cycle to be unsatisfactory. In a working paper version of their paper, Burhop and Wolff (2002) analyze the cyclical behavior of the four different series using Beveridge-Nelson decompositions, and find the implied business cycle chronologies to be grossly inconsistent with each other. Being just an unweighted average of those four series, their compromise estimate does not help to clarify matters. Moreover, all of the rivaling business cycle chronologies found by Burhop and Wolff (forthcoming) contradict the business cycle dating of an older literature that employed disaggregate evidence, most prominently Burns and Mitchell (1946) and Spiethoff (1955). The present paper sets out to shed further light on the issue by introducing additional information. We refrain from refining one or the other of Hoffmann’s series, which given the improvements made
by Burhop and Wolff (forthcoming) might be subject to decreasing returns. Instead, our approach is to exploit the information content in a completely different set of data that has been neglected in the debate so far, namely financial data. After 1870, when the stock market law in Germany was deregulated massively, a public offering boom set in. It resulted in a ratio of market capitalization to GDP of over 40 percent, a level that was only reached again in the 1990s (Rajan and Zingales 2003). Thus, stock prices reflected information on a substantial portion of the German economy.

According to established asset pricing models, stock prices should be procyclical and lead the business cycle (Campbell, Lo, and MacKinlay 1997, Cochrane 2001). Our idea is to exploit the cyclical movement in German stock prices to help determine the business cycle chronology before World War I. To this end, we explore the frequency domain characteristics of the various national income estimates, and apply a bivariate coherency measure to assess which of the series are explained best by the stock market.

Research over the recent years has brought substantial advances in the construction of representative stock market indices for the pre-World War I period, with new indices constructed by Eube (1998) and Ronge (2002). As each index has its own comparative advantage, we employ them alongside each other. Examining univariate spectra and the multivariate coherence between each national income series and the stock market index, we find the cyclical characteristics of most series to be obfuscated by deflating. For this reason, we focus our attention on nominal series. Hoffmann’s (1965) income/employment series turns out to be closest to the stock market, whereas Hoffmann and Müller’s (1959) income tax series, despite its plausible information on levels, is too smooth before 1890. Nominal wages as a subseries of Hoffmann’s (1965) income/employment series are preceded by stock markets by one to two years, and both series show an impressive comovement across all cycles between 1870 and 1914. In that period the German economy experienced six cycles with an average length of 7.5-8 years. We can show that nominal stock prices and nominal wages do not only represent price movements, but comove with real business cycle indicators such as railway transport, and iron, coal and steel production. The results are pretty much in line with Burns and Mitchell’s (1946) reference turning points, also
Spiethoff’s (1955) *Wechsellagen* are mainly confirmed. At the same time, Burhop and Wolff’s (2005) compromise estimate performs very poorly.

We present our findings in the following order: The next section includes a more detailed discussion of the relevant research. In Section 3, a brief presentation of the stock market data follows. Section 4 contains a description of spectral analysis and how we apply it, whereas results are presented and discussed in Section 5. Section 6 concludes and explores avenues for further research.

2 Literature

Two different fields of literature have to be merged for our project. One is the German historical national accounting literature, starting with Hoffmann and Müller’s (1959) approach to estimate the net national product (NNP) from (mainly) Prussian income tax data. The other one is that of consumption-based asset pricing models which justifies theoretically why stock prices can be used as a leading indicator of output.

Hoffmann’s book from 1965 is still one of the most important economic data compilations for Germany 1850-1913 (Hoffmann 1965). However, his NNP-series experienced a long history of criticism and today are largely regarded as flawed (Burhop and Wolff forthcoming, Fremdling 1988, Holtfrerich 1983, Ritschl and Spoerer 1997, Schremmer 1987). Nevertheless, they are still used, especially in international data sets (Maddison 1995, Craig and Fisher 2000). Burhop and Wolff (forthcoming) present a comprehensive overview of the improvements on Hoffmann’s (1965) and Hoffmann and Müller’s (1959) series, in addition to their own substantial efforts in this regard. The starting point of their work is an upward revision of the capital stock and investment series, along with a new series of returns on capital. As pointed out by Schremmer (1987), Hoffmann’s own estimate of capital had systematic downward bias, while his series of returns on capital was a simple static estimate of 6.68 percent. Correcting for this bias affects three of the four series of Hoffmann (1965). The income tax estimate of national income

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1Hoffmann and Müller’s work was essentially the backward extension of a series by Germany’s Statistical Office (Statistisches Reichsamt 1932) that went back to 1890.
remains unaffected. Here the revision by Burhop and Wolff (2005) is limited to accounting for indirect taxes and depreciation, extending a revision made by Ritschl and Spoerer (1997).

Our choice of stock market data against which to evaluate the business cycle information in the national income and product estimates is motivated by asset pricing and investment theory.

The consumption-based asset pricing model links aggregate consumption to asset returns. Under suitable assumptions about the representative agent’s utility function it predicts that the price of an asset is positively correlated with the expected future payoff from the asset, valued by the stochastic discount factor that depends on utility (Campbell, Lo, and MacKinlay 1997, Cochrane 2001). Note also that stock price indices are utilized in business cycle forecasting as leading indicators (U.S. Bureau of Economic Analysis 1984).

Another way to think about the link between stock prices and real activity is Tobin’s Q (Tobin 1969). It is a formulation of the marginal decision if to invest more in a firm or not. This depends on the ratio of the market value of the firms assets to their replacement cost, called Q. If the ratio is greater than one, more will be invested, but since returns to capital are diminishing, the ratio will always converge to one, where an additional unit of capital equals its replacement cost. Theoretically that model is very appealing, but empirical applications have led to low regression coefficients between investment and Q, albeit significant ones. (Hayashi (1982) estimates 0.04 for US-data.)

For our purpose, however, it is sufficient to have predictive properties of asset prices for the business cycle. As we are working in the frequency domain, the amplitude of any comovement, related to the regression coefficient, is immaterial. The information we intend to exploit comes solely from frequency.

3 Data

We employ two sets of data: four NNP estimates, given by Hoffmann (1965) and Hoffmann and Müller (1959), and two stock price indices. The NNP series start in the early 1850s, but the stock price indices are only available begin-
ning in 1870 (Ronge 2002) or 1876 (Eube 1998). Thus for the quantitative analysis, only 44 data points can be used if Ronge’s index is employed, and only 38 in the case of Eube’s index. This data restriction has important methodological implications, as will be explained later.

3.1 The NNP-series

National income and output is estimated by Hoffmann (1965) from three different sides, namely output, expenditure and income (which is how the series will be named hereafter.) The fourth series in Hoffmann & Müller (1959) estimates the NNP from the income side as well, but uses income tax data to do so. Therefore we call it Taxes.

Hoffmann’s (1965) “Income” series is the sum of average annual wages and capital income. The wage series is mainly calculated from social security statistics, enriched with daily wage data from the duchy of Baden in southwest Germany, whereas capital income is the capital stock times return on capital. Hoffmann (1965) originally assumed the return on capital to be 6.68% for the whole period of 1850-1913, whereas Burhop & Wolff (2005) calculated a new return series from joint stock firm’s dividend yields. The resulting income series is first calculated in current prices, and then deflated by Hoffmann’s (1965) implicit GNP deflator.

“Expenditure” is the sum of private and public consumption, investment and exports minus imports. These series are calculated from various sources, where some are originally in current prices and deflated, and others in volumes and connected to a prices series afterwards. Because of this it is not possible to entirely filter out the possible bias from deflating.

The investment series is just the annual net change of the capital stock. It is an extrapolation of the capital stock of the grand duchy of Baden, derived from capital tax data, which was revised by Schremmer (1987). Burhop and Wolff (2005) present an improved capital stock and thus also a new investment series.

“Output” is constructed as an index of industrial production volumes connected to an estimate of the production value in 1913. The twelve series are weighted by the number of workers in each industry and the industry’s
per capita production value, measured for the whole period in 1936. Burhop & Wolff (2005) use additional employment data and use the new capital stock value for 1913 for their improved “Output” version. Since it was originally constructed from volume indices, it has to be inflated to analyze it in current prices.\footnote{The IP index has recently been subject to major revisions. Ritschl (2004) revises the income-based metal making and processing series with output data and obtains very different results for post-1913. Burhop (2005) presents a revised IP series up to 1913 incorporating additional data and corrections for a number of flaws in Hoffmann’s (1965) calculation.}

Finally, the series by Hoffmann and Mueller (1959) is based on income tax data for all of Germany from 1891 on. For earlier years, data from Prussia and some other states is used. The nominal series is the smoothest of all for the first 20 years. Applying the price deflator, it becomes the most volatile of all. This is the spurious volatility phenomenon observed by (Romer 1986, Romer 1989) for U.S. historical data.

### 3.2 The stock market indices

The two stock market series employed here were constructed with different intentions. Ronge’s (2002) series is a backward extrapolation of the German DAX index, which includes the 30 biggest stocks, annually chosen by their market capitalization. In contrast, the index by Eube (1998) aims to cover as many firms as possible, and thus his index consists of 415 companies in 55 sectors. Thus, while the Ronge index is a typical blue chip index akin to the Dow Jones, the Eube index could roughly be compared to the much broader Standard & Poors 500.

Unfortunately, Eube’s (1988) index has three drawbacks. First, it starts only in 1876, which swallows more than ten percent of the data points. Second, Eube (1998) does not consider ten of the biggest railroad companies, that were included in Ronge’s (2002) index, without justifying this decision. Ronge (2002, p. 167) argues that this might be the reason for the relatively bad performance of Eube’s index in the 1880s. Usually railway stocks did relatively well during that period, because of the huge compensations paid to the owners after the nationalizations of the 1870s/80s.
Eube (1998) neither accounts for a component of the yield, the *Stückzins-Usancen*, a fixed interest paid on a stock in addition to dividends. The latter is likely only to change the intra-year movement of a stock, but especially because of the data shortage we will mostly work with Ronge’s (2002) index, and use Eube’s index only to check for robustness.

4 Spectral Analysis

A simple correlation coefficient could measure which of the proposed NNP-series is closest to the stock market, but this has a serious disadvantage: The series might be forward or backward shifted in time, but still represent the same business cycle. Spectral analysis, however, abstracts from time by representing a series with respect to frequency. The transformation from time to frequency domain and multivariate applications will be covered here. We will also deal with the issue of filtering and spectral estimation.

4.1 Basics and application

According to *Fourier*’s theorem any periodic function can be represented as a (possibly infinite) sum of weighted sine and cosine waves (Priestley 1981). One way to express the frequency content of a stochastic discrete time series
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$x_t$ is to transfer its autocovariance sequence to the frequency domain by multiplying it at every lag $k$ by a factor $e^{-ik\omega}$ which is complex valued$^3$

$$S_{xx}(\omega) = \sum_{k=-\infty}^{\infty} \gamma(k) e^{-ik\omega},$$ (1)

where $\gamma(k)$ is the autocovariance sequence of $x_t$, and $i$ is the imaginary number $\sqrt{-1}$. The result is called power spectral density (PSD) and is a summary of the frequency content of a time series. It is represented as a graph that peaks at the frequency $\omega$ which dominates the series. In Figure (2) we plot two monthly time series and their respective power spectra$^4$. The upper time series is moving slowly through time, i.e. it is dominated by low frequencies. That corresponds to a peak close to the origin. Here we find it at ca. 0.1 radians, which represents a cycle of $2\pi/0.1 \approx 63$ months or 5 1/4 years.

The lower series has more cycles per unit of time, and thus is dominated by higher frequencies. The peak shifts to the right, and with $\omega = 0.5$ the cycle takes $2\pi/0.5 \approx 12 - 13$ months.

The frequency content of a time series can also be described as the variance of a time series ordered by frequency. Thus the area under the spectrum is the total variance of the series. The area between two specified values of $\omega$ then is the share of variance corresponding to a certain range of frequencies, e.g. business cycles of a length between 7 and 11 years.

For our application we need to look at two time series and their cross spectral density. This can be represented as the Fourier-transform of the covariance sequence $\rho(k)$ of the time series $x_t$ and $y_t$

$$S_{xy}(\omega) = \sum_{k=-\infty}^{\infty} \rho(k) e^{-ik\omega}. $$ (2)

The cross spectral density is used to obtain the squared coherency measure, which is defined similarly to a correlation coefficient as

$^3$ $e^{-ik\omega}$ is according to DeMoivre’s theorem just another way to write the sum of sine and cosine waves: $e^{-ik\omega} = \cos(k\omega) - i \cdot \sin(k\omega)$.

$^4$The difference between a power spectrum and a power spectral density is that the area under the power density spectrum is normalized to one, while the area under the power spectrum varies.
Squared coherency shows to which extent $x_t$ and $y_t$ are linearly related to one another, so for every $\omega$ it yields a number $0 \leq C_{xy} \leq 1$.

Squared coherency is used to calculate the frequency domain counterpart to $R^2$ (the coefficient of variation) that tells us the share of $x_t$’s variance explained by $y_t$ with respect to $\omega$

$$\int_{-\pi}^{\pi} S_{xx}(\omega)d\omega = \int_{-\pi}^{\pi} C_{yx}(\omega)S_{xx}(\omega)d\omega + \int_{-\pi}^{\pi} S_e(\omega)d\omega,$$

where the left hand side is $\text{Var}(x_t)$, the first term of the right hand side is the variance explained by $y_t$ and the second term is unexplained variance.

Figure 2: High- and low-frequency content of monthly stock market index.
In the results section we will use the ratio of explained variance to total variance, and therefore provide a percentage number.

Sometimes it can be of interest how much of the shared variance at certain frequencies is shifted in time relative to the variation of the explaining series. This measure can be obtained by recalling that cross spectral density is a complex number consisting of a real and an imaginary part $r_{xy}(\omega)$, and $q_{xy}(\omega)$

$$S_{xy}(\omega) = r_{xy}(\omega) - iq_{xy}(\omega),$$

where $r_{xy}$ is the co-spectrum and $q_{xy}$ the quadrature spectrum. Using that definition squared coherency can be split up into

$$C_{xy}(\omega) = \frac{|(S_{xy}(\omega)|^2}{S_{xx}(\omega)S_{yy}(\omega)} = \frac{r_{xy}^2(\omega) + q_{xy}^2(\omega)}{S_{xx}(\omega)S_{yy}(\omega)}.$$  

Then the explained variance measure (4) can be further decomposed into

$$\int_{-\pi}^{\pi} S_{xx}(\omega)d\omega = \int_{-\pi}^{\pi} C_{yx}(\omega) S_{xx}(\omega)d\omega + \int_{-\pi}^{\pi} S_{e}(\omega)d\omega = \int_{-\pi}^{\pi} \frac{r_{xy}^2(\omega) + q_{xy}^2(\omega)}{S_{xx}(\omega)S_{yy}(\omega)} S_{xx}(\omega)d\omega + \int_{-\pi}^{\pi} S_{e}(\omega)d\omega$$

producing the explained variance of one series in-phase and out-of-phase of another series.

### 4.2 Filtering

Typically, national product series contain a time trend and/or a unit root. Trends or unit roots are, when seen from the frequency domain, variations with a very low frequency. They deviate heavier from the mean than their high frequency counterparts and thus request a higher share of the series’ total variance. Thus the spectrum would always peak at very low frequencies,
irrespective of which frequencies dominate apart from them — if the series is not rendered stationary first.

Filtering, or rendering a time series stationary, however, is a difficult task, since it might distort the frequency content of the remaining cyclical part. Simple first-differencing has proven to severely bias a series towards higher frequencies. Under first-differencing, the peak in Figure 2 would artificially be shifted to the right (Hamilton 1994, p. 177).

The very popular Hodrick-Prescott filter also distorts the frequency content of a non-stationary time series if the series contains a unit root (Canova 1998, Cogley and Nason 1995). Since we do not want to rely on unit-root tests we use a modified Baxter-King filter that has good properties both in the case of stationarity or non-stationarity (Baxter and King 1999). The modification relative to Baxter and King’s (1999) filter consists of applying Lanczos’ $\sigma$-factors that solve the problem of spurious side-lobes (Woitek 1998, Woitek 2001). However, this has the disadvantage of taking away $k$ data points according to the length of the moving-average window. Thus we will return to the Hodrick-Prescott filter and always double-check with the Baxter-King-filtered series.\footnote{Generally we find that Baxter-King filtered series have cycles that are ca. 6 months longer than Hodrick-Prescott-filtered ones.}

Note that we apply a $\lambda$ of 6.25 as Ravn and Uhlig (forthcoming) recommend for annual data.

4.3 Spectral estimation

The definition of power spectral density given in equation (1) requests unlimited data, namely the autocorrelation sequence $\gamma(k)$ for $-\infty \leq k \leq \infty$. In reality we need to approximate that measure by an estimation.

Two estimators can be differentiated: Non-parametric and parametric ones. Non-parametric estimators calculate the PSD directly from the data. Unfortunately, they are inconsistent, but the estimator’s variance can be reduced by averaging over segments of the data. This increases the amount of data needed.

Parametric estimators assume a time series model for the given process, the parameters of which are estimated from the data. Then the parameters
are transformed to the frequency domain. This second method is less data demanding, but depends on the right time series model.\(^6\)

In our case we are very short of data. Although Ronge’s (2002) index is provided on a weekly basis, we have to use annual averages, since the NNP-data is given annually, and we can only estimate cross-spectra from series measured at the same frequency. Similarly, although the NNP-series start already in 1850, we can only use them from 1870 on, since Ronge’s index is not available before.

Thus we have to rely on parametric estimation. We will estimate a bivariate vector autoregression (VAR) model, which is the most common approach in the literature.\(^7\) To ensure comparability we use a VAR-order of \(p = 3\) for all models.\(^8\)

The VAR-parameters could be obtained by OLS, but we prefer a multivariate version of the Burg-method, which yields better estimates than OLS (Trindade 2000). It minimizes the mean of the forward- and the backward prediction error. The multivariate version was developed by Strand (1977) and Morf and A. Vieira (1978).\(^9\)

5 Results

5.1 Real vs nominal variables

In this section we first show that the deflated NNP series, although employed intensively in the literature so far, are bad indicators for the business cycle. Instead we propose to look at nominal variables. In a second step, we show that looking at real single indicators such as iron and steel production justifies our findings.

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\(^6\)Broersen (2000) shows that for reasonably small samples, parametric estimators yield better spectral estimates than non-parametric estimators.

\(^7\)A’Hearn and Woitek (2001) use a VAR(5) to estimate explained variance between IP-series from various countries. In a univariate context, Broersen (2000) also showed that for sample sizes \(N < 250\) AR-models are to be preferred.

\(^8\)We experimented with other lag structures, however with little effect on the results. Data availability imposes narrow limits on feasible lag lengths.

Next, note that we can only compare three series in current prices with each other, because Output was constructed in volumes, not in values, and thus is originally a real index. We would have to introduce prices by force, thus creating the bias we want to avoid here. However, for completeness we will compare Output to the small set of real indicators and show that is far from performing well.

![Graph](image)

Figure 3: NNP (current prices) Germany 1851-1913.

Comparing the other NNPs in current prices to the deflated NNPs (Figure (3)) one can make at least three observations: First, nominal Expenditure and nominal Income move similarly, but Expenditure’s level is higher, which is because Expenditure is measured at market prices, whereas Income and Taxes at factor costs. Second, Taxes is smoother than the other two, and starts at a higher level. Third, all series’ variation changes severely after deflating, especially Taxes’ variation. It is very smooth in current prices, but outstandingly variable after deflating. Income, however, seems to loose variability especially up to ca. 1890. The 1870s hump almost disappears. Expenditure, however, seems to increase in variability after 1890, a heavy kink is introduced just prior to 1900.¹⁰

Turning to the cycles around the HP(6.25)-trend (Figure 5) it becomes clear that the nominal series exhibit a much clearer picture than the deflated series. This is surprising, as one should expect the correlation between the

¹⁰Note that we refer here to Hoffmann’s (1965) series and not to Burhop and Wolff’s (2005) revised series to be sure that the change is due to deflating alone.
different series to increase when multiplying them with the same price index. The explanation is twofold: First, Taxes’ is up to 60 percent higher in levels than the other series. Thus, multiplying it with the deflator, which can be as big as 1.74, results in much bigger changes. Second, the deflator and Income and Expenditure partly cancel each other out, so that variation decreases.

The interpretation of the deflated series led to a misinterpretation of the German business cycle before World War I in Burhop and Wolff’s (2002) working paper. They argue that there might have been a downturn in the early 1870s, since the deflated Taxes series exhibits a downturn around various trend measures (pp. 8ff). They also notice that Taxes exhibits a larger variance than Income and Expenditure (pp 13f). However, those observations are caused by deflating the nominal series with Hoffmann’s (1965) price index that went up in the early 1870s, and is very volatile before 1880 (Figure 4).

The overall result is that the cycles from the real series are anything but clear, and that some interpretations about the business cycle found in the literature are a figment of the deflation procedure.
5 RESULTS

Figure 5: NNP (current prices), deviation from trend, Germany 1851-1913.

5.2 Comparison of nominal variables with the stock market

We will first introduce some results from spectral analysis in detail and give an overview over the explained variance for a number of series. Figure (6) shows the bivariate spectrum matrix of Expenditure and Ronge’s (2002) stock market index (hereafter “Ronge”). The upper left graph is the normalized autospectrum of Ronge, the middle right one Expenditure’s autospectrum. The upper right and middle left graphs are cross spectra, from which squared coherence (lower left) is calculated. Explained variance is the area below the dotted line in the lower right graph relative to the area below the straight line.\(^{11}\) Since explained variance is not symmetric (similar to \(R^2\)), we present an arithmetic average of the two values at hand. The model specification is a VAR(3), where the coefficients are estimated with the Nutall-Strand method. If not stated otherwise, HP(6.25)-filtered data are used, and we employ Ronge’s stock market index. Baxter-King-filtered data are presented where necessary as well as variance explained by Eube’s (1998) index.\(^{12}\) Here we find that 58 percent of Expenditure’s variance is explained by Ronge. Together, the two series follow a common cycle of 7 years and 2 months.

\(^{11}\)We cover the frequency range of 3-10 years, i.e. common cycles of longer or shorter duration do not contribute to explained variance.

\(^{12}\)Results for other specifications can be obtained from the authors on request.
Results for Income are given in Figure (7), among others. It shows only the graphs of explained variance, as it contains the most important information. Ronge’s index explains 61 percent of the variance in Income, with the same cycle length as in Expenditure.

Figure (7) shows also the variance in Taxes (upper right) explained by the Ronge stock market index. The area under the dotted line covers only 46 percent of the total area that represent total variance. The cross spectrum peaks at 6 years, 10 months.

Table (1) provides an overview of the analyzed series. Note that Hoffmann’s (1965) and Hoffmann and Müller’s (1959) original series are covered as well as Burhop and Wolff (forthcoming) revisions. We present HP-filtered series as well as Baxter-King filtered ones. Additionally, the variance explained over frequency bands is provided: the first corresponds to 3-10 years,
Figure 7: Share of variance in Income, Taxes, and Capital stocks explained by Ronge’s stock market index.

which covers Kitchin and Juglar cycles, and the second the narrower band of 7-10 years, which corresponds only to Juglars.

The table shows that Income is explained better by Ronge’s stock market index than Expenditure and Taxes. The bad performance of Taxes may confirm a suspicion by Burhop and Wolff (forthcoming): Due to the Prussian income tax code in force until 1890, the cycles in Taxes should be damped.\textsuperscript{13}

\textsuperscript{13}Taxes were raised in Prussia by distinguishing between fixed and variable income. Fixed income was taxed within the same year, whereas variable income with a delay of one year, sometimes averaging over the three preceding years (Hettlage 1984). As a result, tax revenues are a time-varying moving average of past realizations of the tax base.
Table 1: Shares in variances of nominal series explained by Ronge’s (2002) stock price index

After tax reforms in 1891, this system was abolished, which might be the reason for Taxes’ more pronounced cycles after 1890.

It is astonishing that the stock market does not explain the corrected Expenditure series as well as the original one. This applies also to Income, which at least is not explained significantly better after correction. Both series are based on Burhop and Wolff (forthcoming) new capital stock. They introduced a method to extrapolate the Baden capital stock from Schremmer (1987) to Germany, and try to account for regional differences in industrial development. Surprisingly, this seems not to have improved the cyclical properties of the new capital stock series (see Figure (7), lower graphs). Explained variance over for 3-10 year-cycles is only 28 percent for the new capital stock series, but 40 percent for the old one. Thus series that depend on the new capital stock are likely to have worse cyclical properties, when compared to old capital stock-dependent series.

Since Income is found to be the series being closest to the financial market benchmark, we need to investigate this series more closely. It consists of capital income, labor income and foreign capital income. Foreign capital income is assumed to be zero by Hoffmann (1965, p. 510). Which of these subseries contributes most to the good cyclical properties of Income? The average wages are left untouched by Burhop and Wolff (forthcoming), but the capital stock and the return series are changed. The former has rather introduced worse cyclical behavior, but the return series – assumed by Hoff-
mann to be simply a constant (Hoffmann 1965, p. 502) — is now changing over time. Burhop & Wolff (forthcoming) proxy firms’ profits by dividends and obtain a series with pronounced cycles.

![Graph](image)

Figure 8: Burhop and Wolff’s (2005) return series and the variance explained by Ronge’s stock market index.

Figure (8) shows the cyclical behavior of the new return series. With our default model specification, 65 percent of the variance are explained by the stock market. Thus we have identified a major source of Income’s cyclical behavior.

This result is not surprising, though, since the return series was derived from dividends. With our research strategy it must perform well by construction, and therefore contains no information for our purpose.

The construction of the wage series, on the other hand, is not connected to the stock market. It was calculated from social security statistics collected in seven single years between 1884 and 1914, which are interpolated by daily wages in the grand duchy of Baden. For this reason, there is no a priori reason to assume the cyclical properties of Wages to be particularly good. However, it turns out that with 70 percent the variance in Wages is in fact even better explained by the stock market than that of Returns (Figure 9).

To sum up, the capital stock series seems to distort the cyclical properties of the return series, and the return series is partly connected to the stock market by construction. Since Wages are constructed independently from financial data, but have similar cyclical properties, we conclude that they
should be investigated more closely for business cycle dating.

5.3 Nominal indicators and real business cycles

Before finally dating the business cycle, we have to check that we are not only talking about price changes, since both Wages and stock prices are denoted in nominal terms here. Recall that we decided to look at nominal series, because the quality of deflated series is distorted by our insufficient knowledge about the correct amount of price information contained in the nominal series. Thus our strategy is first to look at nominal series and then justify afterwards why we still can learn something about real business cycles.

First, we compare different price indices to our nominal series in order to assess how much of their movement is due to prices. Being aware that none of the given indices reflects the behavior of the price level correctly, we compare across three indices: Hoffmann’s (1965) price index, the wholesale price index by Jacobs and Richter (1935), and an index proposed by Ronge (2002) to deflate his stock price index. We find that prices seem to drive around 50–60 percent of the stock market’s variation, and for roughly 30–40 percent of the variation of Wages (Table 2). We also looked at the share of explained variance that is due to cycles of the same frequency and is in phase. The variance by Wages that is explained by prices is almost entirely
in phase, whereas the explained variance of the stock price index is not, but shifted in time by 2–3 years (Table 2 and Figure 10).\footnote{This implies that real wages might be more or less acyclical, which would confirm the empirical motivation for the debate about RBC-models and the relation between real wages and hours worked (See e.g. Christiano and Eichenbaum (1992)). However, when we deflate Wages, the result is not a flat series, but one with a cyclical time-series behavior that neither resembles the stock price index nor any price index.}

<table>
<thead>
<tr>
<th>Prices</th>
<th>Stock Market (Ronge 2002)</th>
<th>Wages (Hoffmann 1965)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EV \textit{in phase}</td>
<td>EV \textit{in phase}</td>
</tr>
<tr>
<td>HP, 3-10 y.</td>
<td>62% 6%</td>
<td>48% 24%</td>
</tr>
<tr>
<td>HP, 7-10 y.</td>
<td>26% 0.3%</td>
<td>12% 6%</td>
</tr>
<tr>
<td>BK, 3-10 y.</td>
<td>54% 4%</td>
<td>36% 20%</td>
</tr>
<tr>
<td>BK, 7-10 y.</td>
<td>27% 0.2%</td>
<td>20% 16%</td>
</tr>
<tr>
<td>HP, 3-10 y.</td>
<td>38% 94%</td>
<td>53% 83%</td>
</tr>
<tr>
<td>HP, 7-10 y.</td>
<td>13% 92%</td>
<td>22% 93%</td>
</tr>
<tr>
<td>BK, 3-10 y.</td>
<td>32% 95%</td>
<td>34% 73%</td>
</tr>
<tr>
<td>BK, 7-10 y.</td>
<td>14% 93%</td>
<td>19% 92%</td>
</tr>
</tbody>
</table>

EV: Explained variance, HP: Hodrick-Prescott (6.25)
BK: modified Baxter-King (K=3, 2-15 years band), VAR(3)

Table 2: Variance explained of nominal stock prices and nominal wages by various price indices.

Second, comparing the stock price index to typical business cycle indicators for the 19th century we find that nominal stock prices are driven by real business cycle indicators as well as by price movements. Table (3) shows that heavy industry production explains between 44 and 52 percent of stock price movements. From Figure (11) we can obtain that both turning points as well as amplitudes of the volume indicators are reflected well in the stock prices. Note that the stock market leads real indicators by one to two years.
Figure 10: Hoffmann’s (1965) wages series and three price indices

An interesting finding here is that steel and iron production have around 30 percent variance in phase with the stock price index, whereas coal production and railway transport exhibit greater time shifts. We can show that the stock market in fact leads those industries by one to three years. This indicates that coal production and railway transport lag the business cycle more than iron and steel production.\textsuperscript{15}

Finally, we checked how much of Hoffmann’s (1965) Output series is explained by the real indicators we use. It consists mainly of an industrial production index, so the single indices we used above should be parts of it. It turns out that Output only captures a quarter to a third of the real indicator’s variation. Note that Burhop and Wolff’s (2005) revised Output

\textsuperscript{15}This will be investigated more deeply in a later version of this paper.
Table 3: Variance explained of nominal stock prices and real business cycle indicators.

<table>
<thead>
<tr>
<th></th>
<th>Steel</th>
<th>Railway</th>
<th>Coal</th>
<th>Pig Iron</th>
</tr>
</thead>
<tbody>
<tr>
<td>EV</td>
<td>in phase</td>
<td>EV</td>
<td>in phase</td>
<td>EV</td>
</tr>
<tr>
<td>HP, 3-10 y.</td>
<td>48%</td>
<td>68%</td>
<td>44%</td>
<td>52%</td>
</tr>
<tr>
<td>HP, 7-10 y.</td>
<td>24%</td>
<td>24%</td>
<td>16%</td>
<td>19%</td>
</tr>
<tr>
<td>BK, 3-10 y.</td>
<td>48%</td>
<td>54%</td>
<td>42%</td>
<td>44%</td>
</tr>
<tr>
<td>BK, 7-10 y.</td>
<td>32%</td>
<td>33%</td>
<td>28%</td>
<td>28%</td>
</tr>
</tbody>
</table>

EV: Expl. variance, HP: Hodrick-Prescott (6.25), BK: modified Baxter-King (K=3, 2-15 years band), VAR(3)

series explains less than Hoffmann’s (1965) original series. There seem to be additional sources of cyclical variation in Output.

Thus we could show that around half of the variation of the stock prices we look at is not driven by prices, but reflects real movements. Additionally, there is a time shift between stocks prices and the general price level. Wages are in phase with the price level, but 60–70 percent are not explained by prices. We therefore allegedly have found a way to bypass the problems in business cycle dating arising from incorrect price indices. We argue that nominal indicators, although containing price information, tell more about the correct dating of real business cycles than incorrectly deflated NNP series.

5.4 The business cycle 1870–1914

We begin this section by plotting wages and Ronge’s stock market index across time (Figure (12)).

Note that not only have wages and the stock market a similar cyclical structure in the frequency domain, but exhibit also a very similar cyclical pattern in the time domain. What matters here is not the amplitude of the cycles but rather the phase of its turning points. In order to make sure that this is not a figment of the data, we plot also a Baxter-King filtered series against Eube’s (1988) index (Figure 13).

In Figure (13) there is no major deviation from the predominant pattern: Stock markets and wages moved mainly in the same direction, and stocks
Figure 11: Ronge’s (2002) stock prices and four real indicators.

precede wages by roughly one year. This can be explained by forward looking investors (see Section 2).

A comparison of Ronge’s stock market index with the NBER reference cycle, Spiethoffs (1955) dating scheme and Burhop and Wolff’s (2005) “Compromise”-series shows mainly a congruency of the indicator based dating procedures, but some difference to the national accounting methods.

Except for the additional NBER cycle of 1904–1907 and the last peak before World War I, all peaks and troughs in Ronge/NBER occur at the same year plus/minus one year, which is very close for annual data. Ronge’s

\[\text{Gründerszeit} \]

boom of the 1870s (15%) compared to the other plots (~8%).

\[\text{Differences appear in the volatility of the series. The HP-filtered plot with Ronge's (2002) stock market index exhibits a particularly sharp upswing during the Gründerszeit boom of the 1870s (15%) compared to the other plots (~8%).}\]
Figure 12: The cyclical behavior of Hoffmann’s (1965) wages series and Ronge’s stock market index in the time domain.

(2002) stock market index seems to have a slight tendency to lead the NBER reference dates. Spiethoff (1955) finds an additional trough in 1883/84, and a peak in 1906/07, which is two years later than Ronge and NBER. He also finds a peak directly before the war in 1912/13.

Although we already excluded the minor cycles from Burhop and Wolff’s (2005) “Compromise”-series, their business cycle dating differs more from the already mentioned ones. It finds an additional peak 1874, right after the Gründerzeit-boom, and a trough in 1891, not found by the others. The late peak in the first decade of the 20th century is also included in their dating, but after that they find no peak anymore at all.

In our view, Burhop and Wolff’s averaging procedure does not clarify the picture, since it takes an average of four series that are already biased by the price deflator. Since this led to series being partly countercyclical to each other or shifted in time, the resulting series spuriously exhibit a number of smaller additional cycles, and the important ones are damped.
At the same time, the comparison of our results to the NBER reference cycle shows a striking similarity, which can be understood as a confirmation of the indicator method for 19th century business cycle dating, as opposed to the national accounting approach.

Bry (1960) reports evidence of wages lagging the business cycle.\textsuperscript{17} He explains the delay by an observation lag of business cycle conditions, and the lags in the wage series resulting from collective bargaining between employers and workers. However, when plotting Hoffmann’s (1965) wage series against one of Bry’s (1960) most prominent wage series, hourly wage rates for hewers and haulers from Dortmund, we find a high similarity between those series.

\textsuperscript{17}Earnings seem to lead the business cycle less than wages (Bry 1960, pp. 139ff)
(69% explained variance), and no evidence of a phase shift (Figure 14). Both series are shifted by only one or two years relative to Ronge’s (2002) index and the NBER’s reference turning points. This appears to call Bry’s view into question, as some of the lag should be explained by the forward looking property of the stock market. Still, we hesitate to discard Bry’s (1960) interpretation entirely, as he reports evidence from a wide range of industries which goes beyond Hoffmann’s data base. Thus we should look for the “true” business cycle between Ronge’s index and Hoffmann’s average wages. This could be done by disregarding the slight tendency of the stock market to precede the reference cycle, thus bringing our dating even closer to the NBER reference points. Except for the troughs in 1871 and 1887, the NBER dating can be confirmed then. The stock market peak of 1910 should be substituted by a later date, since wages peak only in 1912. Table (3) contains the dating which follows from considering wages and the stock market.

The historical impact of our series therefore is not revolutionary. Quite on the contrary, we are broadly able to reconfirm the traditional business cycle dating by the NBER and Spiethoff. What we can clearly rule out,
5 RESULTS

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Trough</td>
<td>Peak</td>
<td>Trough</td>
<td>Peak</td>
</tr>
<tr>
<td>1    1871</td>
<td>1872</td>
<td>1870</td>
<td>1872</td>
</tr>
<tr>
<td>2    1878</td>
<td>1881</td>
<td>1878</td>
<td>1882</td>
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<td>3    1887</td>
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<td>1902</td>
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<tr>
<td>6    –</td>
<td>–</td>
<td>1904</td>
<td>1907</td>
</tr>
<tr>
<td>7    1908</td>
<td>1910</td>
<td>1908</td>
<td>1913</td>
</tr>
</tbody>
</table>

NBER as cited in Bry (1960, pp474f)
Spiethoff’s dating procedure adapted for comparison: Peaks between slumps and booms, troughs between booms and slumps.
Compromise from Burhop and Wolff (2005). They report troughs also in 1873, 1877, 1886/87, 1906, and peaks in 1874, 1878, 1883/84, 1893, and 1905, but with lower intensity.

Table 4: Comparison of business cycle dating for Germany, 1870-1913.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trough</td>
<td>1871</td>
<td>1878</td>
<td>1887</td>
<td>1894</td>
<td>1902</td>
<td>1908</td>
</tr>
<tr>
<td>Peak</td>
<td>1873</td>
<td>1882</td>
<td>1890</td>
<td>1900</td>
<td>1905/6</td>
<td>1911</td>
</tr>
</tbody>
</table>

Table 5: Business cycle dating for Germany, 1870-1913.

however, is a tendency in parts of the literature to question the real effects of the Gründerzeit/Gründerkrise boom and bust of the 1870s on national product (Burhop and Wolff 2002). This view is suggested by the deflated Taxes series. We find that this results from the cycle-distorting impact of the price deflator and can therefore be dismissed as a figment of the data. Looking again at the nominal series, the business cycle of the 1870s reappears and is alive and well.

However, we are unable to revive an older long-swing hypothesis of a downturn between 1873-1896 (the "Great Depression" of the late 19th century), which had already be proclaimed dead by e.g. Spree (1978). There seems to be no resurrection of the Great Depression from our data.
6 Conclusions

Business cycle analysis for the 19th century with national accounting methods generally suffers from a weak data base and often inadequate statistical methods. As a result, alternative estimates of doubtful reliability lead to conflicting business cycle chronologies. In this paper, we examine the cο-movement of financial markets and national income for a number of rivaling series for Germany, applying spectral analysis. Under the efficient capital market hypothesis, there should be tight cο-movement between stock markets and the real economy, expressed in the frequency domain by high cοherency between the power spectra. We employ cοherency with financial markets as a selection device between the rivaling income series, and construct a new business cycle chronology for Germany between 1850 and 1913. some

We find that the real series provided by Hoffmann (1965) and Hoffmann and Mueller (1959) suffer strongly from the deflating procedure. We therefore propose to look at nominal series. Among these, Hoffmann’s (1965) Income series has the highest share of variance explained by a representative stock market index. Its subcomponent, an average wage series for Germany, exhibits surprisingly high cοherency with the stock market. We show that the same property obtains for an alternative wage series from Bry (1960), which cover a wider set of industries than the series reported by Hoffmann (1965).

Using those series to date business cycle, we are able to confirm the traditional views for Germany from Burns’ and Mitchell’s (1946) NBER chronology, as well as those of Spiethoff (1955). This also implies that we discard later interpretations that have suggested different chronologies. Among our main findings is the reappearence of both Gründerzeit and Gründerkrise, the boom and bust of the 1870s, in the income and output data. On the other hand, we are unable to resuscitate the Great Depression of the 1880s, which is absent from any of the series we examined.

Our findings have potential implications for the methodology of historical business cycle research. We add to a small but growing literature that for-goes reconstructed national account data in favor of the higher information content in real time price data. In a companion paper Sarferaz and Uebele
(unpublished) go further by employing dynamic factor models to reconstruct the business cycle chronology for Germany, further confirming the results of the present paper.

Our methodology also lends itself to application for other countries, and may help to shed further light on long-standing debates about business cycle dating and frequency.
References


REFERENCES


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