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Moments of cross-sectional stock market returns and the German business cycle

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Abstract

Based on monthly data covering the period from 1987 to 2021, we analyse whether cross-sectional moments of stock market returns may provide information about the future position of the German business cycle. We apply in-sample forecasting regressions with and without leading indicators as control variables, pseudo-out-of-sample exercises, autoregressive distributed lag models, and impulse-response functions estimated by local projections. We find in-sample predictive power of the first and third cross-section moments for the future growth of industrial production, even if one controls for well-established leading indicators for the German business cycle. Out-of-sample tests show that these variables reduce the relative mean squared error compared with benchmark models. We do not find a long-run relation between the moment series and industrial production. The dynamic response of industrial production to a shock on the cross-section moments is in line with the other results.

KEYWORDS

business cycle, Germany, leading indicator, stock market cross-sectional moments

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1 | INTRODUCTION

For decades, the relationship between stock markets and the real economy has been of substantial interest to academics, investors, and policymakers (Panetta, 2002). In particular, prices on stock markets have always been considered as a potential major indicator of the business cycle. This might be motivated by the discounted-cash-flow valuation model, which states that stock prices reflect investors' expectations about economic variables such as corporate earnings (Hahn, 2005; Kuosmanen & Vataja, 2011, 2019). As long as these expectations are generally correct, lagged stock returns should correlate with the future development of the business cycle. It is possible, though, that not only the average return may help to predict future economic conditions, but information incorporated in the cross-section of stock market returns might also be valuable. First, as already mentioned, a change in the mean of returns will correspond to changed expectations about economic prospects (Fama, 1990; McMillan, 2021). Second, a change in the second moment of the returns represents an uncertainty shock (Bloom, 2009) or an idiosyncratic (supply) shock hitting the economy (see, among others Loungani et al., 1990). Third, variations of the third moment can be due to waves of optimism or pessimism (Di Bella & Grigoli, 2019; Ferreira, 2022).

Much of the relevant empirical literature on the relationship between stock returns and economic activity focuses on the US. There is significantly less research on other countries (Kuosmanen & Vataja, 2011; Tsouma, 2009). Against this background, we investigate whether the first three moments of cross-sectional measures of stock market returns have predictive power for the German business cycle. The limitation of the analysis to Germany has two reasons.

First, small and medium-sized enterprises (SMEs) form the backbone of the German economy, but are not listed on the stock exchange (Audretsch & Elston, 2002; Mueller & Spitz-Oener, 2006). However, compared with the SMEs in the other EU states, small and medium-sized enterprises in Germany are, on average, larger. In 2018, for example, some 3.47 million companies were SMEs, which corresponds to 99.5% of all companies that had sales from goods and services in Germany. Furthermore, in 2018, SMEs generated 34.4% of total sales in Germany with almost 2.40 trillion euros. In 2018, German SMEs had around 17.77 million employees subject to social security contributions, which was 57.6% of all employees subject to social security contributions. The contribution of SMEs to the total net value added of all enterprises was about 61.1% in 2018 (Institut für Mittelstandsforschung, 2022).

Second, Germany has a bank-based financial system. Against this background, it is interesting to examine the extent to which the stock returns of listed German companies have predictive power for the German business cycle. For example, Angelidis et al. (2015) examined the information content of stock market liquidity on economic conditions for the UK and Germany. Their empirical results suggest that stock market liquidity and economic indicators are strongly related in both economies, even though the UK is a capital market-based economy and Germany is a bank-based economy. In addition, they demonstrate—for both countries—that small-cap firm liquidity is more important for predicting the business cycle than large-cap firm liquidity. The reason for this is arguably that investors shift their portfolios from illiquid small-cap stocks to less risky large-cap stocks with higher liquidity (the 'flight to quality' effect) when expectations for the future state of the economy change. Since the German economy is predominantly composed of small and medium-sized firms, we want to build on the findings on the importance of small-cap stocks to investigate whether the first three moments of cross-sectional measures of stock market returns have predictive power for the German business cycle.

We use monthly German data from 1987¹ to 2021 and employ a wide range of techniques to analyse the leading indicator properties of a time series: First, we run in-sample forecast regressions with and without other leading indicators as control variables. Second, we employ pseudo-out-of-sample exercises, and autoregressive distributed lag (ARDL) models to check whether the variables help to forecast industrial production at business cycle frequencies and test for a possible long-run relation between the variables. Third, we present an impulse-response function (IRF) analysis estimated by local projection to illustrate the dynamic interaction between the cross-section moments and industrial production. We also

¹The CDAX[®] was created in 1987 and, thus, the sample starts with this first observation. We use the largest possible sample, since we found no hint for a structural break related, for example, to German unification.

compare our results with those from previous evidence and explain the differences. To the best of our knowledge, this is the first paper to investigate whether cross-sectional moments of stock market returns may provide information about the future prospects of the German business cycle. With the cross-sectional skewness, we continue to consider a measure that is currently gaining in importance in the literature (Ferreira, 2022; Vicente & Araujo, 2018). Therefore, we look at a wider range of information that is helpful in the context of extreme movements in the form of tail risks.

We find that the first and third moments of the cross-section of stock market returns provide information about the future stance of the economy: they appear to be statistically significant with the expected sign of the coefficient in a simple in-sample forecasting regression. Moreover, in a pseudo-out-of-sample exercise, the use of indicators substantially reduces the relative mean squared errors (MSEs) compared with forecasts backed out from a simple autoregressive process as a benchmark, at least for forecast horizons of 3 and 6 months. Results concerning the second moment are less encouraging: in this case, the coefficients in the forecasting regressions are often not significantly different from zero, and the relative MSE is close to one. We cannot establish a long-run relationship between the possible indicators and industrial production using an ARDL framework. IRFs obtained from local projections point to a negative impact of cross-sectional skewness on industrial production within 9 months.

We organize the remainder of the paper as follows: Section 2 reviews a selection of the related literature; Section 3 describes the data used and the data transformations made; Section 4 presents the main empirical results, and the last section concludes.

2 | LITERATURE REVIEW

A broad strand of the literature is related to our analysis of the leading indicator properties of the cross-sectional moments of stock market returns for the German business cycle. To give a brief overview, we organize this section along with the different moments of stock market returns. We also ask which additional evidence on cross-sectional measures based on variables other than stock market returns might be of interest in this context.

2.1 | Mean returns

A large body of work found evidence that financial variables, in general, and stock market returns, in particular, can predict future economic activity. For instance, Fama (1990) and Schwert (1990) investigate the relationship between stock returns and industrial production for the US and find evidence that stock returns provide information about the prospects of the country's economy. Furthermore, Choi et al. (1999) show that this also holds for most G7 countries. Drechsel and Scheufele (2012) find that stock market returns are part of a large data set that helps to predict industrial production in Germany. Similarly, Kitlinski (2015) finds share prices among those financial variables that help to forecast German industrial production.

2.2 | Variance, standard deviation, dispersion

Several studies argue that measures of the second moment of the cross-section of stock market returns provide information regarding the macroeconomic situation. For example, Loungani et al. (1990) argue—based on a seminal paper of Lilien (1982)—that the dispersion measures of stock markets can be used to investigate the influence of reallocation shocks on unemployment. Similarly, Loungani et al. (1991) find that stock market cross-section variance might serve as a leading indicator for the US business cycle. Ball and Mankiw (1995) use the dispersion of prices to disentangle aggregate demand and supply shocks. The approach is also applied to German data by Döpke and Pierdzioch (2003). The use of the dispersion owes to the idea that a supply shock hits the sectors of an economy in a rather asymmetric way and, therefore,

drives relative prices apart, while a demand shock, by contrast, is assumed to influence all sectors of an economy in a more or less similar way and has no considerable impact on price dispersion. Bloom (2009) employs vector autoregressive (VAR) models to obtain estimations of volatility shocks for the US. The results show a rapid fall and a subsequent recovery to the previous level of industrial production and employment in the first 12 months after the shock. In more recent studies, Angelidis et al. (2015) find evidence that the cross-sectional standard deviation of stock returns from the G7 countries reliably predicts time variations in economic activity. They show that a relatively high return dispersion predicts a deterioration in business conditions. Furthermore, Vu (2015) investigates the time series and cross-sectional responses of output to fluctuation in stock market volatility across 27 countries over 40 years. He shows that high levels of stock market volatility are detrimental to future output growth. However, the focus on the first (mean) and the second moment (variance) does not consider the importance of tail risks as measured by the third moment (skewness).

2.3 | Cross-sectional skewness

Primarily, our paper investigates the cross-sectional skewness of stock returns as a leading indicator of the business cycle. In this context, Vicente and Araujo (2018) propose three leading indicators related to the tail of the cross-sectional distribution of stock returns: (1) the left tail percentile of stock returns at each point in time; (2) the expected shortfall of the cross-sectional stock returns; (3) an indicator that uses the extreme value theory to model the behaviour of asset prices, according to Kelly and Jiang (2014). For Brazil, they find evidence that the three leading indicators have a high correlation with future economic conditions, and that the indicators usually make better out-of-sample predictions than the random walk and the average of previous observations. Furthermore, Dew-Becker et al. (2021) examine the asymmetry of economic activity over the business cycle. To this end, they develop a multi-sector model in which the complementarity of inputs leads to a left skewness of aggregate activity. Subsequently, they examine the implications for time-series skewness, cyclicity of cross-sectional dispersion and skewness, and conditional covariances of sectoral growth rates. They find that the data are in favour of each of these factors. In addition, they show empirically that skewness increases with the level of aggregation, consistent with the model's assumption that it is due to nonlinearity in the structure of production. Related, Ferreira (2022) argues that the cross-sectional skewness of stock market returns is a leading indicator for the US business cycle, even if one controls for other standard leading indicators. Beyond that, Dew-Becker (2022) measures option-implied skewness for individual firms and the entire stock market between 1980 and 2021, which provides real-time measures of conditional micro and macro skewness. His results show that skewness at the microeconomic level is significantly procyclical, while macro skewness is acyclical. Further, micro skewness leads the business cycle and is strongly associated with credit spreads, suggesting a possible causal channel. Moreover, he shows that the micro skewness is significant but not mechanically correlated with macro volatility, implying that there is a common shock driving both that is also associated with the business cycle. Also, Salgado et al. (2019) establish a procyclical behaviour of the skewness of the growth rates of sales.

They argue that two other relations are already well-known: a first-moment shock and a second-moment shock, which they interpret as an uncertainty shock. Additionally, a negative third-moment shock (skewness shock) 'implies that, during economic downturns, a subset of firms and countries does extremely bad, leading to a left tail of very negative outcomes' (Salgado et al., 2019, p. 1). While the cross-section of prices or sales/production provides information on the contemporaneous state of the economy, the respective information for stock market returns might have additional information, since stock markets are forward-looking. Furthermore, in another strand of literature, several authors have pointed out that rare disasters—presumably due to an asymmetric distribution of shocks—can cause large fluctuations in economic activity, such as the Great Recession. For example, Barro (2006) revisits the ideas of Rietz (1988) and uses a country panel to estimate the probability of large disasters, arguing that these low-probability events can have significant effects on aggregate economic activity and asset pricing. The importance of variations in disaster risk for aggregate economic activity has been confirmed by various works (see, among others, Gabaix, 2012; Gourio, 2012; Kozeniasukas et al., 2018). Beyond the work mentioned above, there continues to be a broader finance literature that examines

skewness at the firm level, but almost exclusively in the context of option prices or return forecasts (e.g., Dennis & Mayhew, 2002, Bollerslev & Todorov, 2011, and conrad2013ex, among others).

3 | DATA

3.1 | Stock market data

We calculate three cross-sectional distribution measures of German stock market returns based on monthly data covering the period from 1987 to 2021. Each is calculated in a conventional manner, as well as by a robust measure. Thus, we consider the mean of the distribution and the median. In a similar vein, we look at the standard deviation and the interquartile range. Finally, we calculate the skewness and the skewness in a robust form, as suggested by Kelley (1947). We apply continuously compounded total returns² for each of the $j = 1, \dots, N$ stocks within the sample as: $r_{j,t} = \log(SR_{j,t}/SR_{j,t-1})$. Where (SR_j) denotes the monthly closing price of stock j and t denotes the month. With these returns at hand, we calculate the following cross-section moments of the returns: (i) The cross-sectional mean ($\bar{M}_t = \omega_j r_{j,t}$) and the respective median ($\bar{M}_t = r_{j,t}^p$) where $r_{j,t}^p$ is the p th percentile of the distribution of log-returns at time t .³ (ii) The cross-sectional standard deviation ($S_t = \sqrt{\sum_{j=1}^N \omega_j (r_{j,t} - \bar{M}_t)^2}$) and its robust counterpart, the interquartile range ($IQR_t = r_{j,t}^{0.75} - r_{j,t}^{0.25}$). (iii) We focus, however, on the cross-sectional skewness:

$$SK_t = \sum_{j=1}^N \omega_j \left(\frac{r_{j,t} - \bar{M}_t}{S_t} \right)^3. \quad (1)$$

The disadvantage of the conventional skewness measure is that its values can be spuriously large, especially when there are outliers in the returns. For this purpose, we use a second robust measure of skewness: The Kelley (1947) measure (Kim & White, 2004; Salgado et al., 2019), which is defined as⁴

$$SKR_t = \frac{(r_t^{90} - r_t^{50}) - (r_t^{50} - r_t^{10})}{(r_t^{90} - r_t^{10})}. \quad (2)$$

We calculate all measures for two weights given to each share: First, we use an equal $\omega_j = 1/N$ weight; second, we use a weight based in the market capitalization for each firm.

We calculate cross-sectional return measures based on all stocks that have been part of the CDAX^{®5} at a certain point in time. In all, our sample comprises 413 individual stocks, some of them only temporarily.

²We restrict the analysis to this kind of returns since the correlation with discrete returns is very high in our sample (e.g., +0.97 for the cross-section mean of the returns).

³Consequently, $r_{j,t}^{0.5}$ denotes the respective median.

⁴The Kelley skewness can also be calculated using any pair of (symmetric) percentiles. Hence, as a robustness check, we also run some regression using the Kelly skewness defined as

$$SKR_{2,t} = \frac{(r_{j,t}^{0.99} - r_{j,t}^{0.50}) - (r_{j,t}^{0.50} - r_{j,t}^{0.01})}{(r_{j,t}^{0.99} - r_{j,t}^{0.01}) - (r_{j,t}^{0.99} - r_{j,t}^{0.01})}.$$

⁵The abbreviations DAX[®] and CDAX[®] stand for 'Deutscher Aktien Index' (German Stock Index) and 'Composite' DAX[®], respectively. The full spectrum of the German stock market the CDAX[®] was launched on 17 September 1993 and is calculated as a price and performance index by Deutsche Börse (2022). The calculation is based on 30 December 1987 at a value of 100 points. The historical time series goes back to 1970. All German companies in the Prime Standard and General Standard are represented in the CDAX[®]. The index thus presents the full spectrum of the German equities market and serves as an indicator of economic development Deutsche Börse (2022).

TABLE 1 Descriptive statistics of the cross-section return moments, 1987–2021

Cross-section moment	Descriptive statistics				
	Number of observations	Mean	Standard deviation	Min.	Max.
<i>Measures based on 1/N weights</i>					
Mean	420	−0.0002	0.054	−0.255	0.158
Median	420	0.0003	0.047	−0.260	0.127
Standard deviation	420	0.131	0.056	0.037	0.425
Interquartile range	420	0.106	0.036	0.040	0.276
Skewness	420	−0.038	2.476	−12.447	10.441
Kelley (1947) skewness	420	0.006	0.162	−0.492	0.499
<i>Measures based on market capitalization weights</i>					
Mean	420	0.008	0.059	−0.262	0.191
Median	420	0.008	0.059	−0.262	0.191
Standard deviation	420	0.064	0.030	0.027	0.350
Interquartile range	420	0.075	0.038	0.016	0.383
Skewness	420	0.071	1.328	−6.645	8.052
Kelley (1947) skewness	420	0.006	0.257	−0.883	0.706

Note: Own calculation based on data from Deutsche Börse (2022).

In contrast to the DAX[®], which contains the 30 largest German listed companies⁶ and represents around 75% of the total capital stock of domestic stock-listed companies, the CDAX[®] comprises more than 400 companies. This means that the CDAX[®] also includes many firms with small market capitalization, which are more representative of the German economy.

Table 1 presents the descriptive statistics for the equally and market capitalization weighted cross-section return moments. The mean (−0.0002) and median (0.0003) of the equally weighted monthly returns is almost zero. By contrast, the measures for mean (0.008) and median (0.008) based on market capitalization weights are slightly positive. Furthermore, the volatility for the market capitalization-weighted returns is lower (0.064) than the respective volatility calculated for the equally weighted returns (0.131). The skewness for equally weighted returns is negative (−0.038) or almost zero (0.006), whereas both skewness measures based on market capitalization-weighted returns are positive.

3.2 | Business cycle data

The position of the business cycle is measured by the seasonally adjusted index of industrial production in Germany, excluding construction, provided by the Deutsche Bundesbank.⁷

⁶In September 2020, the number of companies included in the DAX[®] was increased from 30 to 40.

⁷The choice of this variable is, first, in line with many papers analyzing the position of the German business cycle. See, for example, Andreou et al. (2000) and Schreiber et al. (2012). Second, procedures to define crises or recessions, which are of particular interest from the perspective of economic policy, often refer to this kind of data. Third, industrial production is still the most volatile part of GDP and, thus, dominates the cyclical behaviour of broader measures of economic activity. Finally, in Germany, industry still represents a relatively large share of overall GDP as compared with other developed countries.

As control variables, we include the following well-established leading indicators of the German business cycle:

- The term spread, that is, the long-term interest rate minus the short-term interest rate. The short-term interest rate is the EURIBOR 3-month funds money market rates (monthly average, source Deutsche Bundesbank (2022)); the long-term interest rate is the yield on debt securities outstanding issued by residents with mean residual maturity of more than 9 and up to 10 years (monthly average, source Deutsche Bundesbank (2022)).
- The change over the previous month of orders received by the German industry at constant prices, calendar and seasonally adjusted (source: Deutsche Bundesbank (2022))
- The business climate index is provided monthly by the Ifo Institute ifo institute (2022).

The control variables enter the estimation as standardized variables, that is, we have subtracted the mean from each variable and divided it by its standard deviation.

4 | EMPIRICAL RESULTS

4.1 | In-sample forecasting regressions

In a first step, we follow Ferreira (2022) and employ simple in-sample forecasting equations. This kind of analysis has been successfully used to evaluate possible leading indicators (Estrella & Hardouvelis, 1991). The basic approach can be described as follows (Kitlinski, 2015): Let Y_t the time series to measure the position of the business cycle - in our case, industrial production. The variable to forecast is given by the annualized average growth rate over the next h months:

$$\hat{Y}_{t|t+h} = \frac{12}{h} \ln \left(\frac{Y_{t+h}}{Y_t} \right). \quad (3)$$

The forecasting equation is given by (Stock & Watson, 2003):

$$\hat{Y}_{t|t+h} = \beta_0 + \underbrace{\sum_{i=1}^p \beta_{1,i} \hat{Y}_{t-i}}_{\text{Lagged endogenous variable}} + \underbrace{\sum_{j=0}^q \beta_{2,j} M_{t-j}}_{\text{Moments}} + \underbrace{\sum_{k=1}^3 \sum_{j=0}^q \beta_{3k,i} \text{IN}_{k,t-j}}_{\text{Control variables}} + \epsilon_t, \quad (4)$$

where stands for M for the cross-section moments and IN represents other potential leading indicators as control variables. The lag lengths p and q were determined by the Akaike (1998) information criterion (AIC) by a backward selection procedure with a maximum of 3 months.⁸ We set the forecast horizon (h) to 3 months.⁹ We assume the lag lengths p equal to 1 and q equal to 0. Under this assumption, the approach of equation (4) boils down to a simple forecast equation as it is suggested by Estrella and Hardouvelis (1991). As is well known, this leads to an overlapping forecast horizon problem and a moving average error term (Estrella & Hardouvelis, 1991). Hence, the estimates are consistent but inefficient. Thus, we employ Newey and West (1987) corrected standard errors. To make the relative importance of the regressors visible, we report beta weights, that is, the regressions are based on standardized time series on both side of the equations. Hence, a typical coefficient represents the impact of the dependent variable measured in standard deviations to a one standard-deviation change of the independent variable.

Table 2 shows a first rough look at the data. The results show a positive impact of mean and median on the future average growth of industrial production, with coefficients significantly different from zero. This holds for 1/ N

⁸We use the procedure provided by Lindsey (2014).

⁹Results for forecast horizons of 6 and 9 months are available upon request from the authors.

TABLE 2 Forecasting equations including cross-sectional stock market cross-section moments for Germany, 1987–2021

	Dependent variable: Standardized average growth rate of industrial production over the next 3 months							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Based on 1/N weights</i>								
Lagged endogenous variable	–0.138 (0.12)	–0.136 (0.12)	–0.134 (0.14)	–0.136 (0.13)	–0.119 (0.13)	–0.135 (0.13)	–0.145 (0.13)	–0.149 (0.12)
Mean	0.244*** (0.09)						0.245*** (0.09)	
Median		0.244** (0.10)						0.196** (0.10)
Standard deviation			–0.145 (0.14)				–0.120 (0.13)	
Interquartile range				–0.118 (0.10)				–0.068 (0.09)
Skewness					–0.025 (0.07)		–0.071 (0.08)	
Robust skewness						0.174*** (0.05)		0.086** (0.04)
Observations	416	416	416	416	416	416	416	416
R ²	0.0738	0.0739	0.0357	0.0285	0.0152	0.0450	0.0932	0.0851
<i>Based on market capitalization weights</i>								
Lagged endogenous variable	–0.134 (0.12)	–0.134 (0.12)	–0.136 (0.12)	–0.130 (0.12)	–0.119 (0.13)	–0.123 (0.13)	–0.145 (0.12)	–0.142 (0.12)
Mean	0.188** (0.09)						0.166** (0.08)	
Median		0.188** (0.09)						
Standard deviation			–0.181 (0.14)				–0.158 (0.14)	
Interquartile range				–0.115 (0.11)				–0.104 (0.11)
Skewness					0.021 (0.05)		0.012 (0.05)	
Robust skewness						0.046 (0.04)		0.032 (0.04)

TABLE 2 (Continued)

	Dependent variable: Standardized average growth rate of industrial production over the next 3 months							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	416	416	416	416	416	416	416	416
R ²	0.0495	0.0495	0.0474	0.0279	0.0150	0.0167	0.0545	0.0609

Note: The results of the regression model described in Equation (4) are reported. Beta weights, that is, coefficients from regressions based on standardized time series are reported. Robust (Newey & West, 1987) standard errors are given in parentheses. *** (**, *) denotes rejection of the null hypothesis at the 1% (5%, 10%), level.

weighted statistics, as well as for those based on market capitalization weighting. Moreover, both measures of cross-sectional variance show the expected negative impact on the average growth over the coming 3 months, albeit not statistically different from zero at conventional significance levels.

Expectedly, an increase in both skewness variables relates to higher future growth, because a positive value of the skewness is a sign of optimism. Additionally, the findings are in line with the results of Ferreira (2022) for US data. In the case of the variables calculated based on market capitalization, the signs of the coefficients are similar, but they are estimated more imprecisely. Therefore, one of the considered cross-section measures is not significantly different from zero.¹⁰

4.2 | In-sample forecasting regressions with control variables

Table 3 shows the results of simple forecasting regressions including selected business cycle indicators as control variables. Again, we present beta weights.

Remarkably, even as the control variables are significantly different from zero, have the expected sign and a notable magnitude, most of the cross-sectional moment variables remain statistically significant for all forecast horizons. The series that represents the cross-section variance constitutes an exception: while the estimations show the expected negative sign and are of substantial magnitude, they are not statistically different from zero. The exercise shows no notable differences between the series based on 1/N-weights and those based on weights from market capitalization, except that the coefficient for the Kelley (1947) skewness measure turns out to be insignificant in the latter case.

4.3 | Comparing out-of-sample forecasting performance

To consider the out-of-sample predictive power of forecasting models with and without cross-sectional skewness variables, we refer to the simplest form of the Diebold and Mariano (1995)-test (DM-test). We calculate the forecast error of a model excluding the moment variable (e_{Base}) and including the moment variable (e_{Moment}), and we determine the relative (mean) squared error as the relation of the MSE_{Moment} to the MSE_{Base} . The loss differential ($d_t = L(e_{Moment,t}) - L(e_{Base,t})$) is regressed on a constant (Diebold, 2015, p. 3):

$$d_t = \beta_0 + u_t \tag{5}$$

¹⁰We have also conducted regressions based on a forecast horizon of 6 and 9 months, respectively, with qualitatively similar results. Detailed results are available upon request from the authors.

TABLE 3 Forecasting equations including cross-sectional stock market moments and control variables for Germany, 1987–2021

	Dependent variable: average growth rate of industrial production over the next 3 months					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Based on 1/N weights</i>						
Mean	0.473** (0.20)					
Median		0.201** (0.10)				
Standard deviation			−0.175 (0.12)			
Standard deviation, $t - 1$			−0.219 (0.23)			
Standard deviation, $t - 2$	0.027*** (0.01)	0.198*** (0.07)	0.189*** (0.07)	0.203*** (0.08)	0.204*** (0.08)	0.199** (0.08)
Standard deviation, $t - 3$			0.313 (0.24)			
Interquartile range				−0.186 (0.12)		
Interquartile range, $t - 1$				0.157 (0.12)		
Skewness					−0.037 (0.08)	
Kelley (1947) skewness						0.103** (0.04)
+ Control variables	see Appendix Table A1 for details					
Observations	413	413	413	413	413	413
R^2	0.159	0.163	0.181	0.141	0.127	0.135
AIC	−538.5	−540.1	−544.9	−527.8	−523.2	−526.7
<i>Based on market capitalization weights</i>						
Mean	2.680** (1.22)					
Median		0.161** (0.08)				
Standard deviation			−0.147 (0.10)			
Standard deviation, $t - 1$			−0.011 (0.10)			

TABLE 3 (Continued)

	Dependent variable: average growth rate of industrial production over the next 3 months					
	(1)	(2)	(3)	(4)	(5)	(6)
Interquartile range				−0.102 (0.09)		
Skewness					0.019 (0.04)	
Kelley (1947) skewness						0.018 (0.04)
+ Control variables	see Appendix Table A1 for details					
Observations	413	413	413	413	413	413
R ²	0.129	0.129	0.126	0.114	0.104	0.104
AIC	1135	1135	1136	1142	1146	1147

Note: The results of the regression model described in Equation (4) are reported. Beta weights, that is, coefficients from regressions based on standardized time series are reported. Robust (Newey & West, 1987) standard errors are given in parentheses. *** (**, *) denotes rejection of the null hypothesis at the 1% (5%, 10%), level.

using Newey and West (1987) standard errors. Testing the hypothesis $H_0 : \beta_0 = 0$ is then equivalent to the DM-test.

Table 4 reports the results of an out-of-sample exercise. We have calculated 3 (6, 9) months' forecasts based on Equation (4) for the period 2010–2021 for an equation with and without cross-section moments as a predictor. Within each step of our (pseudo-)out-of-sample exercise, the equation is re-estimated and used for a forecast.

The results show that mean and median cross-section returns reduce significantly the MSE compared with a model without these variables for a forecast horizon of 3 and 6 months. In contrast, the gain of forecast accuracy is relatively small considering the standard deviations and the interquartile range. And, according to the results of the Diebold–Mariano test, both measures are not statistically significant. In the case of 3- and 6-month horizons, the results for the third moments are mixed. The robust Kelley (1947) measure improves significantly the forecast accuracy for the 1/*N*-based scenario, whereas the predictive power cannot be observed for the market capitalization-weighted measures as well as for the skewness measures for both weighting systems. In line with previous evidence (see, e.g., Breitung & Knüppel, 2021; Drechsel & Scheufele, 2012) the predictive power of the models breaks more or less down when the 9-month horizon is considered. All in all, the out-of-sample forecasting performance of the moments of cross-sectional German stock market returns suggest some predictive power, even the second moments perform relatively weak, and the results for the third moments are mixed.

4.4 | ARDL models

Another approach to test the relationship between cross-sectional moments of stock market returns and the German business cycle is the ARDL model suggested by Pesaran and Shin (1998) and Pesaran et al. (2001). The ARDL model is a familiar approach to investigate the (long-run) relationship between variables in a single-equation time-series setting. Engle and Granger (1987) show that an error-correction (EC) process corresponds to a long-run (cointegrating) relationship of nonstationary variables. The advantage of the ARDL model is that variables can be integrated of order zero (*I*(0)), order one (*I*(1)), or a combination of both (Nkoro & Uko, 2016; Pesaran et al., 2001).

TABLE 4 Out of sample forecasting performance

	Horizon: 3 Months			Horizon: 6 Months			Horizon: 9 Months		
	Relative			Relative			Relative		
	MSE	t Value	p Value	MSE	t Value	p Value	MSE	t Value	p Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Based on 1/N weights									
Mean	0.973	−2.53	(0.01)	0.966	−2.46	(0.01)	0.986	−1.28	(0.20)
Median	0.973	−2.54	(0.01)	0.969	−2.38	(0.02)	0.985	−1.38	(0.17)
Standard deviation	1.000	0.01	(0.99)	1.001	0.19	(0.85)	1.015	1.06	(0.29)
Interquartile range	0.996	−0.78	(0.44)	0.999	−0.23	(0.82)	0.999	−0.06	(0.95)
Skewness	1.006	0.70	(0.49)	1.005	1.00	(0.32)	1.013	0.98	(0.33)
Kelley (1947)	0.986	−2.61	(0.01)	0.980	−2.40	(0.02)	1.004	0.32	(0.75)
Based on market capitalization weights									
Mean	0.984	−2.47	(0.01)	0.985	−2.19	(0.03)	0.997	−0.33	(0.74)
Median	0.984	−2.47	(0.01)	0.985	−2.19	(0.03)	0.997	−0.33	(0.74)
Standard deviation	0.995	−0.49	(0.62)	0.996	−0.34	(0.73)	1.002	0.14	(0.89)
Interquartile range	0.999	−0.19	(0.85)	0.999	−0.16	(0.87)	1.003	0.24	(0.81)
Skewness	1.003	0.88	(0.38)	1.003	0.65	(0.52)	1.011	0.86	(0.39)
Kelley (1947) skewness	1.000	0.25	(0.80)	1.001	0.68	(0.50)	1.012	0.96	(0.34)

Note: *p* Values refer to a Diebold and Mariano (1995) test for equal forecast accuracy as compared with a simple AR(1) model.

The bounds test, suggested by Pesaran et al. (2001), allows detecting cointegrating relationships between the variables. Therefore, the ARDL model is more flexible than the popular approach of Engle and Granger (1987).

Until now, the lag structure in the models used has been rather restrictive. In this section, we use a more empirically driven approach. To this end, we use the (log-)level of industrial production as the variable to be explained and the cross-section moments as explanatory variables, and, for the sake of brevity, only one control variable: the term spread. The ARDL(*p,q,q*) model is given by

$$y_t = c_0 + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=0}^q \beta_j' x_{t-j} + \epsilon_t \tag{6}$$

referring to the general form (see, among others, Hassler & Wolters, 2006) but with constant term *c*₀. Given the (log-)level of industrial production as dependent variable *y*_{*t*}, *φ_i* are the coefficients of the endogenous lagged variables *y_{t-i}*. The *K*-dimensional column vector *x_{t-j}* represents the regressors and *β_j*['] their coefficients. *ε_t* is the zero-mean error term. ARDL (*p,q,q*) denotes the lag lengths of the ARDL model, starting with the number of lags for the endogenous variable (*p*) and followed by the indicator variable and control variable. The optimal lag lengths *p* and *q* will be obtained by minimizing the Akaike information criterion (AIC).¹¹ To apply this method, it is necessary, in a first step, to ensure that none of the variables used in the model is integrated of order two (*I*(2)). We do so by using the augmented Dickey and Fuller (1979)

¹¹The lag order can differ across regressors in the ARDL framework.

test for a unit root.¹² Given that the (log-)level of industrial production is $I(1)$ and all cross-sectional moments of stock market returns, as well as the term spread, are $I(0)$, we can rearrange the ARDL model to the EC-form

$$y_t = c_0 - \alpha(y_{t-1} - \theta x_t) + \sum_{i=1}^{p-1} \psi_{yi} \Delta y_{t-i} + \sum_{j=0}^{q-1} \psi'_{xi} \Delta x_{t-i} + \epsilon_t \quad (7)$$

with the adjustment coefficient $\alpha = 1 - \sum_{i=1}^p \phi_i$ and the long-run coefficient $\theta = \frac{\sum_{j=0}^q \beta_j}{\alpha}$. The potential cointegration relationship between cross-sectional moments of stock market returns and German business cycle variables will be tested with the bounds test. In addition, to test the adequacy of each model specification, we apply a series of diagnostic tests. These include the Breusch–Pagan/Cook–Weisberg test for heteroscedasticity of the residuals, the Breusch–Godfrey Lagrange multiplier test for autocorrelation of the residuals, and the Shapiro–Wilk test for normality of the residuals.

Table 5 reports the results of ARDL estimates including stock market cross-section moments for Germany.¹³ The lagged log of industrial production represents the adjustment coefficient, which reports how strongly the dependent variable reacts to a deviation from the equilibrium relationship, followed by the indicator, and the spread (in levels), which display the long-run coefficients and thus the equilibrium effects of the independent variables on the dependent variable (Kripfganz & Schneider, 2018). The short-run coefficients and test results for ARDL model assumptions are omitted here (see Tables A2 and A3 for details). As Table 5 shows, some long-run coefficients are statistically significant, at least at the 10% level. These results hold for both the $1/N$ weighting statistics and the market capitalization weighting schemes. To formally test for a potential cointegration and long-run relationship, we use the bounds F -test of the joint null hypothesis $H_0^F: \alpha = 0 \cap \sum_{j=0}^q \beta_j = 0$. The necessary condition for a cointegration relation is the rejection of the null hypothesis. We use the critical values of Kripfganz and Schneider (2020) for the bounds tests, which improve and extend the critical values provided by Pesaran et al. (2001) and Narayan (2005). Considering bounds F -test results in Table 5, the null hypothesis can be rejected for all ARDL specifications, at least with a p value of 0.01 for the upper $I(1)$ bound. In the second step, we test the single null hypothesis $H_0^t: \alpha = 0$ with a t -test for each model. These hypotheses cannot be rejected for any ARDL specification. Hence, the sufficient condition of the bounds test procedure for a cointegration relation is not given.¹⁴ Besides, the diagnostic tests are not always completely satisfying.¹⁵ All in all, these outcomes do not indicate long-run relationships between cross-sectional moments of stock market returns and German business cycle variables. As a result, a long-run relationship between the variables has to be rejected.

4.5 | Impulse responses from local projections

To obtain some insights into the dynamic interactions between the cross-section moments and the (log-)level of industrial production, we use the technique local projection proposed by Jordà (2005).¹⁶ Specifically, the equation:

$$\hat{Y}_{t+h} = \beta_0 + \sum_{i=1}^p \beta_i Y_{t-i} + \epsilon_t \quad (8)$$

is estimated by OLS for several horizons h . From the coefficients β_i it is possible to calculate the impulse-response function $\widehat{\text{IFR}}_{j,h} = \beta_j^h p_j$ for the endogenous variable j and the horizon h .

¹²The results are not presented in this paper but available upon request from the authors.

¹³Following Ferreira (2022), these enter the equation as standardized variables, that is, the mean is subtracted from the value, and the difference between the variable and its mean is divided by its standard deviation.

¹⁴Usually, the bounds test procedure comprises three steps. If we can reject H_0^F too, we test in the third step if $\theta \neq 0$ individually with a z -test and jointly with a Wald test. The results in Table 5 show that the second step is sufficient in our case.

¹⁵Given a significance level of 1%, we have to reject the null of normally distributed residuals for 2 out of 12 model specifications. See Table A2.

¹⁶We use simplest, merely illustrative example shown by Jordà (2022). Thus, since we are interested in forecasting, i.e., in the leading indicator properties of the cross-section moments, we do not pretend to identify a macroeconomic shock from the data.

TABLE 5 ARDL estimates including cross-sectional stock market moments for Germany, 1987–2021

	Cross-sectional indicator included in the model					
	Dependent variable: first difference of logarithm of industrial production					
	Mean	Median	Standard deviation	Interquartile range	Skewness	Kelley (1947) skewness
<i>Based on 1/N-weights</i>						
Model specification	ARDL(3,2,4)	ARDL(3,2,4)	ARDL(3,2,1)	ARDL(3,2,4)	ARDL(3,0,4)	ARDL(3,1,4)
Lagged endogenous, level	−0.008 (0.01)	−0.007 (0.01)	−0.006 (0.01)	−0.006 (0.01)	−0.009 (0.01)	−0.008 (0.01)
Indicator, level	0.119*** (0.03)	0.152*** (0.03)	−0.018 (0.03)	−0.057* (0.03)	0.001 (0.00)	0.021*** (0.01)
Spread, level	0.001 (0.00)	0.002 (0.00)	0.002** (0.00)	0.002** (0.00)	0.002* (0.00)	0.002 (0.00)
Observations	416	416	416	416	416	416
Adj. R^2	0.124	0.132	0.0695	0.123	0.0729	0.0835
Bounds-test (F value)	9.061	10.035	2.772	3.396	3.201	5.073
Bounds-test (t value)	−1.055	−1.025	−0.569	−0.812	−1.241	−1.063
Bounds-test decision ^{a)}	NR	NR	NR	NR	NR	NR
<i>Based on market capitalization weights</i>						
Model specification	ARDL(3,2,4)	ARDL(3,2,4)	ARDL(3,1,4)	ARDL(3,1,4)	ARDL(3,0,1)	ARDL(3,1,1)
Lagged endogenous, level	−0.009 (0.01)	−0.009 (0.01)	−0.008 (0.01)	−0.008 (0.01)	−0.010 (0.01)	−0.010 (0.01)
Indicator, level	0.123*** (0.03)	0.123*** (0.03)	−0.104*** (0.04)	−0.082*** (0.03)	−0.001 (0.00)	−0.002 (0.01)
Spread, level	0.002* (0.00)	0.002* (0.00)	0.002** (0.00)	0.002** (0.00)	0.002** (0.00)	0.002** (0.00)
Observations	416	416	416	416	416	416
Adj. R^2	0.114	0.114	0.0864	0.0826	0.0631	0.0664
Bounds-test (F value)	8.957	8.957	5.118	4.772	2.950	2.785
Bounds-test (t value)	−1.176	−1.176	−1.021	−1.151	−1.332	−1.328
Bounds-test decision ^{a)}	NR	NR	NR	NR	NR	NR

Note: The results of the regression model described in Equation (7) and estimated using the STATA module developed by Kripfganz and Schneider (2018) are reported. Robust (Newey & West, 1987) standard errors are given in parentheses.

*** (**, *) denotes rejection of the null hypothesis at the 1% (5%, 10%), level. ARDL (p,q,q) denotes the lag lengths of the ARDL model, starting with the number of lags for the endogenous variable and followed by the indicator variable and control variable. The short-run coefficients and test results for ARDL model assumptions are omitted here (see Tables A2 and A3 for details). ^{a)}denotes the decision according to the package of Kripfganz and Schneider (2018): 'NR' denotes: 'no rejection', 'IN' denotes 'inconclusive', and 'R' denotes 'rejection' of the hypothesis 'no cointegration'.

The results in Figure A1 show, first, the response of the logarithm of industrial production to a one standard deviation shock to the cross-section moment time series calculated as described above (red dashed line) and, second, the response of the same variable in a VAR in levels (solid blue line). The findings are roughly in line with, for example, the ones by (Salgado et al., 2019, fig. 7, p. 35): The responses to shocks to mean and median of the cross-section returns are positive and relatively large. The response to a shock to the second moments are negative, but estimated with large standard errors. With one exception, the shocks related to the third moments are negative as expected, but also with relatively large standard errors.

5 | DISCUSSION AND CONCLUSION

Based on monthly data from 1987 to 2021, we analyse whether the cross-sectional moments of stock market returns may serve as a leading indicator of the German business cycle. The cross-sectional moments are calculated on up to 413 firms incorporated in the CDAX[®] index.

Starting with the results of the in-sample forecasting regressions, we find evidence that the vast majority of the cross-section moments are statistically significant predictors for future production and have the expected signs. This confirms the suitability of cross-sectional moments of stock market returns as leading indicators for the development of the German economy. When we add selected business cycle indicators as control variables, most of the cross-sectional moment variables remain statistically significant with the expected signs. Nevertheless, our results are less promising than Ferreira (2022) results using US data. This concerns, in particular, the explanatory power of the regression results, which are significantly lower for both regressions with and without additional control variables. The same holds for the comparison in terms of cross-sectional skewness with the results for Vicente and Araujo (2018) cross-sectional tail risk measures for Brazil.

Considering the out-of-sample power of forecasting models with and without cross-sectional moments, our results show that the mean and median, and the Kelley (1947) measure (for 1/N weighting), reduce the MSE compared with the model without these variables for forecast horizons of 3 and 6 months. As expected from previous evidence, the predictive power of the models breaks down within the 9-month horizon.

Additionally, the ARDL framework suggests no long-run relationship between the level of industrial production, on the one hand, and the moment variables under investigation, on the other hand, once the term spread as on prominent leading indicator of the business cycle is taken into account as a control variable. IRFs based on local projections point to an—albeit statistically insignificant—impact of the moment variables at least with the expected sign.

A possible explanation for the differences in the results from those of Ferreira (2022) for the US and those of Vicente and Araujo (2018) for Brazil is likely the marked differences in the financial systems between Germany on the one hand and the US and Brazil on the other hand. For example, Lee (2012) examined the relative merits of bank-based and market-based financial systems in promoting long-term economic growth. He found that in the US, which is characterized by a market-based financial system, the stock market plays an important role in financing economic growth. In contrast, in Germany, which has a bank-based financial system, the banking sector plays a more prominent role in this respect. Moreover, the sample of Ferreira (2022) is much larger and thus much more informative.¹⁷ The larger sample enabled Ferreira (2022)—in contrast to our cross-sectional sample—to differentiate between financial and nonfinancial companies when calculating the skewness. Ferreira (2022) justifies this approach with the argument that a close relationship between financial skewness and the economic cycle responds to the exposure of financial firms to the economic performance of their borrowers.¹⁸ This is also confirmed by his results. Comparing our results with those of Bloom (2009), one possible

¹⁷Ferreira (2022) uses the CRSP US stock database, which contains data for over 32,000 active and inactive companies. In contrast, our sample consists of 413 companies listed on the CDAX[®].

¹⁸In this context Ferreira (2022) defines financial skewness as a measure comparing cross-sectional upside and downside risks of the distribution of returns of financial firms. For the classification between financial and nonfinancial sectors, he uses the NAICS codes.

explanation for the differences between the results may lie in the different financial systems in the US and Germany mentioned above. Another explanation could be the differences in the methodology used. Bloom (2009) uses a time-varying VAR approach, while we use a single-equation forecast and an ARDL framework. Moreover, the volatility shocks in Bloom (2009) are based on an indicator function and 17 large exogenous shocks, while our results are based on regressions of the second cross-sectional moments. Given that a bank-based financial system prevails in Germany, the influence of the banking sector on economic growth in Germany is an interesting topic for future studies. This could be done, for example, by using the domestic credit ratio: the ratio of total domestic lending to nominal GDP. This variable captures the development of the banking system. Using it is recommended in an economy that is expected to be highly dependent on bank loans (Marques et al., 2013). Future research could investigate and compare the property of cross-sectional moments of stock market returns as leading indicators of the business cycle for additional countries. Another point, that needs further clarification, how our results for stock market cross-section moments relate to other approaches to measure uncertainty and its impact on German business cycles. For example, Bachmann et al. (2013), following the seminal paper of Bloom (2009), find that the cross-section standard deviation of survey data on firms' expectations on their future business conditions has a significant negative impact on real GDP growth.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data subject to third party restrictions. In principle, data are available in the public domain, but we have used a commercial third party (Macrobond) to access them.

ETHICS STATEMENT

The authors have followed the required ethical standards.

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APPENDIX A

See Tables [A1](#)

See Table [A2](#)

See Table [A3](#)

See Figure [A1](#)

TABLE A1 Forecasting equations including cross-sectional stock market cross-section moments and control variables for Germany, 1987–2021

	Dependent variable: Average growth rate of industrial production over the next 3 months					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Based on 1/N weights</i>						
Ind. prod., mom, $t - 1$	−0.026 (0.02)	−0.193 (0.12)	−0.224 (0.14)	−0.217* (0.13)	−0.222 (0.14)	−0.210 (0.13)
Ind. prod., mom, $t - 2$	−0.027* (0.01)	−0.202* (0.11)	−0.148* (0.08)	−0.177* (0.10)	−0.183* (0.10)	−0.179* (0.10)
Ind. prod., mom, $t - 3$	−0.023 (0.01)	−0.172 (0.11)	−0.158* (0.09)	−0.169 (0.11)	−0.159* (0.10)	−0.163 (0.10)
Order Infl., mom.	−0.016 (0.02)	−0.116 (0.13)	−0.105 (0.13)	−0.118 (0.13)	−0.104 (0.13)	−0.106 (0.13)
Order Infl., mom, $t - 2$	0.020** (0.01)	0.155** (0.07)	0.137** (0.06)	0.138* (0.07)	0.145** (0.07)	0.135* (0.07)
Order Infl., mom, $t - 3$	0.023** (0.01)	0.171** (0.08)	0.160** (0.08)	0.162** (0.08)	0.154** (0.07)	0.155** (0.08)
ifo business climate	0.049** (0.02)	0.367** (0.18)	0.404** (0.17)	0.428** (0.17)	0.421** (0.19)	0.384** (0.19)
ifo bus. clim, $t - 3$	−0.033 (0.02)	−0.240 (0.18)	−0.298** (0.15)	−0.306* (0.17)	−0.294* (0.17)	−0.266 (0.18)
Mean	0.473** (0.20)					
Median		0.201** (0.10)				
Standard deviation			−0.175 (0.12)			
Standard deviation, $t - 1$			−0.219 (0.23)			
Standard deviation, $t - 2$	0.027*** (0.01)	0.198*** (0.07)	0.189*** (0.07)	0.203*** (0.08)	0.204*** (0.08)	0.199** (0.08)

(Continues)

TABLE A1 (Continued)

	Dependent variable: Average growth rate of industrial production over the next 3 months					
	(1)	(2)	(3)	(4)	(5)	(6)
Standard deviation, $t - 3$			0.313 (0.24)			
Interquartile range				-0.186 (0.12)		
Interquartile range, $t - 1$				0.157 (0.12)		
Skewness					-0.037 (0.08)	
Kelley (1947) skewness						0.103** (0.04)
Observations	413	413	413	413	413	413
R^2	0.159	0.163	0.181	0.141	0.127	0.135
AIC	-538.5	-540.1	-544.9	-527.8	-523.2	-526.7
<i>Based on market capitalization weights</i>						
Ind. prod., mom, $t - 1$	-0.195 (0.14)	-0.195 (0.14)	-0.216 (0.14)	-0.213 (0.14)	-0.214 (0.15)	-0.214 (0.15)
Ind. prod., mom, $t - 2$	-0.185** (0.09)	-0.185** (0.09)	-0.171* (0.09)	-0.172** (0.09)	-0.177** (0.09)	-0.174* (0.09)
Ind. prod., mom, $t - 3$	-0.164* (0.10)	-0.164* (0.10)	-0.152 (0.10)	-0.161* (0.10)	-0.158* (0.09)	-0.156 (0.10)
Spread	0.209*** (0.07)	0.209*** (0.07)	0.213*** (0.07)	0.220*** (0.08)	0.215*** (0.07)	0.213*** (0.08)
Order Infl., mom, $t - 2$	0.161** (0.07)	0.161** (0.07)	0.135* (0.07)	0.146** (0.07)	0.143** (0.07)	0.145** (0.07)
Order Infl., mom, $t - 3$	0.168** (0.08)	0.169** (0.08)	0.151** (0.07)	0.158** (0.07)	0.157** (0.07)	0.155** (0.07)
ifo bus. clim, $t - 1$	0.325 (0.23)	0.325 (0.23)	0.330* (0.19)	0.339* (0.21)	0.368 (0.23)	0.367 (0.23)
ifo bus. clim, $t - 3$	-0.224 (0.23)	-0.224 (0.23)	-0.270 (0.21)	-0.262 (0.22)	-0.271 (0.23)	-0.271 (0.23)
Mean	2.680** (1.22)					
Median		0.161** (0.08)				

TABLE A1 (Continued)

	Dependent variable: Average growth rate of industrial production over the next 3 months					
	(1)	(2)	(3)	(4)	(5)	(6)
Standard deviation			-0.147 (0.10)			
Standard deviation, $t - 1$			-0.011 (0.10)			
Interquartile range				-0.102 (0.09)		
Skewness					0.019 (0.04)	
Kelley (1947) skewness						0.018 (0.04)
Observations	413	413	413	413	413	413
R^2	0.129	0.129	0.126	0.114	0.104	0.104
AIC	1135	1135	1136	1142	1146	1147

Note: The results of the regression model described in Equation (4) are reported. Beta weights, that is, coefficients from regressions based on standardized time series are reported. Robust (Newey & West, 1987) Standard errors in parentheses. *** (**, *) denotes rejection of the null hypothesis at the 1% (5%, 10%), level.

TABLE A2 ARDL estimates including cross-sectional stock market moments for Germany, 1987–2021

	Cross-sectional indicator included in the model					
	Dependent variable: First difference of logarithm of industrial production					
	Mean	Median	Standard deviation	Interquartile range	Skewness	Kelley (1947) skewness
	(1)	(2)	(3)	(4)	(5)	(6)
Based on 1/N weights						
Lagged endogenous, level	-0.008 (0.01)	-0.007 (0.01)	-0.006 (0.01)	-0.006 (0.01)	-0.009 (0.01)	-0.008 (0.01)
Lagged endogenous, level, $t - 1$	-0.078 (0.05)	-0.084* (0.05)	-0.042 (0.05)	-0.047 (0.05)	-0.047 (0.05)	-0.054 (0.05)
Lagged endogenous, level, $t - 2$	-0.208*** (0.05)	-0.208*** (0.05)	-0.197*** (0.05)	-0.210*** (0.05)	-0.219*** (0.05)	-0.220*** (0.05)
Indicator, level	0.119*** (0.03)	0.152*** (0.03)	-0.018 (0.03)	-0.057* (0.03)	0.001 (0.00)	0.021*** (0.01)
Indicator, level, $t - 1$	-0.027 (0.02)	-0.042* (0.02)	-0.057* (0.03)	-0.163*** (0.04)		

(Continues)

TABLE A2 (Continued)

	Cross-sectional indicator included in the model					
	Dependent variable: First difference of logarithm of industrial production					
	Mean	Median	Standard deviation	Interquartile range	Skewness	Kelley (1947) skewness
	(1)	(2)	(3)	(4)	(5)	(6)
Spread, level	0.001 (0.00)	0.002 (0.00)	0.002** (0.00)	0.002** (0.00)	0.002* (0.00)	0.002 (0.00)
Spread, level, $t - 1$	-0.002 (0.01)	-0.002 (0.01)		-0.000 (0.01)	-0.000 (0.01)	-0.001 (0.01)
Spread, level, $t - 2$	-0.012** (0.01)	-0.012** (0.01)		-0.011** (0.01)	-0.010* (0.01)	-0.010* (0.01)
Spread, level, $t - 3$	0.012** (0.01)	0.012** (0.01)		0.010* (0.01)	0.011** (0.01)	0.011** (0.01)
Indicator, first difference	-0.109*** (0.02)	-0.143*** (0.03)	-0.009 (0.03)	0.018 (0.04)		-0.013** (0.01)
Spread, first difference	-0.017*** (0.01)	-0.017*** (0.01)	-0.017*** (0.01)	-0.017*** (0.01)	-0.018*** (0.01)	-0.018*** (0.01)
Constant	0.033 (0.03)	0.032 (0.03)	0.026 (0.04)	0.032 (0.03)	0.040 (0.03)	0.034 (0.03)
Observations	416	416	416	416	416	416
Adj. R^2	0.124	0.132	0.0695	0.123	0.0729	0.0835
RMSE	0.0196	0.0195	0.0202	0.0196	0.0202	0.0201
Bounds-test (F value)	9.061	10.03	2.772	3.396	3.201	5.073
Bounds-test (t value)	-1.055	-1.025	-0.569	-0.812	-1.241	-1.063
Bounds-test decision ^{a)}	NR	NR	NR	NR	NR	NR
Test for heteroscedasticity (p-value)	<0.01	<0.01	<0.01	<0.01	0.133	0.937
Test for normality (p value)	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Test for autocorrelation (p value)	0.836	0.866	0.710	0.975	0.646	0.943

Note: The results of the regression model described in Equation (7) and estimated using the STATA module developed by Kripfganz and Schneider (2018) are reported. Robust (Newey & West, 1987) standard errors are given in parentheses. *** (**, *) denotes rejection of the null hypothesis at the 1% (5%, 10%), level. ^{a)} denotes the decision according to the package of Kripfganz and Schneider (2018): 'NR' denotes: 'no rejection', 'IN' denotes 'inconclusive', and 'R' denotes 'rejection' of the hypothesis 'no cointegration'.

TABLE A3 ARDL estimates including cross-sectional stock market moments for Germany, 1987–2021

	Cross-sectional indicator included in the model					
	Dependent variable: First difference of logarithm of industrial production					
	Mean	Median	Standard deviation	Interquartile range	Skewness	Kelley (1947) skewness
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Based on market capitalization weights</i>						
Lagged endogenous, level	−0.009	−0.009	−0.008	−0.008	−0.010	−0.010
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lagged endogenous, first difference, $t - 1$	−0.078	−0.078	−0.059	−0.057	−0.047	−0.042
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Lagged endogenous, first difference, $t - 2$	−0.214***	−0.214***	−0.227***	−0.223***	−0.201***	−0.210***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Indicator, level	0.123***	0.123***	−0.104***	−0.082***	−0.001	−0.002
	(0.03)	(0.03)	(0.04)	(0.03)	(0.00)	(0.01)
Indicator, level, $t - 1$	−0.041**	−0.041**				
	(0.02)	(0.02)				
Spread, level	0.002*	0.002*	0.002**	0.002**	0.002**	0.002**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spread, level, $t - 1$	−0.001	−0.001	0.000	−0.000		
	(0.01)	(0.01)	(0.01)	(0.01)		
Spread, level, $t - 2$	−0.011**	−0.011**	−0.011*	−0.011*		
	(0.01)	(0.01)	(0.01)	(0.01)		
Spread, level, $t - 3$	0.012**	0.012**	0.010*	0.010*		
	(0.01)	(0.01)	(0.01)	(0.01)		
Indicator, first difference	−0.105***	−0.105***	0.097**	0.061**		0.006
	(0.02)	(0.02)	(0.04)	(0.03)		(0.00)
Spread, first difference	−0.018***	−0.018***	−0.016***	−0.016***	−0.017***	−0.018***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.036	0.036	0.039	0.043	0.043	0.043
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	416	416	416	416	416	416
Adj. R^2	0.114	0.114	0.0864	0.0826	0.0631	0.0664
RMSE	0.0197	0.0197	0.0200	0.0201	0.0203	0.0202
Bounds-test (F value)	8.957	8.957	5.118	4.772	2.950	2.785
Bounds-test (t value)	−1.176	−1.176	−1.021	−1.151	−1.332	−1.328

(Continues)

TABLE A3 (Continued)

	Cross-sectional indicator included in the model					
	Dependent variable: First difference of logarithm of industrial production					
	Mean	Median	Standard deviation	Interquartile range	Skewness	Kelley (1947) skewness
	(1)	(2)	(3)	(4)	(5)	(6)
Bounds-test decision ^{a)}	NR	NR	NR	NR	NR	NR
Test for heteroscedasticity (p value)	<0.01	<0.01	<0.01	0.035	0.788	0.833
Test for normality (p value)	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Test for autocorrelation (p value)	0.963	0.963	0.867	0.778	0.884	0.848

Note: The results of the regression model described in Equation (7) and estimated using the STATA module developed by Kripfganz and Schneider (2018) are reported. Robust (Newey & West, 1987) standard errors are given in parentheses. *** (**, *) denotes rejection of the null hypothesis at the 1% (5%, 10%), level. ^{a)} denotes the decision according to the package of Kripfganz and Schneider (2018): 'NR' denotes: 'no rejection', 'IN' denotes 'inconclusive', and 'R' denotes 'rejection' of the hypothesis 'no cointegration'.

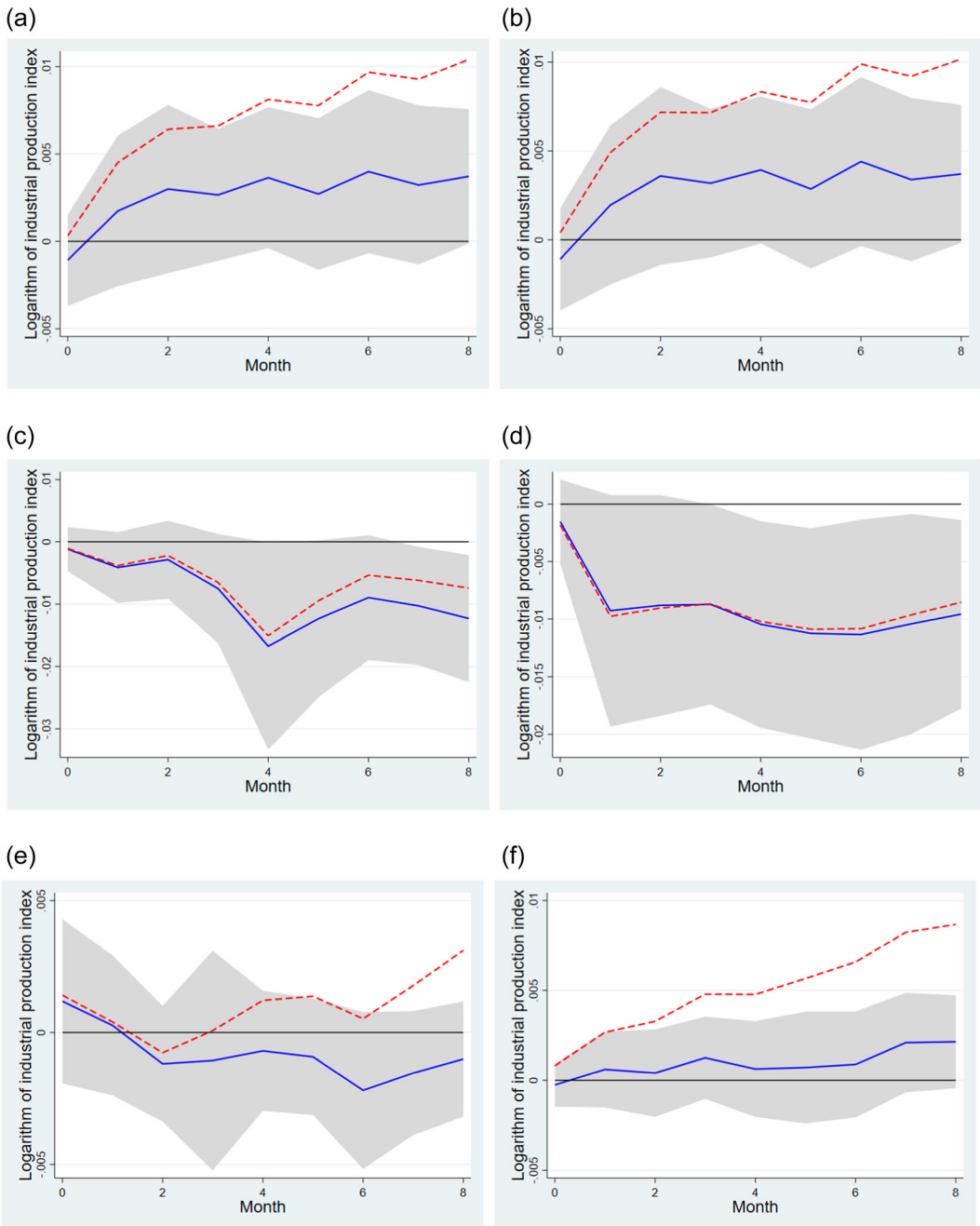
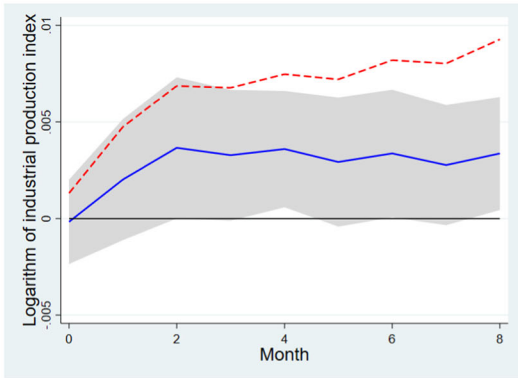
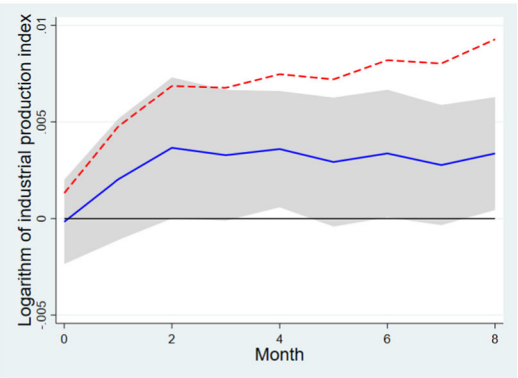


FIGURE A1 Cumulated impulse responses of the log-level of industrial production to a one standard deviation shock to the respective variable. The figures show the cumulated response of the log-level of industrial production estimated from a local projection, see Equation (8) (dashed red line) and the impulse response from a VAR including the level of both variables (solid blue line). The shaded areas represent a respective 90% confidence interval. For the sake of brevity, the impulse responses in the first differences are not shown here, but are available upon request from the authors. (a) Based on 1/N weights, (b) mean, (c) median, (d) standard deviation, (e) interquartile range, (f) Skewness, (g) Kelley (1947) skewness, (h) based on market capitalization weights, (i) mean, (j) median, (k) standard deviation, (l) interquartile range, (m) skewness, (n) Kelley (1947) skewness.

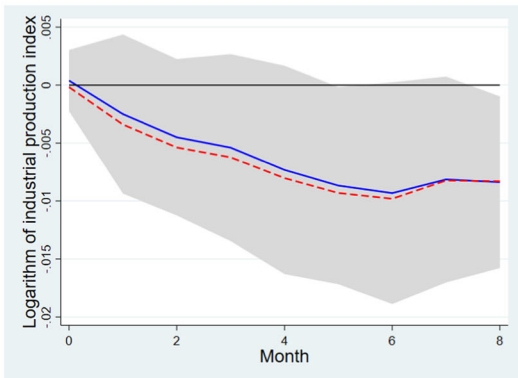
(g)



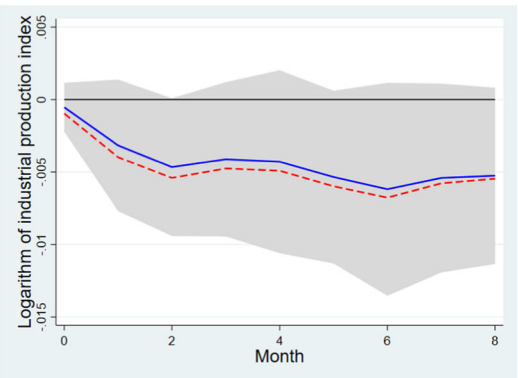
(h)



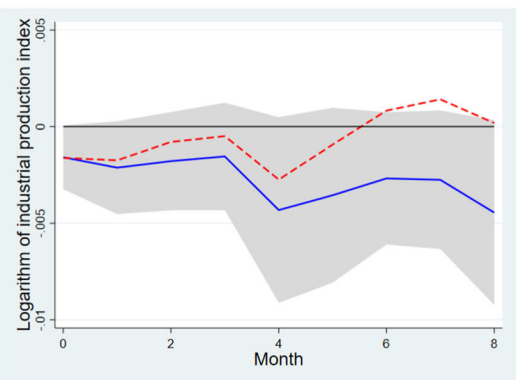
(i)



(j)



(k)



(l)

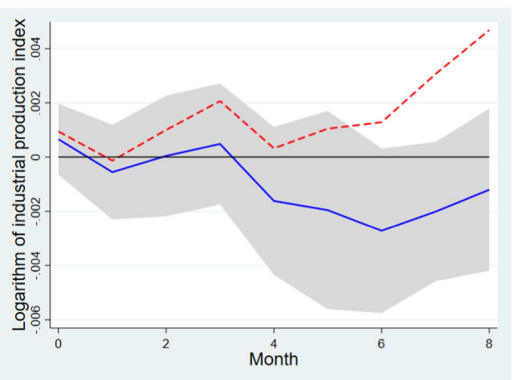


FIGURE A1 Continued