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 2019, 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, Probit models, and Autoregressive Distributed Lag Models. 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. In addition, out-of-sample tests show that these variables reduce the relative Mean Squared Error compared to benchmark models. The results for the second moment are less promising. Also, we do not observe a long-run relation between the moment series and industrial production.

Keywords: Stock market cross-sectional moments, leading indicator, business cycle, Germany

JEL classification: E32, E37, C32

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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. In particular, prices on stock markets have always been considered as a potential major indicator of the business cycle (Camilleri et al. (2019); Kuosmanen et al. (2019)). This might be motivated by the discounted-cash-flow valuation model, which states that stock prices reflect investors' expectations about future economic variables such as corporate earnings. As long as these expectations are generally correct, lagged stock returns should be correlated 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 future economic prospects (e.g., Fama, 1990). Second, a change in the second moment of the returns represents 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 (Ferreira (2018); Di Bella and Grigoli (2019)).

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. We use monthly German data from 1987 to 2019 and employ a wide range of well-established techniques to analyse the leading indicator properties of a time series. In particular, we run in-sample forecast regressions with and without other leading indicators as control variables. Additionally, we employ pseudo-out-of-sample exercises, Autoregressive Distributed Lag (ARDL), and Probit models to check whether the variables help to predict business cycle turning points. We also compare our results with those for the USA 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 (Vicente and Araujo (2018); Ferreira (2018)). We therefore 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 (MSE) compared to forecasts backed out from a simple autoregressive process as a benchmark, at least for forecast horizons of three and six 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 close to one. All three considered moments show no notable ability to forecast recessions. Furthermore, we cannot establish a long-run relation between the possible indicators and industrial production using an ARDL framework.

The remainder of the paper is organized 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 presents the conclusions.

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. In order to give a brief overview, we organize this section along with the question as to which moment of stock market returns has been considered. We also ask which additional evidence on cross-sectional measures that are based on variables other than stock markets might be of interest in this context.

Mean returns

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

Variance, standard deviation, dispersion

Several studies argue that measures of the second moment of the cross-section o f 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) finds that stock market cross-section variance might serve as a leading indicator for the U.S. 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. 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 a period of 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).

Cross-sectional skewness

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 observation. Furthermore, Ferreira (2018) argues in a recent paper that the cross-sectional skewness of stock markets returns is a leading indicator for the U.S. business cycle, even if one controls for other standard leading indicators.

Salgado et al. (2019) use the cross-section of the growth rates of sales to establish a pro-cyclical behaviour of the skewness of the rates. 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 badly, 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.

3 Data

3.1 Stock market data

We calculate three cross-sectional distribution measures of German stock market returns. 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.

Let $R_{j,t} = log(S_{j,t}/S_{j,t-1})$ denote the continuously compounded total return for each of the $j = 1, \ldots, N$ stocks (S_i) within the sample. With these returns at hand, we calculate the following cross-section moments of the returns. All numbers are calculated for two weights given to each share: on the one hand, we assume an equal $\omega_i = 1/N$ weight; on the other, we calculate a weight based on the market capitalization for each firm:

- The cross-sectional mean:

$$\bar{R}_t = \omega_i R_{t,j} \tag{1}$$

- The cross-sectional median:

$$\tilde{R}_t = R_{0.5} \tag{2}$$

  where R_t^p is the p^{th} percentile of the distribution of log-returns at time t

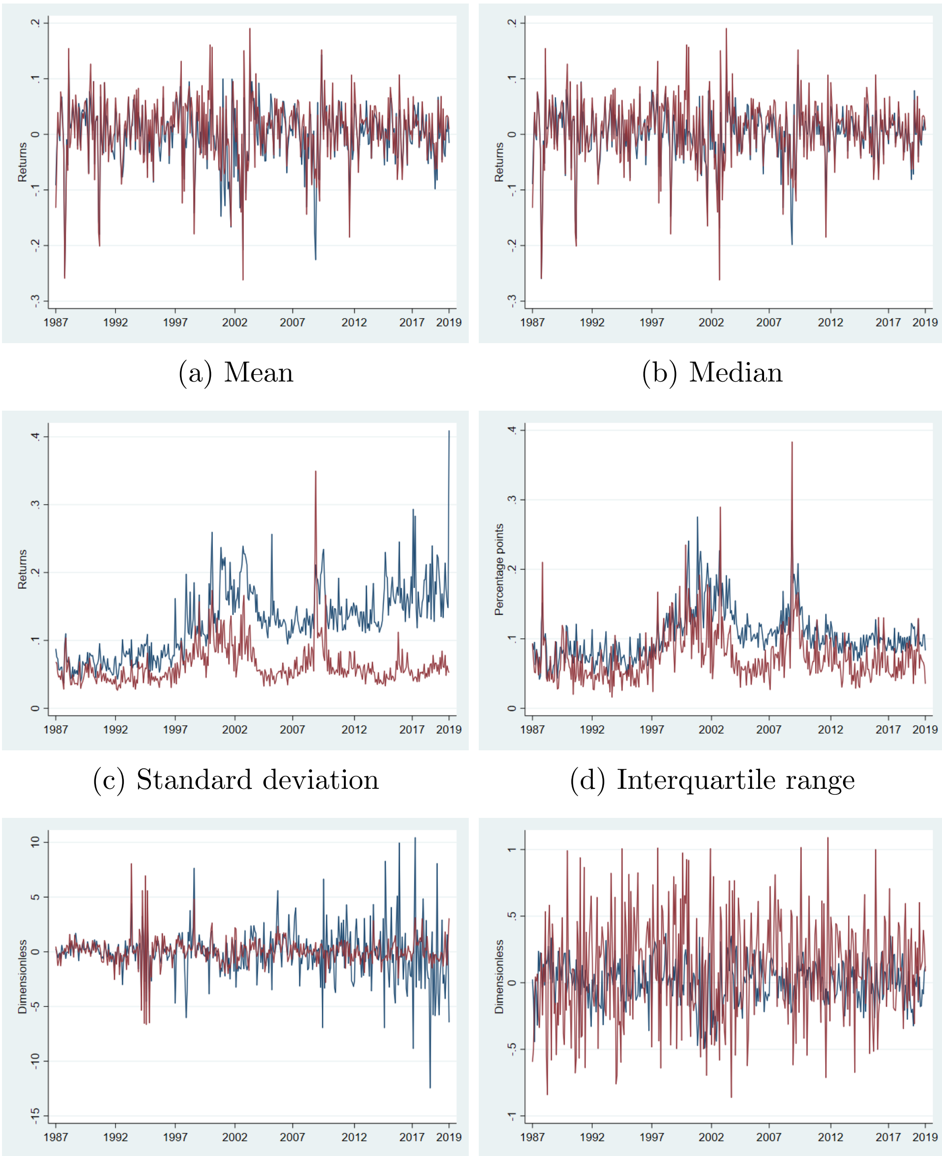
- The cross-sectional standard deviation:

$$S_t = \sqrt{\sum_{j=1}^{N} \omega_i (R_{t,j} - \bar{R})^2} \tag{3}$$

- The cross-sectional interquartile range:

$$IQR_t = R_{0.75} - R_{0.25} \tag{4}$$

Figure 1: Cross-section moments of German stock market returns, 1987 to 2019



(a) Mean

(b) Median

(c) Standard deviation

(d) Interquartile range

(e) Skewness

(f) Robust skewness

Note: Blue lines: based on $1/N$ weighted statistics, red lines: based on market capitalization-weighted statistics.

- The cross-sectional skewness:

$$SK_t = \sum_{j=1}^{N} \omega_i \left(\frac{R_j - \bar{R}}{S} \right)^3 \tag{5}$$

The advantage 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:

- Kelly's measure (Kim and White, 2004; Salgado et al., 2019), which is defined as:

$$SKR_t = \frac{(R_t^{90} - R_t^{50}) - (R_t^{50} - R_t^{10})}{(R_t^{90} - R_t^{10})} \tag{6}$$

Figure 1 shows measures of cross-sectional moments over time. We include both measures based on equally weighted firms and respective numbers based on market-capitalization weights.

We calculate cross-sectional stock-market measures based on all stocks that have been part of the CDAX[1] at a certain point in time. In all, we examine 413 individual stocks, some of them only temporarily. Figure 2 shows the number of total firms included in the investigation.

3.2 Business cycle data

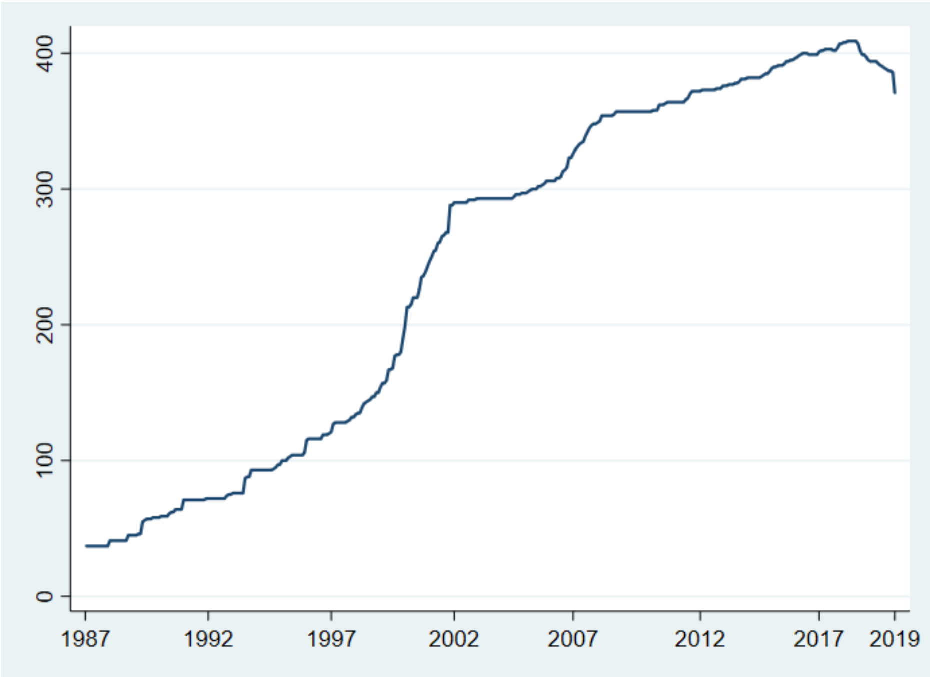
The position of the business cycle is measured by the seasonally adjusted index of industrial production in Germany, excluding construction, provided by the Deutsche Bundesbank[2], which is shown in Figure 3. Since we aim to evaluate the predictive power of stock market moments for impending recessions, we also add the recession phases according to the 'growth cycle' definition of business cycle phases from Economic Cycle Research Institute (2020) to the exhibit (also see Figure 3).

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

[1]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 AG (2020). 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 AG (2020)

[2]The choice of this variable is in line with many papers analysing the position of the German business cycle. See, for example, Schreiber et al. (2012).

Figure 2: Number of firms included in the calculations, 1987 to 2019



Source: Deutsche Börse AG (2020).

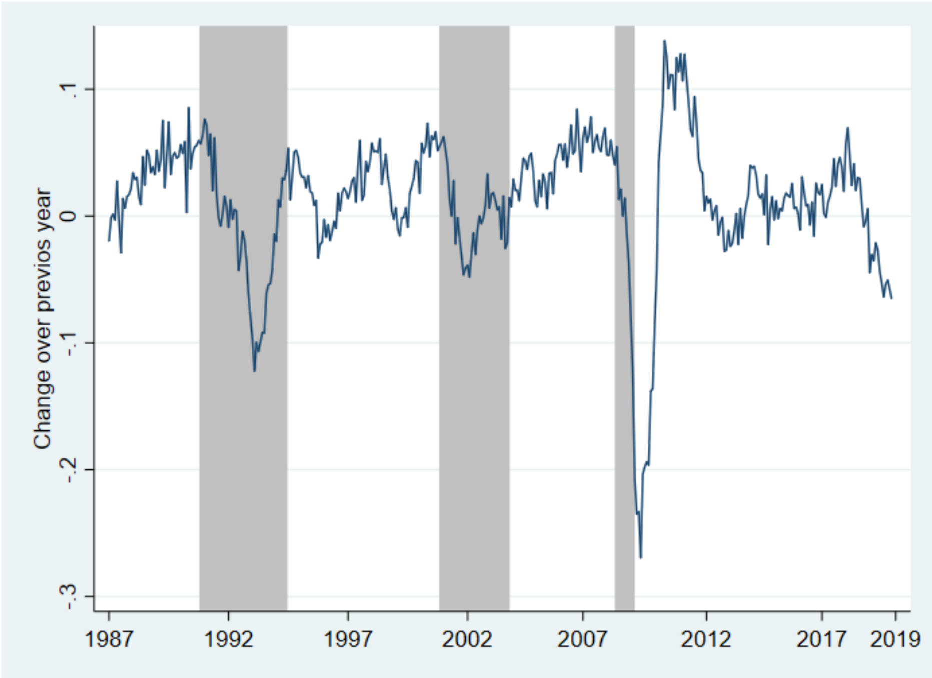
- The term spread, i.e. the long-term interest rate minus the short-term interest rate. The short-term interest rate is the EURIBOR three-month funds money market rates (monthly average, source Deutsche Bundesbank (2020)); the long-term interest rate is the yield on debt securities outstanding issued by residents with mean residual maturity of more than 9 and up to 10 years (monthly average, source Deutsche Bundesbank (2020)).

- The change over the previous month of orders received by the German industry at constant prices, calendar and seasonally adjusted (source: Deutsche Bundesbank (2020))

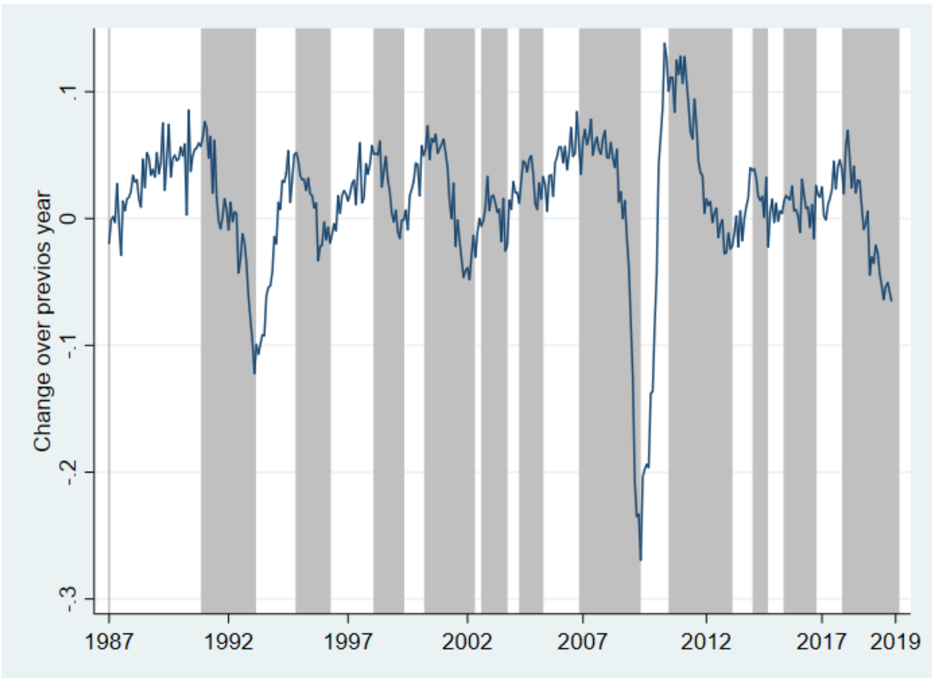
- The business climate index provided monthly by the Ifo Institute ifo institute (2020).

The time series enter the estimation as standardized variables, i.e. we have subtracted the mean from each variable and divided it by its standard deviation.

Figure 3: Industrial Production and Recession phases in Germany, 1987 to 2019



(a) Classical Recessions



(b) Growth Cycle Recessions

Sources: Deutsche Bundesbank (2020) and Economic Cycle Research Institute (2020).

4 Empirical results

4.1 In-sample forecasting regressions

In a first step, we follow Ferreira (2018) and employ simple in-sample forecasting equations. This kind of analysis has been successfully used to evaluate possible leading indicators (Estrella and 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:

$$\hat{Y}_{t|t+h} = \frac{12}{h} ln\left(\frac{Y_{t+h}}{Y_t}\right) \tag{7}$$

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

$$\hat{Y}_{t|t+h} = \beta_0 + \underbrace{\sum_{i=1}^{p} \beta_{1,i}\hat{Y}_{t-i}}_{\text{Lagged endogenous variable}} + \underbrace{\sum_{j=0}^{q} \beta_{2,i}M_{t-j}}_{\text{Moments}} + \underbrace{\sum_{k=1}^{3}\sum_{j=0}^{q} \beta_{3k,i}\mathrm{IN}_{k,t-j}}_{\text{Control variables}} + \epsilon_t \tag{8}$$

where stands for M for the cross-section moments and IN represents other potential leading indicators as control variables. For the sake of simplicity, we set the lag lengths p equal to zero and q equal to one. We set the forecast horizon (h) to three, six, and nine months, respectively. Under this assumption, the approach of equation 8 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 and Hardouvelis, 1991). Hence, the estimates are consistent but inefficient. To make inference reasonable, we employ Newey and West (1987) corrected standard errors.

Table 1 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 $1/N$ 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 three months. However, in case the of the $1/N$ weights, the standard deviation, and in case of market-capitalization weights, the interquartile range, show coefficients not statistically different from zero at conventional significance levels.

Table 1: Forecasting equations including cross-sectional stock market cross-section moments for Germany 1987 to 2019

	Dependent variable: average growth rate of industrial production over the next three months					
	Based on $1/N$ weights					
Lagged endogenous variable	0.163	0.193	0.303	0.247	0.327	0.186
	(0.51)	(0.51)	(0.54)	(0.50)	(0.55)	(0.54)
Mean	0.452***					
	(0.14)					
Median		0.465***				
		(0.17)				
Standard deviation			-0.128			
			(0.11)			
Interquartile range				-0.413*		
				(0.24)		
Skewness					0.005***	
					(0.00)	
Robust skewness						0.129***
						(0.02)
Constant	0.013***	0.013***	0.029**	0.056**	0.013***	0.012***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)
Observations	390	390	390	390	390	390
R-squared	0.0779	0.0610	0.00804	0.0312	0.0195	0.0600
	Based on market capitalization weights					
Lagged endogenous variable	0.231	0.231	0.148	0.240	0.279	0.324
	(0.52)	(0.52)	(0.45)	(0.51)	(0.54)	(0.55)
Mean	0.239***					
	(0.08)					
Median		0.239***				
		(0.08)				
Standard deviation			-0.882**			
			(0.39)			
Interquartile range				-0.425		
				(0.29)		
Skewness					0.008**	
					(0.00)	
Robust skewness						0.002
						(0.01)
Constant	0.011**	0.011**	0.068***	0.045**	0.012**	0.012**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)	(0.01)
Observations	390	390	390	390	390	390
R-squared	0.0277	0.0277	0.0919	0.0375	0.0158	0.00304

Notes: This table reports the results of the regression model described in equation 8. Robust (Newey and West, 1987) Standard errors in parentheses. *** (**,*) denotes rejection of the null hypothesis at the 1 (5,10) % level.

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 (2018) for U.S. 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. Appendix Tables A1 and A2 show results based on a forecast horizon of six and nine months, respectively, with qualitatively similar results.

4.2 In-sample forecasting regressions with control variables

Table 2 shows the results of simple forecasting regressions including selected business cycle indicators as control variables.

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 represent 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 robust skewness measure turns out to be insignificant in the latter case.

4.3 Probit models

We also check whether cross-sectional skewness may serve as a leading indicator of recessions. To this end, we refer to simple Probit models, following, among others, Estrella and Mishkin (1998) and Bernard and Gerlach (1998):

$$R_t^* = \beta_0 + \beta_1 M_{t-k} + u_t \tag{9}$$

where R^* is an unobservable variable representing the state of the economy and M represents the respective cross-sectional moment. For the latent variable an observable indicator variable is used:

$$R_i = \begin{cases} 1 & if\ R_i^* > 0 \\ 0 & else \end{cases} \tag{10}$$

Table 2: Forecasting equations including cross-sectional stock market cross-section moments and control variables for Germany 1987 to 2019

	Dependent variable: average growth rate of industrial production over the next three months					
	Based on $1/N$ weights					
Lagged endog. var.	-1.194***	-1.182***	-1.153***	-1.116***	-1.158***	-1.180***
	(0.28)	(0.28)	(0.29)	(0.30)	(0.30)	(0.30)
Interest rate spread	0.023***	0.024***	0.025***	0.025***	0.024***	0.023***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Order Inflow	0.024***	0.024***	0.025***	0.025***	0.027***	0.025***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ifo business climate	0.026***	0.026***	0.026**	0.025***	0.026**	0.025**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mean	0.358***					
	(0.12)					
Median		0.370**				
		(0.15)				
Standard deviation			-0.130			
			(0.13)			
Interquartile range				-0.179		
				(0.24)		
Skewness					0.005***	
					(0.00)	
Robust skewness						0.091***
						(0.02)
Constant	0.014**	0.014**	0.030**	0.033	0.014**	0.014**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Observations	390	390	390	390	390	390
R-squared	0.320	0.310	0.279	0.278	0.292	0.301
	Based on market capitalization weights					
Lagged endog. var.	-1.166***	-1.166***	-1.097***	-1.117***	-1.169***	-1.130***
	(0.29)	(0.29)	(0.30)	(0.30)	(0.30)	(0.30)
Interest rate spread	0.025***	0.025***	0.026***	0.026***	0.024***	0.025***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Order Inflow	0.024***	0.024***	0.023***	0.024***	0.026***	0.026***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ifo business climate	0.027***	0.027***	0.021***	0.024***	0.026***	0.026**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mean	0.180***					
	(0.06)					
Median		0.180***				
		(0.06)				
Standard deviation			-0.611			
			(0.45)			
Interquartile range				-0.256		
				(0.25)		
Skewness					0.007**	
					(0.00)	
Robust skewness						-0.004
						(0.01)
Constant	0.012*	0.012*	0.052**	0.033**	0.013**	0.014**
	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)
Observations	390	390	390	390	390	390
R-squared	0.287	0.287	0.312	0.285	0.283	0.274

Notes: This table reports the results of the regression model described in equation 8. Robust (Newey and West, 1987) Standard errors in parentheses. *** (**,*) denotes rejection of the null hypothesis at the 1 (5,10) % level.

The indicator variable takes the value of 1 if the economy is in a recession according to the Economic Cycle Research Institute (2020) concept. If PR denotes the probability of being in a recession in period t, it follows that (Greene, 2003, p. xx ff.):

$$\text{PR}(R_t^* > 0) = \text{PR}(R_t = 1) = \Phi(b_k' m) \tag{11}$$

where b_k is a vector of coefficients to be estimated, m is a vector of lagged cross-section moments, and $\Phi(\cdot)$ denotes the cumulative normal distribution function. Every moment might be an indicator with a certain lead with respect to recession phases. Thus, in a first step, we estimate Probit equations for alternative lags of the possible indicator variables and choose the model with the highest McFadden (1973)-R^2. As mentioned above, we consider both 'classical' recessions and 'growth cycles'.

The results in Table 3, based on the classical recession concept, are sobering. Some coefficients are statistically significant with the expected sign. However, the skewness variable based on $1/N$ weights and both skewness variants based on market capitalization weights are not. Moreover, for all models the statistics for sensitivity and specificity are bad, and the area under the receiving operating curve (AUROC) hardly differs from the value of 0.5, which a coin-flip classification would produce (for a discussion of the evaluation of related models see: Berge and Jordà, 2011). Thus, we have to conclude that cross-sectional moments are no valid predictors for recessions in Germany. This does also hold for the 'growth cycle' concept of economic downturns (see the results in Appendix Table A3).

4.4 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):

$$d_t = \beta_0 + u_t \tag{12}$$

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

Table 3: Probit estimates including cross-sectional stock market cross-section moments for Germany 1987 to 2019 - classical recession concept

	Dependent variable: Classical recession phases					
	Based on $1/N$ weights					
$\text{Mean}_{\text{t-5}}$	-5.998***					
	(1.47)					
$\text{Median}_{\text{t-5}}$		-5.520***				
		(1.66)				
$\text{Standard deviation}_{\text{t-10}}$			-2.499			
			(1.62)			
$\text{Interquartile range}_{\text{t-1}}$				7.573***		
				(2.13)		
$\text{Skewness}_{\text{t-2}}$					-0.040	
					(0.03)	
$\text{Robust Skewness}_{\text{t-5}}$						-1.836***
						(0.42)
Constant	-0.859***	-0.840***	-0.500**	-1.650***	-0.829***	-0.864***
	(0.08)	(0.07)	(0.21)	(0.25)	(0.07)	(0.08)
Observations	391	391	386	395	394	391
Pseudo-R:	0.0551	0.0344	0.00764	0.0422	0.00370	0.0742
Correctly:	79.80	79.28	79.02	79.75	79.44	81.33
AUROC:	0.655	0.638	0.577	0.569	0.582	0.668
Sensitivity:	6.173	3.704	0	3.704	0	11.11
Specificity:	99.03	99.03	100	99.36	100	99.68
	Based on market capitalization weights					
$\text{Mean}_{\text{t-5}}$	-3.961***					
	(1.26)					
$\text{Median}_{\text{t-5}}$		-3.961***				
		(1.26)				
$\text{Standard deviation}_{\text{t-1}}$			7.675***			
			(2.39)			
$\text{Interquartile range}_{\text{t-11}}$				1.775		
				(1.82)		
$\text{Skewness}_{\text{t-4}}$					-0.113	
					(0.07)	
$\text{Robust skewness}_{\text{t-4}}$						-0.161
						(0.19)
Constant	-0.806***	-0.806***	-1.322***	-0.940***	-0.821***	-0.803***
	(0.07)	(0.07)	(0.18)	(0.16)	(0.07)	(0.07)
Observations	391	391	395	385	392	392
Pseudo-R:	0.0277	0.0277	0.0283	0.00248	0.0107	0.00193
Correctly:	79.28	79.28	80	78.96	79.34	79.34
AUROC:	0.607	0.607	0.549	0.515	0.636	0.533
Sensitivity:	1.235	1.235	3.704	0	0	0
Specificity:	99.68	99.68	99.68	100	100	100

Notes: This table reports the results of the regression model described in equation 11. Robust standard errors in parentheses. *** (**,*) denotes rejection of the null hypothesis at the 1 (5,10) % level. The lag lengths are determined based on the maximum McFadden (1973)-Pseudo-R^2.

Table 4 reports the results of an out-of-sample exercise. We have calculated three (six, nine) months' forecasts based on Equation 12 for the period 2010–2019 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 both the mean and median cross-section returns, along with the skewness measures, reduce the Mean Squared Error compared to a model without these variables for a forecast horizon of three and six months. Again, the standard deviations and the interquartile range stand out as exceptions, since in these models the gain of forecast accuracy is quite small, and according to the results of the Diebold–Mariano test, not statistically significant. In case of a three-month horizon, the skewness is also insignificant (for the $1/N$-based measure) or significant at the 10 % level only (in case of the market-based weighted number). The picture, however, reverses with regard to the six-month forecast horizon, where all skewness measures significantly reduce the MSE, except the robust measures in the case of market-capitalization-weighted numbers, which is a borderline case. Not surprisingly, and in line with previous evidence (see, for example, Drechsel and Scheufele, 2012) the predictive power of the models breaks more or less down when the nine-month horizon is considered.

4.5 Autoregressive Distributed Lag (ARDL) models

Another approach to test the relationship between cross-sectional moments of stock market returns and the German business cycle is the Autoregressive Distributed Lag (ARDL) model suggested by Pesaran and Shin (1998); 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 and Uko, 2016). The bounds test, suggested by Pesaran et al. (2001), allows detecting cointegrating relationships between the variables. Therefore, the ARDL model is more flexible than Engle and Granger (1987)'s popular approach.

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 the term spread as control variable. The ARDL(p,q,...,q) model is given by

Table 4: Out of sample forecasting performance

	Horizon: 3 Months			Horizon: 6 Months			Horizon: 9 Months		
	Relative MSE	t-value	p-value	Relative MSE	t-value	p-value	Relative MSE	t-vlaue	p-value
				Based on 1/N weights					
Mean	0,959	-2,18	(0,03)	0,924	-2,60	(0,01)	0,996	-0,13	(0,89)
Median	0,970	-1,93	(0,05)	0,934	-2,48	(0,01)	0,998	-0,05	(0,96)
Standard deviation	1,002	0,37	(0,71)	0,978	-1,69	(0,09)	1,011	0,38	(0,70)
Interquartile range	0,991	-0,71	(0,48)	0,972	-1,54	(0,12)	1,006	0,23	(0,82)
Skewness	0,994	-1,26	(0,21)	0,976	-2,10	(0,04)	1,014	0,46	(0,64)
Robust skewness	0,970	-3,37	(0,00)	0,945	-3,06	(0,00)	1,001	0,03	(0,98)
				Based on market capitalisation weights					
Mean	0,987	-2,36	(0,02)	0,958	-2,96	(0,00)	1,005	0,15	(0,88)
Median	0,987	-2,36	(0,02)	0,958	-2,96	(0,00)	1,005	0,15	(0,88)
Standard deviation	0,982	-0,59	(0,56)	0,961	-1,17	(0,24)	1,003	0,10	(0,92)
Interquartile range	0,998	-0,23	(0,82)	0,975	-1,47	(0,14)	1,006	0,23	(0,82)
Skewness	0,995	-1,72	(0,09)	0,973	-2,84	(0,00)	1,012	0,39	(0,69)
Robust skewness	1,004	1,51	(0,13)	0,984	-1,63	(0,10)	1,015	0,49	(0,63)

Notes: P-values refer to a Diebold and Mariano (1995) test for equal forecast accuracy as compared to a simple AR(1) model.

$$y_t = c_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=0}^{q} \beta_j' \mathbf{x}_{t-j} + \epsilon_t \tag{13}$$

referring to the general form (see, among others, Hassler and 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. The optimal lag lengths p and q will be obtained by minimizing the Akaike information criterion (AIC).[3] 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) test for a unit root. The results are given in Appendix Table A4. 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

$$y_t = c_0 - \alpha(y_{t-1} - \theta x_t) + \sum_{i=1}^{p-1} \psi_{yi} \Delta y_{t-1} + \sum_{j=0}^{q-1} \psi_{xi}' \Delta \mathbf{x}_{t-i} + \epsilon_t \tag{14}$$

with the adjustment coefficient $\alpha = 1 - \sum_{j=1}^{p} \phi_i$ and the long-run coefficient $\theta = \frac{\sum_{j=0}^{q} \beta_j}{\alpha}$. The long-run relationship between cross-sectional moments of stock market returns and German business cycle variables will be tested with the bounds test. 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 W test for normality of the residuals.

Table 5 reports the results of ARDL estimates including stock market cross-section moments for Germany.[4] The lagged log of industrial production represents the adjustment coefficient, followed by the indicator and spread (level), which display the long-run coefficients. The other variables show the short-run coefficients and the constant term. As Table 5 shows, a series of short-run coefficients are statistically significant, at least at a 5 percent level. Nevertheless, the results do not suggest an error correction and long-run relationship. Their respective coefficients are not statistically different

[3]The lag order can differ across regressors in the ARDL framework.

[4]Following Ferreira (2018), these enter the equation as standardized variables, i.e. the mean is subtracted from the value, and the difference between the variable and its mean is divided by its standard deviation.

Table 5: ARDL estimates including cross-sectional stock market moments for Germany, 1987 to 2019

	Cross-sectional indicator included in the model: Mean	Median	Standard deviation	Interquartile range	Skewness	Robust skewness
Dependent variable: first difference of logarithm of Log of industrial production						
Based on 1/N-weights:						
Lagged endogenous, level	-0.004	-0.004	-0.006	-0.004	-0.004	-0.003
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Indicator, level	0.111***	0.133***	0.003	-0.034	0.001*	0.024***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.00)	(0.01)
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)
Lagged endogenous, first difference	-0.319***	-0.316***	-0.284***	-0.289***	-0.287***	-0.300***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Indicator, first difference	-0.326***	-0.321***	-0.266***	-0.274***	-0.272***	-0.291***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Indicator, first difference t-2	-0.014	-0.010	0.045	0.033	0.040	0.011
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Lagged endogenous, first difference, t-3	0.181***	0.185***	0.222***	0.213***	0.224***	0.191***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Indicator first difference	-0.103***	-0.120***		0.050*	-0.001**	-0.022***
	(0.02)	(0.03)		(0.03)	(0.00)	(0.01)
Indicator first difference, t-1	-0.075***	-0.087***			-0.001***	-0.014**
	(0.02)	(0.02)			(0.00)	(0.01)
Indicator first difference, t-2	-0.049***	-0.052***			-0.001***	-0.012***
	(0.02)	(0.02)			(0.00)	(0.00)
Indicator first difference, t-3	-0.025*	-0.033**				
	(0.01)	(0.01)				
Spread, first difference	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spread, first difference, t-1	-0.003	-0.003	-0.002	-0.001	-0.001	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spread, first difference, t-2	-0.012***	-0.012***	-0.011***	-0.011***	-0.012***	-0.012***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spread, first difference, t-3	0.011***	0.012***	0.013***	0.012***	0.012***	0.012***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.016	0.016	0.026	0.018	0.019	0.015
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Observations	390	390	390	390	390	390
Adj. R-squared	0.219	0.216	0.174	0.180	0.189	0.201
Bounds-test (F-value)	12	11.42	3.579	4.494	4.715	8.383
Bounds-test (t-value)	-0.781	-0.802	-0.951	-0.711	-0.920	-0.727
Test for heteroscedasticity (p-value)	0.261	0.164	0.103	0.032	0.098	0.334
Test for normality (p-value)	0.065	0.127	0.011	0.031	0.005	0.003
Test for autocorrelation (p-value)	0.355	0.409	0.231	0.391	0.409	0.130

Notes: This table reports the results of the regression model described in equation 14 and estimated using the STATA module developed by Kripfganz and Schneider (2018). Robust (Newey and West, 1987) Standard errors in parentheses. *** (**,*) denotes rejection of the null hypothesis at the 1 (5,10) % level.

Table 5, ARDL estimates including cross-sectional stock market moments for Germany, 1987 to 2019

	Cross-sectional indicator included in the model:					
	Mean	Median	Standard deviation	Interquartile range	Skewness	Robust skewness
Dependent variable: first difference of logarithm of Log of industrial production						
Based on markets capitalization weights:						
Lagged endogenous, level	-0.005	-0.005	-0.004	-0.005	-0.005	-0.006
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Indicatorl level	0.072***	0.072***	-0.103***	-0.053**	0.001*	0.002
	(0.02)	(0.02)	(0.03)	(0.02)	(0.00)	(0.00)
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)
Lagged endogenous, first difference	-0.290***	-0.290***	-0.303***	-0.284***	-0.269***	-0.266***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Lagged endogenous, first difference, t-2	0.024	0.024	0.008	0.024	0.041	0.050
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Lagged endogenous, first difference, t-3	0.218***	0.218***	0.195***	0.206***	0.220***	0.224***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Indicator, first difference	-0.055***	-0.055***	0.099***	0.035*		
	(0.02)	(0.02)	(0.03)	(0.02)		
Indicator, first difference, t-1	-0.028**	-0.028**	0.061**			
	(0.01)	(0.01)	(0.03)			
Spread, first difference	-0.011***	-0.011***	-0.008**	-0.009***	-0.010***	-0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spread, first difference, t-1	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spread, first difference, t-2	-0.011***	-0.011***	-0.011***	-0.012***	-0.011***	-0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spread, first difference, t-3	0.013***	0.013***	0.011***	0.012***	0.013***	0.012***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.019	0.019	0.021	0.024	0.021	0.024
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	390	390	390	390	390	390
Adj. R-squared	0.200	0.200	0.202	0.185	0.180	0.177
Bounds-test (F-value)	8.388	8.388	8.465	5.687	4.656	4.154
Bounds-test (t-value)	-0.989	-0.989	-0.750	-1.012	-1.040	-1.180
Test for heteroscedasticity (p-value)	0.326	0.326	0.0378	0.0292	0.0908	0.0650
Test for normality (p-value)	0.084	0.084	0.121	0.075	0.011	0.025
Test for autocorrelation (p-value)	0.096	0.096	0.193	0.158	0.126	0.184

Notes: This table reports the results of the regression model described in equation 14 and estimated using the STATA module developed by Kripfganz and Schneider (2018). Robust (Newey and West, 1987) Standard errors in parentheses. *** (**,*) denotes rejection of the null hypothesis at the 1 (5,10) % level.

from zero. These results hold for both the $1/N$ weighting statistics and the market capitalization weighting schemes.

To test a potential long-run relationship more precisely, the bounds test can be used. Table 5 shows the bounds F-test of the joint null hypothesis whether $H_0^F : \alpha = 0 \cap \sum_{j=0}^{q} \beta_j = 0$. 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). The necessary condition of the bounds test procedure can be rejected for all ARDL specifications, at least with a p-value of 0.01 for the upper I(1) bound. In a second step, we test the single null hypothesis $H_0^t : \alpha = 0$ with a t-test. The bounds t-test results cannot be rejected for any ARDL specification. Hence, the sufficient condition of the bounds test procedure is not given.[5] Besides, the diagnostic tests are not always completely satisfying.[6] 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 has to be rejected.

5 Discussion and conclusion

Based on monthly data from 1987 to 2019, 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. At a first glance, our results are less promising than the findings of Ferreira (2018) using U.S. data.

On the one hand, 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 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.

On the other hand, in comparison with Ferreira (2018) the explanatory power of the regression results is significantly lower for both regressions with and without additional control variables. Concerning the suitability of cross-

[5] Usually, the bounds test procedure comprises three steps. If we can reject H_0^t 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.

[6] Given a significance level of 1%, we have to reject the null of normal distributed residuals for 2 out of 12 model specification.

sectional stock market return moments as a leading indicator for recessions, we must conclude that cross-sectional moments are no valid predictors for recessions in Germany, which also holds for the 'growth cycle' concept of economic downturns. In contrast, Ferreira (2018) shows that the cross-sectional mean, and in particular the cross-sectional (financial) skewness, are powerful predictors for recessions in the USA. Considering the out-of-sample power of forecasting models with and without cross-sectional moments, our results show that the mean and median, as well as the skewness measures, reduce the Mean Squared Error compared to the model without these variables for forecast horizons of three and six months. Furthermore, the results are statistically significant in the vast majority of cases. As expected, the predictive power of the models breaks down within the nine-month horizon. Additionally, the ARDL framework suggests short-run, as opposed to long-run, relationships between the future position of the German business cycle and cross-sectional moments of stock market returns. The results strengthen previous forecasting regression findings, indicating some predictive power of cross-section moments for the future growth of industrial production.

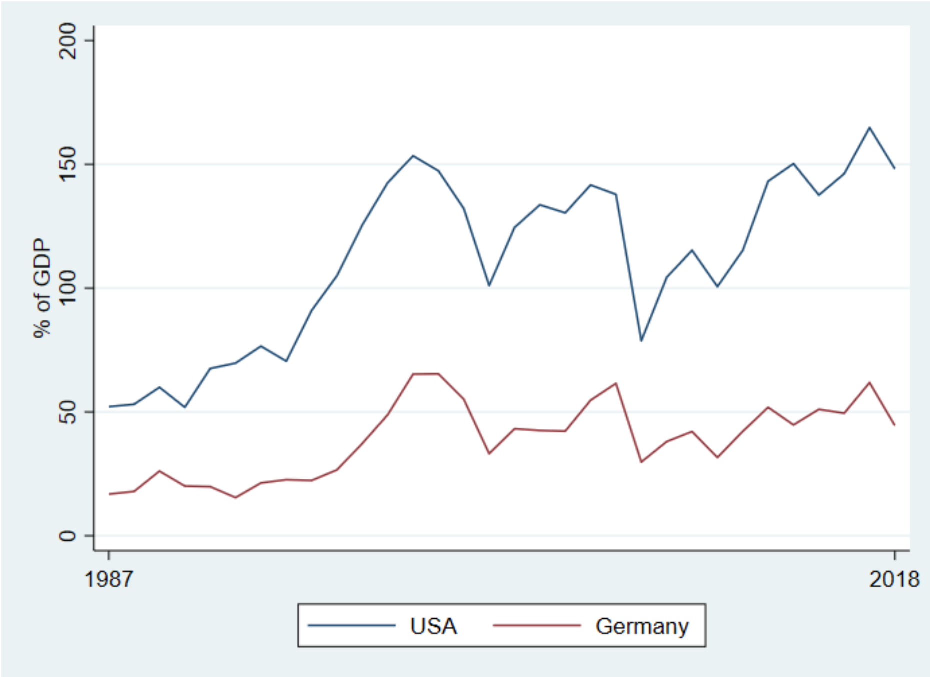
Possible differences in the results from those of Ferreira (2018) for the USA mainly include differences in financial systems between Germany and the USA, the cross-sectional sample size, the length of the observation period, and data frequency.

Typically, the financial systems of developed countries can be divided into two types: a bank-based (German–Japanese) financial system and a market-based (Anglo-Saxon) financial system (Schmidt and Tyrell, 1997; Fecht, 2004). Figure 4 shows two empirical hints that the stock market is less important in Germany than in the U.S.: market capitalization and credits, both in relation to GDP, are much smaller in Germany than in the U.S. Hence, the stock market played an important role in promoting economic growth for the USA, whereas the banking sector played a more important role in Germany (Ang, 2008; Lee, 2012). Because a market-based financial system prevails in the USA, the cross-sectional sample of Ferreira (2018) is considerably larger and thus significantly more meaningful.[7]

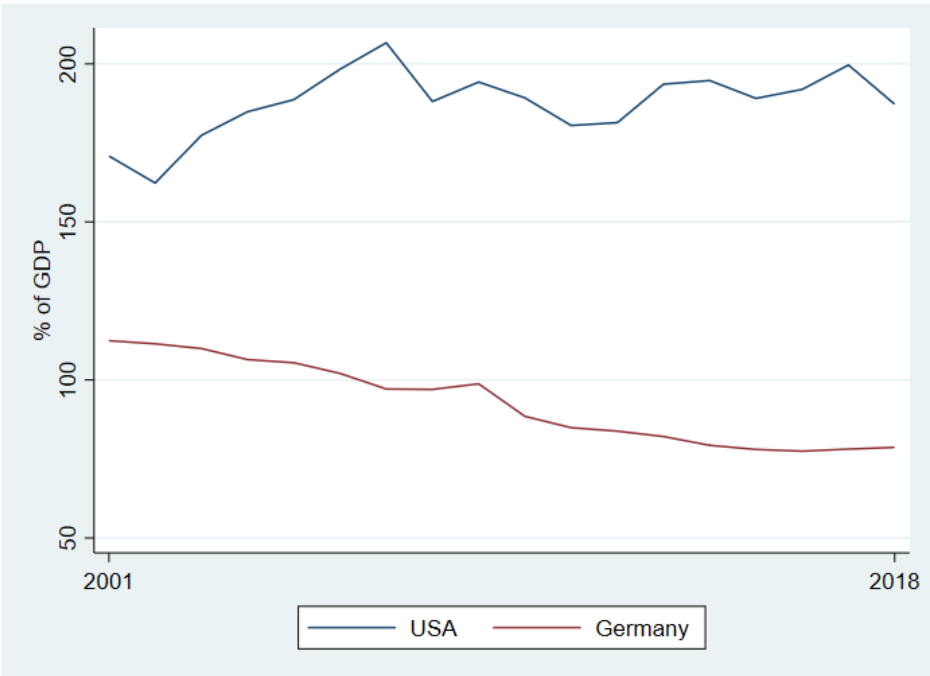
The larger sample enabled Ferreira (2018)–in contrast to our cross-sectional sample–to differentiate between financial and nonfinancial companies when calculating the skewness. Ferreira (2018) justifies this approach with the argument that a close relationship between financial skewness and the economic cycle responds to the exposure of financial firms to the eco-

[7]Ferreira (2018) uses the CRSP US stock database, which contains data for over 32,000 active and inactive firms. In contrast, our sample consists of 413 companies listed in the CDAX.

Figure 4: Importance of stock markets in Germany and the U.S., 1987 to 2019



(a) Market cpitalization in relation to GDP



(b) Credits in relation GDP

Source: World Bank data base (`https://data.worldbank.org/`)

nomic performance of their borrowers.[8] This is also confirmed by his results. Concerning the results of the Probit models, it should be noted that the investigation period of Ferreira—from 1926 to 2015—is significantly longer, making its results much more meaningful as it covers considerably more business cycles. Finally, we use monthly data that are noisier, whereas Ferreira (2018) uses quarterly data that are smoother.

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. This variable shows the ratio of total domestic lending to nominal GDP. It is used to capture the development of the banking system. The use of this variable is recommended in an economy that is expected to be highly dependent on bank loans (Marques et al., 2013).

[8]In this context Ferreira (2018) 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.

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Appendix

Table A1: Forecasting equations including cross-sectional stock market cross-section moments for Germany 1987 to 2019, six months horizon

	Dependent variable: average growth rate of industrial production over the next six months					
	Based on $1/N$ weights					
Lagged endogenous variable	0.107	0.129	0.239	0.202	0.261	0.132
	(0.33)	(0.33)	(0.39)	(0.34)	(0.41)	(0.38)
Mean	0.410***					
	(0.14)					
Median		0.436**				
		(0.18)				
Standard deviation			-0.100			
			(0.12)			
Interquartile range				-0.280		
				(0.27)		
Skewness					0.003**	
					(0.00)	
Robust skewness						0.114***
						(0.02)
Constant	0.013**	0.013*	0.025*	0.043*	0.013*	0.013*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	387	387	387	387	387	387
R-squared	0.101	0.0843	0.00787	0.0237	0.0124	0.0740
	Based on market capitalization weights					
Lagged endogenous variable	0.164	0.164	0.136	0.196	0.229	0.265
	(0.37)	(0.37)	(0.26)	(0.33)	(0.41)	(0.42)
Mean	0.224***					
	(0.08)					
Median		0.224***				
		(0.08)				
Standard deviation			-0.594			
			(0.42)			
Interquartile range				-0.294		
				(0.27)		
Skewness					0.005*	
					(0.00)	
Robust skewness						-0.003
						(0.01)
Constant	0.011	0.011	0.050**	0.035**	0.013*	0.013*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Observations	387	387	387	387	387	387
R-squared	0.0375	0.0375	0.0673	0.0292	0.0113	0.00322

Notes: This table reports the results of the regression model described in equation 8. Robust (Newey and West, 1987) Standard errors in parentheses. *** (**,*) denotes rejection of the null hypothesis at the 1 (5,10) % level.

Table A2: Forecasting equations including cross-sectional stock market cross-section moments for Germany 1987 to 2019, nine months horizon

	Dependent variable: average growth rate of industrial production over the next six months					
	Based on $1/N$ weights					
Lagged endogenous variable	0.107	0.129	0.239	0.202	0.261	0.132
	(0.33)	(0.33)	(0.39)	(0.34)	(0.40)	(0.37)
Mean	0.410***					
	(0.14)					
Median		0.436**				
		(0.17)				
Standard deviation			-0.100			
			(0.11)			
Interquartile range				-0.280		
				(0.26)		
Skewness					0.003**	
					(0.00)	
Robust skewness						0.114***
						(0.02)
Constant	0.013**	0.013**	0.025*	0.043*	0.013**	0.013**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	387	387	387	387	387	387
R-squared	0.101	0.0843	0.00787	0.0237	0.0124	0.0740
	Based on market capitalization weights					
Lagged endogenous variable	0.164	0.164	0.136	0.196	0.229	0.265
	(0.37)	(0.37)	(0.26)	(0.33)	(0.40)	(0.41)
Mean	0.224***					
	(0.08)					
Median		0.224***				
		(0.08)				
Standard deviation			-0.594			
			(0.41)			
Interquartile range				-0.294		
				(0.26)		
Skewness					0.005*	
					(0.00)	
Robust skewness						-0.003
						(0.01)
Constant	0.011	0.011	0.050**	0.035**	0.013*	0.013**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Observations	387	387	387	387	387	387
R-squared	0.0375	0.0375	0.0673	0.0292	0.0113	0.00322

Notes: This table reports the results of the regression model described in equation 8. Robust (Newey and West, 1987) Standard errors in parentheses. *** (**,*) denotes rejection of the null hypothesis at the 1 (5,10) % level.

Table A3: Probit estimates including cross-sectional stock market cross-section moments for Germany 1987 to 2019 - growth cycle concept

	Dependent variable: Growth cycle recession phases					
	Based on $1/N$ weights					
$\text{Mean}_{\text{t-5}}$	-5.400***					
	(1.43)					
$\text{Median}_{\text{t-5}}$		-5.546***				
		(1.73)				
Standard $\text{dev.}_{\text{t-10}}$			5.857***			
			(1.40)			
Interquar. $\text{range}_{\text{t-1}}$				7.516***		
				(1.95)		
$\text{Skewness}_{\text{t-2}}$					-0.046	
					(0.03)	
Robust $\text{Skewness}_{\text{t-5}}$						-2.185***
						(0.43)
Constant	0.061	0.064	-0.681***	-0.743***	0.054	0.056
	(0.06)	(0.06)	(0.18)	(0.21)	(0.06)	(0.06)
Observations	391	391	393	395	392	395
Pseudo-R^2:	0.0365	0.0287	0.0375	0.0304	0.00458	0.0539
Correctly:	61.13	60.36	62.34	60.76	52.27	61.52
AUROC:	0.639	0.631	0.635	0.621	0.569	0.659
Sensitivity:	65.85	68.29	69.27	61.46	80.10	65.37
Specificity:	55.91	51.61	54.79	60	22.11	57.37
	Based on market capitalisation weights					
$\text{Mean}_{\text{t-5}}$	-2.463**					
	(1.11)					
$\text{Median}_{\text{t-5}}$		-2.463**				
		(1.11)				
Standard $\text{deviation}_{\text{t-1}}$			3.968*			
			(2.12)			
Interquartile $\text{range}_{\text{t-11}}$				-2.193		
				(1.78)		
$\text{Skewness}_{\text{t-4}}$					-0.055	
					(0.05)	
Robust $\text{skewness}_{\text{t-4}}$						0.114
						(0.17)
Constant	-0.436***	-0.436***	-0.702***	-0.285*	-0.448***	-0.462***
	(0.07)	(0.07)	(0.15)	(0.15)	(0.07)	(0.07)
Observations	386	386	386	385	386	386
Pseudo-R^2:	0.00979	0.00979	0.00684	0.00315	0.00238	0.000917
Correctly:	54.99	54.99	55.47	53.83	58.48	52.93
AUROC:	0.586	0.586	0.578	0.545	0.627	0.549
Sensitivity:	65.37	65.37	54.15	68.29	72.20	69.76
Specificity:	43.55	43.55	56.91	37.97	43.68	34.57

Notes: This table reports the results of the regression model described in equation 11. Robust standard errors in parentheses. *** (**,*) denotes rejection of the null hypothesis at the 1 (5,10) % level. The lag lengths are determined based on the maximum McFadden (1973)-Pseudo-R^2.

Table A4: Results of Unit Root Tests

	Level		First difference	
Variable	Dickey-Fuller statistic	p-value	Dickey-Fuller statistic	p-value
	Based on $1/N$ weights			
Mean	-8,11	(0,00)	-29,63	(0,00)
Median	-8,72	(0,00)	-30,35	(0,00)
Standard deviation	-2,81	(0,06)	-29,84	(0,00)
Interquartile range	-3,73	(0,00)	-29,40	(0,00)
Skewness	-10,26	(0,00)	-34,37	(0,00)
Robust skewness	-7,64	(0,00)	-30,18	(0,00)
	Based on markets capitalization weights			
Mean	-9,73	(0,00)	-32,59	(0,00)
Median	-9,73	(0,00)	-32,59	(0,00)
Standard deviation	-4,70	(0,00)	-28,21	(0,00)
Interquartile range	-5,21	(0,00)	-35,18	(0,00)
Skewness	-9,79	(0,00)	-39,69	(0,00)
Robust skewness	-9,95	(0,00)	-32,64	(0,00)
Term spread	-3,07	(0,03)	-14,22	(0,00)
Log of indus. production	-1,59	(0,49)	-7,31	(0,00)

Notes: The table presents the results for an augmented Dickey and Fuller (1979) test with the length of the autoregressive process set equal 3. The p-values are calculated based on the critical values of MacKinnon (1994).