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Business cycle and herding behavior in stock returns: theory and evidence

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Abstract

This study explains the role of economic uncertainty as a bridge between business cycles and investors' herding behavior. Starting with a conventional stochastic differential equation representing the evolution of stock returns, we provide a simple theoretical model and empirically demonstrate it. Specifically, the growth rate of gross domestic product and the power law exponent are used as proxies for business cycles and herding behavior, respectively. We find stronger herding behavior during recessions than during booms. We attribute this to economic uncertainty, which leads to strong behavioral bias in the stock market. These findings are consistent with the predictions of the quantum model.

Keywords: Herd behavior, Business cycle, Economic uncertainty, Quantum model, Power law exponent

Introduction

In the twenty-first century, stock trading has predominantly been conducted through electronic platforms rather than on the floor. By the end of 2014, approximately 15% of the total trading on the New York Stock Exchange was conducted on the floor, with the rest handled electronically (Hiltzik 2014). The dominance of anonymous electronic trading implies that more trades are independent of others. However, it has been widely documented that participants in financial markets mimic other traders' actions, termed "herding" in literature. Herding in the stock market often leads to higher volatility, implying greater fluctuations in stock returns (Cont and Bouchaud 2000; Orĺean 1995; Banerjee 1993; Topol 1991). Thus, understanding the origins of herding behavior in financial markets is critically important for regulators and practitioners.

Our definition of "herding" differs slightly from the conventional one because we focus on the tail of the distribution with a scaling exponent. In other words, although investors are likely to herd within the center to follow the larger group of investors, "local" herding among investors who are at the extremes of the distribution is also possible with a certain regularity. Previously, most literature has explained "herding" as the general tendency of market participants to cluster around the center. For example, some studies have focused on the co-movement of stock returns using dynamic correlations and have defined herding as a high correlation among investors across different markets

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(Chiang et al. 2007; Boyer et al. 2006). Other studies use financial assets following extreme market returns to capture herding behavior in financial markets (Sibande et al. 2021; Kumar et al. 2021; Bouri et al. 2021; Bouri et al. 2019; Demirer et al. 2019; Balcilar et al. 2017; Galariotis et al. 2015; Chiang and Zheng 2010; Chang et al. 2000; Christie and Huang 1995). Moreover, prior studies on herding in financial markets have mostly focused on statistical tests of the relationship between herding behavior and business cycles but have failed to explain business cycles as the origin of herding behavior in the marketplace.

This study investigates herding behavior in stock returns based on concepts pioneered by the physics community. Stock markets exhibit universal characteristics similar to physical systems with considerable interacting units, for which several microscopic models have been developed (Shalizi 2001; Lux and Marchesi 1999). For example, the return distribution presents pronounced tails that are thicker than those of the Gaussian distribution (Shalizi 2001; Lux 1996; Mantegna and Stanley 1995). Several models have been proposed that phenomenologically show fat-tail distributions induced by investors' herding behavior (Banerjee 1993; Topol 1991). Furthermore, Cont and Bouchaud (2000), OrĺEan (1995), Banerjee (1993), and Topol (1991) showed that market participants' interactions through imitation can lead to large fluctuations in aggregate demand and heavy tails in the distribution of returns. This approach had been formalized as a power law exponent at the tail of the distribution with a smaller magnitude associated with stronger herding behavior in stock returns (Nirei et al. 2020; Gabaix et al. 2005; Plerou et al. 1999; Gopikrishnan et al. 1999), trading volumes (Gabaix et al. 2006; Gopikrishnan et al. 2000), and commodity returns (Joo et al. 2020), which have been empirically investigated. Another stream of literature theoretically explains the power law in firm size distribution (Ji et al. 2020; Luttmer 2007) and trading volume (Nirei et al. 2020). However, these studies are limited to providing a connection between the power law exponent and other external factors, such as the business cycles and economic uncertainty.

We contribute to literature by explaining the role of economic uncertainty as a bridge between business cycles and investors' herding behavior. Specifically, we propose a parsimonious model that employs quantum mechanics as an intermediate step to obtain the final solution and justify the power law distribution in stock returns. We start with the Fokker–Planck (FP) equation to model the dynamics of stock return distribution and derive the Schrödinger equation for a particular external potential (Ahn et al. 2017). The form of the potential is postulated based on empirical evidence of the evolution of stock returns in the marketplace. The solution suggests the existence of a power law for the tail distribution of stock returns. This also predicts a positive association between business cycles and the power law exponent. Our model provides new insights into existing research that models stock prices using random walks (Bartiromo 2004; Ma et al. 2004), quantum oscillators (Ahn et al. 2017; Ye and Huang 2008), quantum wells (Pedram 2012; Zhang and Huang 2010), and quantum Brownian motions (Meng et al. 2016).

We provide further empirical evidence on whether herding behavior in stock returns is negatively associated with business cycles. Furthermore, business cycles, which are often used as proxies for economic growth, are closely related to economic uncertainty, whereby it is believed that recessions are accompanied by higher economic uncertainty (Bloom 2014). Moreover, greater economic uncertainty leads to higher levels of

Table 1 Descriptive statistics

Variable	Obs	Mean	Std	Min	Max
Return (%)	1,031,914	0.060	1.987	− 61.047	87.736
NBER recession indicator	30	0.133	0.346	0	1
Annual GDP growth (%)	30	2.518	1.871	− 2.775	6.100
Forecaster uncertainty	30	0.418	0.064	0.290	0.538

uncertainty in the stock market. With greater uncertainty in the stock market, investors are more likely to mimic others because increased information asymmetry leads to fewer investors having confidence in their valuations (Alhaj-Yaseen and Yau 2018; Park and Sabourian 2011; Devenow and Welch 1996), amplifying investors' herding behavior in the tail. As hypothesized, we find that herding behavior is stronger during recessions than booms and that economic uncertainty causes significant herding behavior.

Data and methodology

Data description

Our sample includes 137 US firms that were continuously included in the Standard & Poor's 500 (S&P 500) index from January 1992 to December 2021.[1] We exclude firms that either entered or exited the index during our sample period to avoid the influence of abnormal trading around entry or exit events (Chen et al. 2004; Lynch and Mendenhall 1997; Beneish and Whaley 1996; Harris and Gurel 1986; Shleifer 1986). We obtain the daily stock return data from the Center for Research in Security Prices with 1,031,914 firm-day observations for our sample firms. We normalize the return of each firm by subtracting its mean and dividing it by its standard deviation over the entire sample period to remove heterogeneity in stock return volatility among different stocks (Feng et al. 2012; Gabaix et al. 2003). Furthermore, we obtain yearly recession indicators from the National Bureau of Economic Research (NBER) and seasonally adjusted US real Gross Domestic Product (GDP) growth rates from the Federal Reserve Economic Data. As a proxy for economic uncertainty, we adopt Bloom's (2014) definition of forecaster uncertainty as the median of forecasters' subjective variances. It measures the annual average uncertainty of each forecaster. Data for the forecaster probability distribution of the GDP growth rate were obtained from the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia.

Table 1 presents the descriptive statistics of the main variables of this study. The mean daily stock return was 0.060%. During our sample period (January 1992 to December 2021), four years were recessionary periods, including the Dot-com Crash, Global Financial Crisis, and Coronavirus disease (COVID-19) pandemic. The average annual US real GDP growth rate is 2.518%. The forecast uncertainty ranged between 0.290 and 0.538

[1] To check the representativeness of 137 US firms, we calculate the correlation coefficient between the S&P 500 index and our sample index. The composite sample index is derived from the average value of all ticker price data. As a result, the correlation coefficient is close to 1 (0.947 at the 1% significant level); this result provides supporting evidence for the similarity between the S&P 500 and our index. We subsequently investigate the market cap of our sample companies to that of the S&P 500. Throughout the test period, our sample's aggregate market capitalization surpasses half of the total market capitalization of the benchmark on average (see Table A1 in the Appendix).

with a sample mean of 0.418 and a standard deviation of 0.064, indicating a symmetric distribution around the mean.

This table summarizes the descriptive statistics of our sample data. The sample period is from January 1992 to December 2021. We use daily returns of S&P 500 constituent stocks. The annual GDP growth rate is the percentage change in US real GDP from the preceding year. Forecaster uncertainty is defined as the median of forecasters' subjective variances according to Bloom (2009).

Power law exponent

The universal nature of the power law of returns is widely recognized in financial markets (Gabaix 2009). An implication of the presence of a power law in economics is the increased occurrence of extreme events compared to what would be expected in a Gaussian distribution. In other words, according to Gabaix et al. (2005), stock market crashes are not outliers of a power law; therefore, analyzing tail distributions can provide valuable insights into the regular behavior of the market within the tails and the occurrence of extreme events such as herding behavior (Gabaix 2016, 2009). The key to comprehending the stock market as a whole can be unlocked by striving to understand the power law phenomenon.

Typically, a power law distribution is defined by its counter cumulative density function, known as the survival function, which is characterized by the scaling exponent ζ. Our analysis of herding in stock returns (x) is based on the literature on power law distributions, expressed as

$$\mathrm{P}(X \geq x) = 1 - F(x) = kx^{-\zeta}, \tag{1}$$

where $\mathrm{P}(X \geq x)$ is the probability that a random variable X is greater than x, $F(x)$ is the cumulative distribution function, k is a constant, and ζ is the power law exponent. By taking the logarithms of both sides of Eq. (1), the following linear regression model is obtained:

$$\log \mathrm{P}(X > x) = c - \zeta \cdot \log x + \varepsilon, \tag{2}$$

where c is a constant, and ε is the error term following the independent and identically distributed normal distribution. The power law exponent is normally obtained as the slope ζ of the linear function. Due to the autocorrelation of residuals ε, ζ has an asymptotic standard error of $\widehat{\zeta}(n/2)^{-1/2}$, for which n is the number of observations.

We fit the stock return data in our sample to a power law distribution for each year in the sample period. Specifically, for the power law exponents, we take the absolute value of the normalized daily stock return in each year to analyze extreme negative and positive returns together (Gabaix et al. 2003). We definethe tail of the distribution as a region with more than two standard deviations from the mean of the distribution (Gabaix et al. 2006; Plerou et al. 1999). We then estimated the power law exponent ζ using Eq. (2).

Theory development

Quantum model

This subsection derives the power law distribution of stock returns from the Schrödinger equation, which originates from the FP equation. The model also predicts the relationship between the power law exponent and business cycles. Stock return is defined as

$$x = \ln p_t - \ln p_{t-\Delta t},$$

where p and x are the stock price and its log return, respectively. The dynamics of stock returns are then modeled using the following stochastic differential equation:

$$dx = \nu(x,t)dt + \sigma(x,t)dW_t,$$

where $\nu(x,t)$ denotes drift, $\sigma(x,t)$ represents volatility, and W_t is the standard Wiener process.

We assume that the drift of stock returns arises from an external potential $V(x,t)$ and define

$$\nu(x,t) = -\frac{\partial V(x,t)}{\partial x} = -V_x,$$

which is analogous to classical kinetics. We further define the diffusion coefficient $D(x,t)$ as

$$D(x,t) = \frac{1}{2}\sigma^2(x.t).$$

The probability density function of x is denoted as $\rho(x,t)$. According to the FP equation, we have

$$\frac{\partial}{\partial t}\rho(x,t) = \frac{\partial^2}{\partial x^2}(D(x,t)\rho(x,t)) + \frac{\partial}{\partial x}(V_x\rho(x,t)). \tag{3}$$

For simplicity, we assume that the diffusion coefficient is constant, that is, $D(x,t) = D$. Furthermore, $\Psi(x,t)$ and a Hermitian operator $\hat{H}$ are introduced as follows:

$$\begin{aligned}
\Psi(x,t) &= \frac{\rho(x,t)}{\sqrt{\rho_s(x)}},\\
\hat{L}\rho(x,t) &= -\sqrt{\rho_s(x)}\hat{H}\Psi(x,t),\\
\rho_s(x) &= \frac{1}{C}\exp\left(-\frac{V(x)}{D}\right),
\end{aligned}$$

where C is the normalization constant and $\hat{H}$ is the Hermitian operator,

$$\begin{aligned}
C &= \int_{-\infty}^{+\infty}\exp\left(-\frac{V(x)}{D}\right)dx,\\
\hat{H} &= \frac{1}{2}V_{xx} + \frac{1}{4D}V_x^2 - D\frac{\partial^2}{\partial x^2}.
\end{aligned}$$

Then, we define imaginary time $\tau = -i\hbar t$ and a mass $m = \frac{\hbar^2}{2D}$ and Eq. (3) can be rearranged into the well-known Schrödinger equation,

$$i\hbar\frac{\partial}{\partial\tau}\Psi(x,\tau)=\hat{H}\Psi(x,\tau)\equiv\left(-\frac{\hbar^2}{2m}\frac{\partial^2}{\partial x^2}+U(x)\right)\Psi(x,\tau),\tag{4}$$

where $U(x)$ is the effective potential:

$$U(x)=-\frac{V_{xx}}{2}+\frac{V_x^2}{4D}.$$

We chose the functional form of the external potential $V(x)$ based on empirical evidence. Some studies show a contrarian effect on stock markets worldwide (Shi and Zhou 2017; Clare et al. 2014; De Bondt and Thaler 1985). Relatively high or low stock returns revert, indicating a market force that always draws short-run fluctuations back to the long-run equilibrium. Thus, we define the potential as $V(x)=\alpha|x-a|$. If stock returns deviate from the equilibrium return a, the market force from the potential will draw back stock returns at the speed of α. Given $V(x)=\alpha|x-a|$, we have

$$U(x)=-\alpha\delta(x-a)+\frac{\alpha^2}{4D},$$

where the extra drift $\frac{\alpha^2}{4D}$ does not affect the wave function (Bracewell 2000). Following this, we can solve the time-independent Schrödinger equation which is given by:

$$E\psi(x)=\hat{H}\psi(x)=-\frac{\hbar^2}{2m}\frac{\partial^2}{\partial x^2}\psi(x)-\alpha\delta(x-a)\psi(x).$$

The solution is well known with energy $E=-\frac{m\alpha^2}{2\hbar^2}$ (Griffiths 2005):

$$\psi(x)=\frac{\sqrt{m\alpha}}{\hbar}\exp\left(-\frac{m\alpha}{\hbar^2}\right)|x-a|.$$

Hence, the general solution of Eq. (4) is

$$\Psi(x,\tau)=A\psi(x)e^{-\frac{iE\tau}{\hbar}}=A\exp\left(-\frac{m\alpha}{\hbar^2}|x-a|+\frac{m\alpha^2\tau}{2\hbar^3}i\right).$$

Using $\Psi(x,\tau)$, $\rho_s(x)$, $\tau=-i\hbar t$, and $m=\frac{\hbar^2}{2D}$, we obtain

$$\rho(x,\tau)=\sqrt{\rho_s(x)}\mathrm{A}\psi(x)e^{-Et}=A\sqrt{\frac{\alpha}{2D}}\exp\left(-\frac{\alpha}{D}|x-\alpha|+\frac{\alpha^2t}{4D}\right),$$

where A is the normalization multiplier. After normalization, the final form of the solution is a Laplace distribution:

$$\rho(x)=\frac{\alpha}{2D}e^{-\frac{\alpha}{D}|x-\alpha|}.\tag{5}$$

From Eq. (5), we obtain the tail distribution of log returns. We define the gross return as

$$Y=\frac{p_t}{p_{t-\Delta t}}=e^x.$$

In the right tail satisfying $y>e^a$, we have

$$P(Y \geq y) = P(x \geq \ln y) = \int_{\ln y}^{+\infty} \frac{\alpha}{2D} e^{-\frac{\alpha}{D}|x-\alpha|} dx \propto y^{-\frac{\alpha}{D}}.$$

Hence, our result follows power law distribution in the tail, and the power law exponent is $\frac{\alpha}{D}$.

The formula for the power law exponent could be useful for connecting herding behavior in stock returns to business cycles. Recessions are accompanied by economic uncertainty (Bloom 2014). Therefore, the market return moves slowly toward equilibrium (a smaller α) and becomes more volatile (a larger D). Hence, recession leads to strong herding behavior, resulting in a smaller α/D. On the contrary, during booms, the market return reverts quickly toward equilibrium with a larger α with less volatility, implying a smaller D. Thus, a boom leads to a larger power law exponent and, thus, weak herding behavior. Therefore, our model predicts a positive association between business cycles and power law exponent.

Hypothese

Most studies document asymmetric market movements with respect to economic cycles. The literature on return volatility documents substantial volatility clusters during economic downturns (Choudhry et al. 2016; Corradi et al. 2013). Additionally, it is widely accepted that analysts' forecasts are more dispersed during economic troughs than during peaks (Amiram et al. 2018; Hope and Kang 2005). Thus, our first testable hypothesis is as follows:

Hypothesis 1 The herding behavior in stock returns is stronger during recessions than in booms.

To test this hypothesis, we first calculated the power law exponents during booms and recessions and compared their magnitudes. To examine the relationship between business cycles and herding behavior further, we ran the following regression model:

$$\zeta_t = \alpha + \beta g_t + \varepsilon_t, \tag{6}$$

where ζ_t and g_t are the power law exponent and GDP growth rate, respectively, in year t. A significantly positive β indicates that GDP growth rate has explanatory power for herding behavior, as hypothesized.

Herding assumes a certain degree of coordination between groups of agents. This coordination may arise in different ways, either because agents share the same information or follow the same rumor (Cont and Bouchaud 2000). Herding may be stronger when financial markets experience extreme uncertainty (Bouri et al. 2019). When information asymmetry is minimal, market participants do not necessarily need to observe or follow other participants' transactions. However, with severe information asymmetry, traders are more inclined to imitate other participants to compensate for missing information through the behavior of their counterparts (Alhaj-Yaseen and Yau 2018; Park and Sabourian 2011; Devenow and Welch 1996). Moreover, extant literature has documented a significant relationship between economic growth and economic uncertainty. Specifically, a low economic growth rate is associated with high economic uncertainty

(Bloom 2014). Therefore, we conjecture that economic uncertainty (higher volatility) is an intermediary linking the business cycle (lower GDP growth rate) and herding behavior (smaller power law exponent). Our second hypothesis is as follows:

Hypothesis 2 Economic uncertainty is the origin of counter-cyclical herding behavior in stock returns.

To examine whether economic uncertainty is the intermediary, we test the following models:

$$u_t = \alpha + \beta g_t + \varepsilon_t, \tag{7}$$

$$\zeta_t = \alpha + \beta u_t + \varepsilon_t, \tag{8}$$

As a robustness test, we employ the following models:

$$\zeta_t = \alpha + \beta D1_t + \gamma D2_t + \varepsilon_t, \tag{9}$$

$$\zeta_t = \alpha + \beta g_t + \gamma D1_t + \delta D2_t + \varepsilon_t, \tag{10}$$

$$\zeta_t = \alpha + \beta u_t + \gamma D1_t + \delta D2_t + \varepsilon_t, \tag{11}$$

where u_t stands for economic uncertainty in time t. In the first model, we run a regression of economic uncertainty on the GDP growth rate. In the second model, we use economic uncertainty as an explanatory variable for the power law exponent, that is, as a proxy for herding behavior. For the remaining models, we test whether business cycles and herding behavior are connected through economic uncertainty by examining factor loading on the dummy variable: (i) $D1_t = 1$ when $g_t > \overline{g}$ and $u_t < \overline{u}$, and otherwise equals zero; and (ii) $D2_t = 1$ when $g_t < \overline{g}$ and $u_t > \overline{u}$, and otherwise equals zero.

Empirical results

The annual power law exponent is shown in Fig. 1. The Gray-shaded areas indicate years of economic recessions based on the NBER recession indicator. As evident by the figure, the power law exponents are generally smaller in recession years than in non-recession years.

We begin our analysis by confirming prior findings in literature. Overall, most studies on the power law distribution of stock returns, such as those of Feng et al. (2012) and Gopikrishnan et al. (1999), report a range of power law exponents between two and four. Our estimated power law exponent was approximately 3.138 with an R^2 of 97.75% for the entire sample period, which is consistent with the findings of prior studies. It has been suggested that the degree of herding in the tail is stronger when the power law exponent is smaller in magnitude (Feng et al. 2012; Cont and Bouchaud 2000; Eguiluz and Zimmermann 2000).

Further we examined the link between herding behavior and business cycles by comparing power law exponents during recessions with those in booms. For this purpose, power law exponents are divided into two groups, booms and recessions, according to the NBER recession indicator. As is evident in Table 2, the power law

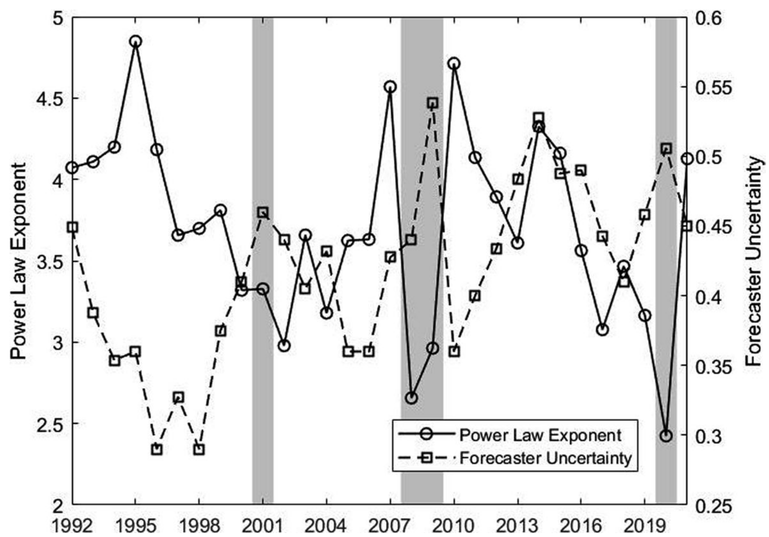

Fig. 1 The power law exponent, economic uncertainty, and business cycle. The solid line is the annual power law exponent calculated by aggregating daily normalized S&P 500 stock returns, and the dashed line is the annual forecaster uncertainty according to Bloom (2009). The shaded areas indicate recession periods identified by the NBER recession indicator

Table 2 Power law exponents in booms and recessions

	Mean	Median
Boom	3.837 ± 0.097	3.755
Recession	2.843 ± 0.196	2.810

The first column shows the average power law exponents and their standard errors during the boom and recession periods. The *p*-values for the *t*-test of equality between means and Wilcoxon rank-sum *z*-test of equality between medians are 0.001 and 0.005, respectively

exponents are significantly larger during booms than during recessions. The difference in power law exponents during booms and recessions is significant at the 1% level for the mean based on the *t*-test and the median based on the Wilcoxon rank-sum test. As a smaller power law exponent indicates stronger herding, we can firmly conclude that there is stronger herding in stock returns during recessions than during booms.

We then estimated the regression model from Eq. (6) using power law exponents and GDP growth rates. The results are shown in Model (1) of Table 3, where we use the heteroskedasticity and autocorrelation consistent estimator for the standard error (Newey and West 1987). The GDP growth rate is significantly and positively associated with the power law exponent at the 1% significance level. If the GDP growth rate decreases by one percentage point, the corresponding power law exponent drops by 0.159, intensifying herding behavior in stock returns.

Additionally, we tested whether economic uncertainty links business cycles and herding behavior. The results are summarized in Table 3. Models (2) and (3) present the estimation results of Eqs. (7) and (8), respectively. In Model (2), the GDP

Table 3 GDP growth rate, economic uncertainty, and the power law exponent

	(1) PLE	(2) Forecaster uncertainty	(3) PLE	(4) PLE	(5) PLE	(6) PLE
GDP growth rate	0.159***	− 0.020***			0.112**	
	(5.614)	(− 3.477)			(2.309)	
Forecaster uncertainty			− 3.436***			− 1.838*
			(− 4.862)			(− 1.683)
Dummy1				− 0.018	− 0.014	− 0.171
				(− 0.130)	(− 0.114)	(− 1.054)
Dummy2				− 0.556***	− 0.270*	− 0.506**
				(− 2.816)	(− 1.658)	(− 2.504)
Constant	3.306***	0.470***	5.143***	3.935***	3.537***	4.750***
	(37.792)	(37.538)	(18.214)	(26.764)	(23.389)	(10.080)
Observations	30	30	30	30	30	30
R^2	0.255	0.358	0.139	0.212	0.281	0.225
Adjusted R^2	0.228	0.335	0.108	0.153	0.198	0.135

This table displays the regression results using annual data. Model (1) is a regression of the power law exponent on the US GDP growth rate. Model (2) is a regression of forecaster uncertainty on the GDP growth rate. Model (3) is a regression of the power law exponent on forecaster uncertainty. Models (4)–(6) are regressions of the power law exponent on two dummy variables: Dummy1 is defined as 1 when the GDP growth rate is higher and forecaster uncertainty is smaller than the sample average, and zero otherwise. Dummy2 is defined as 1 when the GDP growth rate is lower and forecaster uncertainty is larger than the sample average, and zero otherwise. The variance inflation factors (VIF) of Models (4)–(6) are less than 5, implying that multicollinearity does not reduce the precision of our estimated coefficients and cannot weaken the statistical power of our regression models (Table 7). The numbers within parentheses are *z*-statistics calculated with heteroskedasticity and autocorrelation-consistent standard errors, according to Newey and West (1987). *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. PLE denotes the power law exponent.

growth rate is significant and negatively associated with forecaster uncertainty, which is our proxy for economic uncertainty. The adjusted R^2 is approximately 30%, indicating that GDP growth rate explains a significant portion of economic uncertainty. In Model (3), forecaster uncertainty is significant and negatively associated with the power law exponent. Combining the results from Models (2) and (3), economic uncertainty appears to be the link between the GDP growth rate and herding in stock returns.

In Models (4)–(6), we present the results from the estimations of Eqs. (9)–(11). In particular, the factor loading on the dummy variable indicates the importance of economic uncertainty on top of business cycles in explaining herding behavior in stock returns. In Models (5) and (6), Dummy2 ($D2_t = 1$ when $g_t < \overline{g}$ and $u_t > \overline{u}$, and otherwise equals zero) is highly significant. Accordingly, we conclude that GDP growth rate explains herding behavior in stock returns through economic uncertainty. In other words, rising uncertainty accompanied by low economic growth significantly accelerates herding behavior in stock returns.[2]

[2] We consider an inflation rate and federal funds rate as a control variable and still obtain results consistent with Table 3 (see Table 5 in the Appendix). We also deal with media coverage as a control variable using the "Economic Policy Uncertainty Index," which uses news coverage about policy-related economic uncertainty (Baker et al. 2016). We find that it has a strong correlation coefficient with our uncertainty index, the forecaster uncertainty index; therefore, we do not include this index as a control variable (see Table 6 in the Appendix).

Conclusion

This study examined the relationship between business cycles and herding behavior in the US stock market. The recession indicator and GDP growth rate are used as proxies for business cycles, whereas herding behavior is represented by the power law exponent in stock returns. First, we propose a theoretical model of stock returns employing quantum mechanics. Our model predicts a positive association between business cycles and the power law exponent and economic uncertainty links business cycles and herding behavior. We then tested these predictions using empirical data. We find evidence of stronger herding during recessions than booms. Specifically, the GDP growth rate can significantly explain the herding behavior in stock returns. Using forecaster uncertainty as a proxy for economic uncertainty, we confirm that economic uncertainty links business cycles with herding behavior in stock returns. Greater economic uncertainty is accompanied by a recession, which leads to increased information asymmetry, for example, higher dispersion in analysts' forecasts. Accordingly, investors are more likely to mimic others because of lower confidence in their valuations. Finally, information asymmetry leads to greater volatility in firms' activities and drives more extreme stock returns, resulting in smaller power law exponents and implying stronger herding behavior in stock returns.

The findings of this study provide a clear link between herding behavior and business cycles. The results underscore the importance of monitoring herding activities during periods of increased uncertainty accompanied by low economic growth. At the macro level, an increase in policy uncertainty can lead to a decline in economic growth (Baker et al. 2016). Therefore, policymakers should consider how policy uncertainty influences investors' decision-making (Ahn et al. 2021) in the financial market. For individual investors, our results provide a way to formulate hedging strategies to mitigate downside risk in their investment portfolios during a recession. Our empirical setting is designed to confirm the results of the theoretical (toy) model. Future studies can extend our empirical setting to show (i) the robustness of our main results by adding various control variables and (ii) the robustness of the transmission channel.

Appendix

See the Tables 4, 5, 6 and 7.

Table 4 Market capitalization

	Sample S&P500/ Total S&P500 $\times$ 100 (%)
1996.1.2	54
2002.1.2	60
2012.1.2	59
2021.1.4	40
Average	53

Table 5 GDP growth rate, economic uncertainty, and power law exponent with control variables (inflation and federal funds rates)

	(1) PLE	(2) Forecaster uncertainty	(3) PLE	(4) PLE	(5) PLE	(6) PLE
GDP growth rate	0.173***	− 0.012***			0.129**	
	(3.168)	(− 2.610)			(1.779)	
Forecaster uncertainty			− 3.967***			− 2.151*
			(− 3.115)			(− 1.410)
Dummy1				− 0.046	− 0.002	− 0.180
				(− 0.339)	(− 0.015)	(− 1.132)
Dummy2				− 0.560***	− 0.275*	− 0.513***
				(− 3.214)	(− 1.584)	(− 2.703)
Inflation rate	− 0.056	− 0.002	0.023	− 0.001	− 0.058	− 0.020
	(− 0.766)	(− 0.226)	(0.251)	(− 0.036)	(− 0.835)	(− 0.367)
Federal funds rate	0.002	− 0.015***	− 0.030	0.009	− 0.007	− 0.006
	(0.058)	(− 3.088)	(− 0.623)	(0.248)	(− 0.174)	(− 0.163)
Constant	3.394***	0.492***	5.385***	3.929***	3.643***	4.951***
	(23.137)	(35.396)	(7.532)	(24.297)	(30.029)	(6.299)
Observations	30	30	30	30	30	30
R^2	0.262	0.585	0.146	0.212	0.290	0.226
Adjusted R^2	0.177	0.537	0.047	0.086	0.143	0.065

The numbers in parentheses are *z*-statistics calculated with heteroskedasticity and autocorrelation consistent standard errors according to Newey and West (1987). *, **, and *** represent significance at the 10%, 5%, and 1% levels in the one-tailed test, respectively. PLE denotes the power law exponent

Table 6 Correlation between news-based policy uncertainty index and forecaster uncertainty

	News-based policy uncertainty index	Forecaster uncertainty
News-based policy uncertainty index	1.000	
Forecaster uncertainty	0.489***	1.000

*** Indicates 1% statistical significance based on the Pearson correlation coefficient

Table 7 VIF tests

(4)	VIF
Dummy 1	2.04
Dummy 2	2.04
Mean VIF	2.04
(5)	**VIF**
Dummy 1	2.04
Dummy 2	2.88
GDP Growth rate	1.83
Mean VIF	2.25
(6)	**VIF**
Dummy 1	3.35
Dummy 2	2.18
Forecaster uncertainty	3.05
Mean VIF	2.86

The VIF measures the extent of multicollinearity among explanatory variables in models (4)–(6) of Table 3

Abbreviations

FP	Fokker–Planck
GDP	Gross domestic product
NBER	National Bureau of Economic Research
S&P 500	Standard and Poor's 500
VIF	Variance inflation factors

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Author contributions
KA: Supervision, Writing the manuscript, and Reviewing. LC: Data collection, Writing the manuscript, and Data analysis. HJ: Data collection, Writing the manuscript, and Data analysis. DSK: Supervision, Writing the manuscript, and Reviewing.

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Availability of data and materials
We use data from three sources: Center for Research in Stock Prices (CRSP), National Bureau of Economic Research (NBER), Federal Reserve Economic Data (FRED), and Federal Reserve Bank of Philadelphia. Restrictions apply to the availability of data from CRSP, which were used under license for this study. Data are available at https://www.crsp.org/ with license. Data from NBER are available to public at https://www.nber.org/research/business-cycle-dating. Data from FRED are available at https://fred.stlouisfed.org/. Data on forecaster uncertainty from Federal Reserve Bank of Philadelphia is available at https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-ofprofessionalforecasters#:~:text=The%20Survey%20of%20Professional%20Forecasters,over%20the%20survey%20in%201990.

Declarations

Competing interests
The authors declare no competing financial interests nor competing non-financial interests.

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