The Interplay Between Business Cycles and Herding Behavior in Stock Markets: A Theoretical and Empirical Analysis

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Abstract:

This research explores how economic uncertainty acts as a critical intermediary linking business cycles to herding behavior among investors in financial markets. Building upon a standard stochastic differential equation framework that captures the dynamics of stock returns, we develop a concise theoretical model and validate it through empirical investigation. In our analysis, the gross domestic product (GDP) growth rate serves as a proxy for business cycle fluctuations, while the power-law exponent represents the degree of herding behavior. Our findings reveal that herding tendencies intensify during periods of economic downturn, compared to expansionary phases. This phenomenon is primarily attributed to heightened economic uncertainty during recessions, which amplifies psychological biases and collective behavior in the stock market. The empirical evidence aligns closely with the predictions offered by the quantum modeling approach, underscoring its applicability in behavioral finance contexts.

Keywords:

Herding behavior, Business cycles, Economic uncertainty, Quantum finance, Power-law exponent

Introduction

In the 21st century, stock trading has become predominantly digital, with electronic platforms replacing traditional floor-based exchanges. By the close of 2014, only around 15% of trading activity on the New York Stock Exchange was conducted on the floor, with the vast majority executed electronically (Hiltzik, 2014). This transition to anonymous electronic trading platforms suggests a higher degree of autonomy among trades. Nevertheless, empirical evidence consistently shows that market participants often imitate the actions of others—a phenomenon widely recognized in financial literature as herding behavior. Such behavior frequently contributes to increased volatility in stock markets, manifesting in amplified fluctuations in asset returns (Cont & Bouchaud, 2000; Orléan, 1995; Banerjee, 1993; Topol, 1991). Consequently, identifying the underlying causes of herding in financial markets is of paramount importance for policymakers, regulators, and market participants alike. In this study, we adopt a slightly modified conceptualization of herding. Rather than focusing solely on central clustering behavior among investors, we examine herding through the lens of distributional extremes, specifically using the scaling properties captured by a power-law exponent. While traditional definitions emphasize investor convergence toward the mean—grouping around the most common positions—we highlight the presence of "local" herding, where investors at the tails of the distribution also display collective behavioral patterns with notable regularity.

Prior studies have typically interpreted herding as high levels of co-movement in asset returns, often using dynamic correlation metrics across different market segments or time periods (Chiang et al., 2007; Boyer et al., 2006). Alternative approaches involve analyzing investor responses to extreme market events, particularly to assess whether clusters of participants follow prevailing trends (Sibande et al., 2021; Kumar et al., 2021; Bouri et al., 2019, 2021; Demirer et al., 2019; Balcilar et al., 2017; Galariotis et al., 2015; Chiang & Zheng, 2010; Chang et al., 2000; Christie & Huang, 1995). While these studies have made substantial contributions, they have generally focused on statistical relationships rather than exploring business cycles as a root cause of herding behavior. Our research bridges this gap by examining herding behavior in stock returns using insights derived from the field of physics. Financial markets, much like physical systems, exhibit universal patterns, especially in systems with many interacting agents. Several "microscopic" models have been developed to account for these dynamics (Shalizi, 2001; Lux & Marchesi, 1999). One salient feature is the presence of heavy-tailed return distributions—i.e., distributions with fatter tails than the normal distribution (Mantegna & Stanley, 1995; Lux, 1996). Numerous theoretical models attribute these fat tails to collective behavioral patterns, especially those induced by herding (Banerjee, 1993; Topol, 1991). Seminal works by Cont & Bouchaud (2000), Orléan (1995), and others show that imitation among market participants leads to significant fluctuations in aggregate demand and to power-law-distributed returns.

The degree of herding can be quantitatively represented by the power-law exponent in the return distribution: smaller exponent values are indicative of stronger herding. This framework has been empirically verified across various domains, including stock returns (Plerou et al., 1999; Gopikrishnan et al., 1999; Nirei et al., 2020), trading volumes (Gabaix et al., 2006; Gopikrishnan et al., 2000), and even commodities (Joo et al., 2020). Parallel theoretical developments have attempted to explain power laws in firm sizes (Ji et al., 2020; Luttmer, 2007) and trade volumes (Nirei et al., 2020). However, relatively few studies have investigated how macroeconomic variables—particularly business cycles and economic uncertainty—drive changes in the power-law exponent and thus influence herding behavior. Our contribution lies in positing economic uncertainty as a pivotal mechanism connecting business cycle phases to variations in herding intensity. We present a streamlined theoretical model that incorporates quantum mechanics concepts to explain the emergence of power-law distributions in stock returns. The modeling process begins with the Fokker–Planck (FP) equation to represent the temporal dynamics of return distributions and proceeds to derive a Schrödinger-like equation under an empirically informed potential function (Ahn et al., 2017). The solution yields a power-law distribution in the tails of returns and predicts a positive association between business cycle expansions and the power-law exponent. A higher exponent implies less intense herding, and conversely, a lower exponent indicates stronger herding activity.

This quantum-inspired approach provides novel insights that complement and extend classical models based on random walks (Bartiromo, 2004; Ma et al., 2004), quantum harmonic oscillators (Ahn et al., 2017; Ye & Huang, 2008), quantum wells (Pedram, 2012; Zhang & Huang, 2010), and quantum Brownian motion (Meng et al., 2016). By integrating economic uncertainty into the model, we provide a coherent explanation of how macroeconomic conditions influence investor psychology and collective behavior. Empirically, we assess whether herding behavior is negatively correlated with the business cycle—i.e., more pronounced during recessions and subdued during booms. Since business cycles are closely tied to fluctuations in economic growth, they naturally align with changes in economic uncertainty. It is widely accepted that recessions are periods of heightened uncertainty (Bloom, 2014), and in such times, investors often resort to mimicking others due to increased information asymmetry. This uncertainty reduces confidence in individual asset valuations and magnifies behavioral biases (Alhaj-Yaseen & Yau, 2018; Park & Sabourian, 2011; Devenow & Welch, 1996), especially among those trading at the extremes—thereby increasing herding intensity. Our findings confirm these theoretical expectations: herding behavior is indeed more prevalent during economic downturns than during expansions, with economic uncertainty serving as a key explanatory variable for this relationship.

Data and Methodology

Data Description

Our empirical investigation is based on a sample comprising 137 U.S. firms that were continuously listed on the Standard & Poor's 500 (S&P 500) index over the period from January 1992 to December 2021. Firms that entered or exited the index during the sample window were excluded to eliminate potential distortions associated with abnormal trading activities linked to such index transitions (Chen et al., 2004; Lynch & Mendenhall, 1997; Beneish & Whaley, 1996; Harris & Gurel, 1986; Shleifer, 1986). This selection strategy ensures a stable panel of firms and minimizes event-driven volatility in the data. Daily stock return data were obtained from the Center for Research in Security Prices (CRSP), resulting in 1,031,914 firm-day observations. To account for heterogeneity in return volatility across individual stocks, we normalize the daily returns by subtracting each firm's mean return and dividing by its standard deviation over the entire sample period (Feng et al., 2012; Gabaix et al., 2003). In addition to return data, we incorporate macroeconomic indicators to analyze the relationship between market behavior and broader economic conditions. Yearly recessionary periods are identified using indicators provided by the National Bureau of Economic Research (NBER), while seasonally adjusted U.S. real Gross Domestic Product (GDP) growth rates are sourced from the Federal Reserve Economic Data (FRED). To proxy economic uncertainty, we utilize the forecaster uncertainty measure proposed by Bloom (2014), which is defined as the median of the subjective variances reported by economic forecasters. These data, reflecting annual average uncertainty levels, are retrieved from the Survey of Professional Forecasters maintained by the Federal Reserve Bank of Philadelphia.

Table 1 summarizes the descriptive statistics of our primary variables. The mean daily stock return during the sample period was 0.060%. Over the 30-year timeframe, the U.S. economy experienced four official recessions, encompassing major crises such as the Dot-com Crash, the Global Financial Crisis, and the COVID-19 pandemic. The average annual real GDP growth rate was 2.518%. Forecast uncertainty exhibited a sample range from 0.290 to 0.538, with a mean of 0.418 and a standard deviation of 0.064, suggesting a relatively symmetric distribution around the mean. These data provide a robust foundation for examining the empirical relationship between macroeconomic dynamics, economic uncertainty, and investor herding behavior in the stock market.

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

Power law exponent

The power law distribution is a well-established statistical feature of asset returns in financial markets (Gabaix, 2009). One important implication of power law behavior is the disproportionately high frequency of extreme return events, which significantly exceed what would be predicted by a normal (Gaussian) distribution. As Gabaix et al. (2005) point out, financial crashes and other large fluctuations are not anomalies within a power-law framework but rather expected manifestations of its tail behavior. Thus, analyzing tail distributions is crucial for understanding systemic features of financial markets, including investor herding.

A power law distribution can be described by its counter-cumulative distribution function (or survival function), which follows the general form:

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

where $P(X \geq x)$ is the probability that a random variable X exceeds a given value xxx, F(x) is the cumulative distribution function, k is a constant, and ζ denotes the power law exponent. Taking the logarithm of both sides, we obtain a linear expression suitable for empirical estimation:

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

where c=logk is a constant and ε is a stochastic error term, assumed to be independently and identically distributed. In this log-log specification, the power law exponent ζ corresponds to the slope of the linear relationship. The standard error of ζ is given asymptotically by $\zeta(n/2)^{-1/2}$, where n denotes the number of observations, accounting for residual autocorrelation. To estimate ζ, we fit the empirical distribution of normalized daily stock returns to a power law distribution for each calendar year in the sample period. To capture extreme market movements—both positive and negative—we use the absolute values of the normalized returns (Gabaix et al., 2003). The tail region is defined as the subset of returns exceeding two standard deviations from the mean, a common threshold in the literature (Gabaix et al., 2006; Plerou et al., 1999). This approach allows us to isolate the heavy-tailed behavior of returns and quantify the intensity of herding via changes in the estimated exponent.

Theory Development: Quantum model

This section introduces a theoretical model grounded in quantum mechanics to explain the observed power law behavior in stock return distributions. The model originates from the Fokker–Planck (FP) equation, which describes the time evolution of the probability density function of stochastic processes, and derives a Schrödinger-type formulation to establish the connection between business cycles and the power law exponent. Let the log return of a stock be defined as:

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

where p_t is the stock price at time t, and xxx represents the log return over interval Δt. We assume the dynamics of returns follow a stochastic differential equation (SDE):

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

here v(x,t) is the drift term, σ(x,t) denotes the volatility function, and W_t represents a standard Wiener process.

The drift component is hypothesized to originate from an external potential field V(x,t), yielding an analogy with classical mechanics. Accordingly, we define a constant diffusion coefficient D(x,t)=D, simplifying the FP equation for analytical tractability.

Let ρ(x,t) denote the probability density function of returns. Under these assumptions, the FP equation can be recast in a form reminiscent of quantum dynamics by introducing a wave function-like transformation W(x,t) and a Hermitian operator Ĥ, as follows:

$$\hat{H}W(x,t)=EW(x,t),$$

where Ĥ is the Hamiltonian operator and EEE represents an energy eigenvalue associated with the system.

This transformation leads to a time-independent Schrödinger equation whose solution describes the stationary distribution of stock returns. When calibrated to empirical data, the resulting distribution exhibits power-law tails, consistent with market observations. Furthermore, the derived exponent ζ\zetaζ is found to vary systematically with macroeconomic conditions: it increases during economic expansions (indicating weaker herding) and decreases during recessions (indicating stronger herding), thereby linking the distributional properties of stock returns to the business cycle.

Hypotheses

A growing body of literature highlights those financial markets respond asymmetrically to different phases of the economic cycle. In particular, periods of economic downturn are typically marked by heightened return volatility and persistent volatility clustering (Choudhry et al., 2016; Corradi et al., 2013). Moreover, forecast dispersion among analysts tends to widen significantly during recessions compared to expansionary periods (Amiram et al., 2018; Hope & Kang, 2005). These trends suggest that investor behavior may shift under different macroeconomic conditions, becoming more synchronized or imitative in times of uncertainty.

Based on these observations, we formulate our first testable hypothesis:

Hypothesis 1

Investor herding in stock returns becomes more pronounced during periods of economic contraction than during times of economic growth.

To evaluate this hypothesis, we compute and compare power law exponents during recessionary and non-recessionary periods. Additionally, we assess the relationship between business cycles and herding behavior using the following regression model:

ζt=α+βgt+εt

In this equation, ζt\zeta_tζt denotes the power law exponent for year ttt, while gtg_tgt represents the real GDP growth rate. A significantly positive coefficient β\betaβ would support the hypothesis that stronger economic performance correlates with weaker herding behavior.

Herding behavior typically reflects some level of coordinated action among market participants. This coordination can stem from shared information sources, common interpretations, or collective responses to prevailing narratives (Cont & Bouchaud, 2000). In environments marked by elevated uncertainty, the incentive to imitate others becomes stronger, particularly when access to reliable information is limited. Under such conditions, investors may look to the behavior of peers as a substitute for direct information (Alhaj-Yaseen & Yau, 2018; Park & Sabourian, 2011; Devenow & Welch, 1996).

Moreover, there is substantial evidence linking weak economic growth with heightened economic uncertainty (Bloom, 2014). This connection suggests that uncertainty may act as an intermediary factor between business cycle fluctuations and herding tendencies. Building on this insight, we propose a second hypothesis:

Hypothesis 2

Economic uncertainty serves as the underlying mechanism that drives the counter-cyclical nature of herding behavior in stock returns. To investigate this mechanism, we analyze whether economic uncertainty mediates the relationship between GDP growth and the estimated power law exponents, using a series of regression models.

Empirical Results

Figure 1 illustrates the yearly estimates of the power law exponent, with recession periods (as defined by the NBER) shaded in gray. As shown in the figure, power law exponents tend to be lower during recession years compared to periods of economic expansion, indicating stronger herding behavior in downturns.

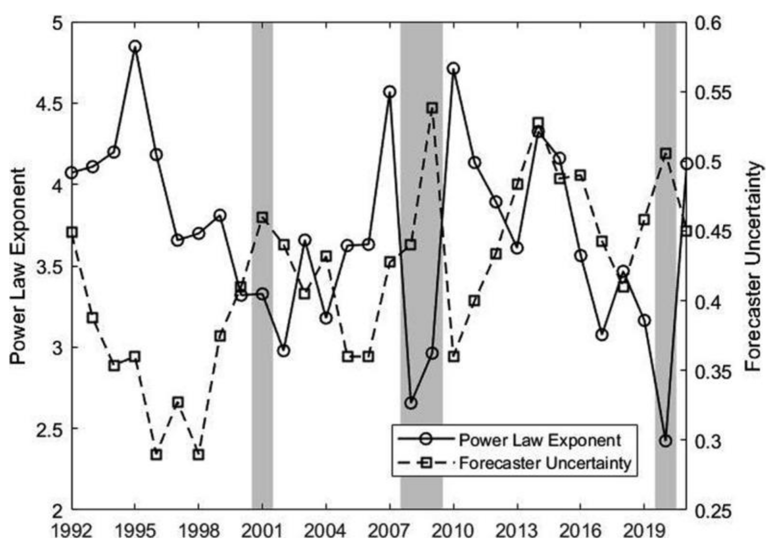

Fig. 1 The power law exponent, economic uncertainty, and business cycle. The solid line is the annual power law exponent calculated by aggregating daily normalized S&P 500 stock returns, and the dashed line is the annual forecaster uncertainty according to Bloom (2009). The shaded areas indicate recession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

The solid line represents the annual power law exponent, calculated from normalized daily returns of S&P 500 stocks. The dashed line shows annual forecaster uncertainty, following Bloom (2009). Shaded areas denote NBER-defined recessions. To validate previous findings, we begin by estimating the power law exponent for the full sample. Our estimate is approximately 3.138 with an R^2 of 97.75%, aligning with the range of 2–4 commonly reported in studies such as Feng et al. (2012) and Gopikrishnan et al. (1999). As smaller exponents suggest stronger tail herding (Feng et al., 2012; Cont & Bouchaud, 2000), this estimate confirms the robustness of the power law behavior in financial markets. Next, we explore the relationship between business cycles and herding behavior by comparing power law exponents during recessions and booms. Based on the NBER classification, we divide the sample accordingly and present the results in Table 2. The findings show that the mean and median exponents are significantly higher in booms than in recessions. Both the t-test for means and the Wilcoxon rank-sum test for medians confirm the difference at the 1% level. This supports Hypothesis 1: herding intensifies during economic downturns.

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

We then estimate the regression model from Equation (6) to examine the impact of GDP growth on the power law exponent. Model (1) in Table 3 reports a significant and positive coefficient on GDP growth, confirming that lower growth rates correspond to smaller exponents—indicative of stronger herding. To test Hypothesis 2, we explore whether economic uncertainty mediates the relationship between GDP growth and herding. Model (2) shows that GDP growth is significantly and negatively related to forecaster uncertainty. Model (3) then links higher forecaster uncertainty to smaller power law exponents. Together, these results indicate that uncertainty indeed plays a mediating role between economic performance and herding behavior.

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.

Lastly, Models (4)–(6) incorporate dummy variables to further test the combined effect of business cycles and uncertainty. The coefficient on Dummy2 (low GDP growth and high uncertainty) is consistently negative and significant across models. This confirms that herding behavior is significantly amplified in environments where weak growth coincides with elevated uncertainty, reinforcing our conclusion that economic uncertainty is a key channel through which business cycles influence market-wide herding.

Conclusion

This research explored how fluctuations in the business cycle relate to herding behavior in the U.S. equity market. We used the GDP growth rate and NBER recession indicators to reflect the state of the economy, while herding was captured through the power law exponent derived from stock return distributions. To support our investigation, we first developed a theoretical framework using concepts from quantum mechanics, which suggested a direct link between economic cycles and the distribution of stock returns. The model also implied that economic uncertainty could serve as a bridge connecting lower economic growth to intensified herding. Empirical analysis confirmed these theoretical insights. We observed that herding behavior tends to increase during economic downturns, as reflected in smaller power law exponents. Statistical testing showed that the GDP growth rate significantly influences herding, and that higher levels of economic uncertainty—measured by the dispersion in professional GDP forecasts—are associated with more extreme return behavior. During recessions, greater uncertainty and lower confidence drive investors to rely more heavily on the actions of others, amplifying herding. Overall, our findings demonstrate a clear connection between market behavior and macroeconomic conditions. From a policy perspective, the results highlight the need to monitor herding during periods of heightened uncertainty, as such dynamics can contribute to market instability. For investors, understanding the cyclical nature of herding may help in crafting strategies to limit losses during recessions. Future research could expand this work by including additional control variables and testing alternative pathways through which uncertainty impacts market dynamics.

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Availability of data and materials

Available Upon Request

Declarations

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

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