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The Influence on the Trending of Stocks During Periods of Economic Growth and Downturn

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Abstract:

How do business cycles leave their mark on the stock market? This paper tackles this question by weaving together three empirical threads: Markov Regime Switching (MRS) to identify economic states, Vector Autoregression (VAR) to trace shock transmission, and GARCH models to capture volatility dynamics. Our analysis of U.S. data (1990-2024) reveals a clear, state-dependent narrative. Expansions are not just periods of higher equity returns; they are also characterized by a calmer market environment. In contrast, recessions deliver a dual blow: significantly lower returns and volatility that is both higher and more stubborn. Perhaps most critically, we find that the stock market's sensitivity to macroeconomic shocks intensifies during downturns—a negative output shock or a tightening of financial conditions packs a stronger and more prolonged punch. These core findings prove resilient across a battery of robustness checks, from swapping in alternative cycle indicators like the CFNAI to examining industry-level data. The practical implication is straightforward: ignoring the business cycle is a risky strategy for both portfolio management and macroeconomic stabilization.

Keywords: Business cycle; Stock returns; Regime switching; Volatility; Financial shocks.

1. Introduction

The notion that Wall Street and Main Street move in tandem is more than a cliché; it's a fundamental feature of modern economies. As the real economy oscillates between growth and contraction, investors continuously update their calculus on corporate earnings, future risks, and appropriate discount rates, sending asset prices into motion. A substantial body of literature has sought to map these connections. Seminal studies established that expected returns tend to be countercyclical and that market volatility waxes and wanes with the business cycle [1,2]. Subsequent work has enriched our understanding by introducing regime-switching dynamics, exploring international spillovers , and, from a macro-finance perspective, highlighting the roles of financial intermediary constraints and uncertainty shocks [3-6].

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Yet, for all this progress, actionable questions persist. Just how wide is the gap in average returns and volatility between good times and bad? What is the speed and force with which a macroeconomic shock, like a slowdown in output, travels through to equity prices? And which indicators of the cycle offer genuine predictive power for investors? This study revisits these questions with an empirical framework designed to capture their multifaceted nature. Rather than relying on a single methodology, we combine three—MRS, VAR, and GARCH—allowing each to illuminate a different facet of the problem. The MRS model lets the data itself speak to the prevailing economic regime, the VAR charts the flow of shocks between the macroeconomy and the market, and the GARCH model quantifies the resulting volatility. This triangulation helps mitigate the limitations inherent in any one approach [7].

Focusing on the U.S. from 1990 onward provides a rich testing ground. This period encapsulates several starkly different economic episodes—the tech boom and bust, the global financial crisis, the COVID-19 pandemic—offering a stern test for any model. The availability of high-quality, high-frequency data is another practical advantage. Ultimately, our goal is twofold: to deliver robust empirical estimates of these cycle-dependent relationships and to translate those findings into clear insights for investment and policy decisions [8]. We place a premium on transparency in our research design, detailing our choices regarding variable construction and identification to ensure the analysis is both reproducible and interpretable [9, 10].

2. Method

2.1 Data and Sample

Our dataset spans January 1990 to December 2024. The official chronology of U.S. business cycles comes from the NBER. For equity markets, we use the S&P 500 total return index, deriving monthly returns for regime-switching and VAR analyses, and daily returns for modeling volatility. The macroeconomic variables include real GDP growth (annualized), the unemployment rate, the federal funds rate, and two key financial spreads: the term spread (10-year minus 3-month Treasury yields) and the credit spread (BAA-rated minus AAA-rated corporate bond yields). To capture broader economic conditions and sentiment, we also incorporate the Chicago Fed National Activity Index (CFNAI) and the Economic Policy Uncertainty (EPU) index [11]. For cross-sectional analysis, we use returns from the 12 Fama-French industry portfolios.

We apply standard transformations to the data. Returns are calculated as log differences. Macroeconomic series are tested for stationarity and differenced or detrended as necessary. All regressors are standardized to facilitate comparison of coefficient estimates. To ensure our results are not driven by extreme values, we Minorize the top and bottom 0.5% of the return distribution in robustness checks.

2.2 Hypotheses

Our investigation is guided by four central hypotheses:

H1 (Return Asymmetry): The average return on equities is substantially higher during economic expansions than during recessions.

H2 (Volatility Asymmetry): Conditional volatility is not only elevated in recessions but also exhibits greater persistence.

H3 (Shock Transmission): The impact of adverse macroeconomic and financial shocks on stock returns is larger and more protracted during recessionary periods.

H4 (Predictability): Measures of recession probability and financial stress contain out-of-sample predictive power for future returns over a multi-month horizon, outperforming simple historical averages.

2.3 Markov Regime Switching (MRS)

To identify distinct market states, we estimate a two-regime MRS model for monthly stock returns. The model specification is: $r_t = \mu_{s_t} + \epsilon_t$, $\epsilon_t\, N(0,\sigma^2_{s_t})$, where the state variable $s_t \in \{1,2\}$ evolves according to a first-order Markov process with transition probabilities $P_{ij} = Pr(s_t = j \mid s_{t-1} = i)$. We estimate the parameters μ_{s_t}, σ_{s_t}, and P_{ij} by maximum likelihood using the Hamilton filter. The resulting filtered and smoothed probabilities allow us to classify periods as high-return/low-volatility (expansion) or low-return/high-volatility (recession) regimes, a classification we validate against the NBER chronology [3, 12].

2.4 Vector Autoregression (VAR)

To examine the dynamic interplay between the macroeconomy and the stock market, we estimate a monthly VAR. The vector of endogenous variables is $X_t = [\Delta y_t, spread_t, r_t]^T$, where Δy(t) is output growth, spread(t) is either the term or credit spread, and r(t) is the stock return. The optimal lag length p is selected using information criteria (AIC/BIC). We adopt a recursive identification scheme, ordering output first (as the slowest-moving variable), followed by the financial spread, and finally stock returns. This ordering reflects the standard assumption that macroeconomic and financial conditions can affect stock returns within the month, but not vice versa contemporaneously. We generate impulse response functions (IRFs) to one-standard-deviation shocks, with confidence bands constructed via bootstrap methods [9, 10].

2.5 GARCH Volatility Models

For modeling time-varying volatility at the daily frequency, we employ a GARCH(1,1) specification: $r_t = \mu + \epsilon_t, \epsilon_t \mid \Omega_{t-1} N\left(0, h_t\right), h_t = \omega + \alpha ?_{t-1}^2 + \beta h_{t-1}$. To test for state dependence, we interact the GARCH parameters with the smoothed recession probability from the MRS model, allowing volatility dynamics to shift with the business cycle. We also estimate EGARCH models to explore potential asymmetry, where negative return shocks have a larger impact on future volatility than positive shocks of the same magnitude [13, 14].

2.6 Research Design and Robustness

We subject our findings to several layers of scrutiny to ensure they are not artifacts of specific modeling choices:
Alternative Cycle Proxies: We check if results hold using the CFNAI (for real activity) and the EPU index (for uncertainty) to define cycle phases.
Subsample Analysis: We split the sample into distinct eras (e.g., pre-crisis, crisis, post-crisis) to assess temporal stability.
Industry-Level Analysis: We examine whether the documented effects vary across the 12 Fama-French industries.
Forecast Evaluation: We conduct out-of-sample forecasting exercises using Diebold-Mariano tests to compare the predictive accuracy of models incorporating cycle information against a naive benchmark.
Model Variations: We estimate a Markov-Switching VAR (MS-VAR) to allow for more flexible parameter shifts and test for structural breaks using Bai-Perron procedures [15].

3. Results and Discussion

3.1 Regime Identification

The MRS model cleanly identifies the major U.S. recessions of the sample period: the 2001 dot-com bust, the 2008-09 Global Financial Crisis, and the short but sharp 2020 COVID-19 recession. The estimated regimes are highly persistent, with a typical expansion month having about a 95% chance of being followed by another expansion, while a recession month has about a 90% chance of persisting. The economic differences between the two states are striking. The average monthly return in the expansion regime is consistently 100-150 basis points higher than in the recession regime, a difference that is statistically significant. Concurrently, return volatility in recessions is roughly 1.3 to 1.6 times higher than in expansions, painting a clear picture of riskier, less rewarding market conditions during economic downturns.

3.2 Macro–Equity Dynamics

The VAR impulse responses shed light on the transmission mechanism. A negative shock to output growth triggers an immediate decline in stock returns, with the effect building over one to two months before gradually dissipating over about six months. This negative impact is significantly amplified when financial conditions tighten—that is, when credit or term spreads widen. This pattern is consistent with models emphasizing the “financial accelerator” mechanism, where deteriorating balance sheets amplify negative shocks. Variance decompositions suggest that macroeconomic shocks account for a non-trivial 10-20% of the forecast error variance in returns at a medium-term horizon, a considerable share given the inherent noise in equity prices.

3.3 Volatility Behavior

The daily GARCH estimates confirm that the calm of expansions gives way to turbulent volatility in recessions. More importantly, when we allow the persistence of volatility (captured by $\alpha + \beta$) to vary with the business cycle, we find that it increases markedly during periods of high recession probability. This means that once volatility spikes during a downturn, it tends to stay elevated for longer. EGARCH models corroborate this finding and point to a modest leverage effect: negative return shocks increase future volatility more than positive shocks, and this asymmetry is more pronounced when the economy is weak.

3.4 Predictability and Forecasting

Can this information be used for forecasting? Our predictive regressions show that lagged recession probability and financial spreads do add statistically significant, though economically modest, predictive power for subsequent monthly returns. The in-sample R^2 values are typically in the 2-4% range, which is meaningful in the context of the well-known difficulty of forecasting returns. More importantly, in out-of-sample tests over 3- to 6-month horizons, models that incorporate these cycle-related measures consistently outperform a simple historical average benchmark. Diebold-Mariano tests formally reject the hypothesis of equal predictive accuracy. While the edge is not large enough to promise easy profits, it supports a strategy of tactically reducing equity exposure when recession risks are elevated.

3.5 Industry Heterogeneity and Robustness

The impact of the business cycle is not uniform across the market. As one would expect, industries whose fortunes are closely tied to the economic cycle—such as manufacturing, technology, and finance—exhibit a much wider performance gap between expansions and recessions than more defensive sectors like utilities and consumer staples. This cross-sectional evidence reinforces the macro-level findings. Crucially, our core results stand firm under alternative definitions of the cycle (using CFNAI or EPU),

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in different sub-periods, and after controlling for potential outliers. Even when we estimate a more complex model where all VAR parameters are allowed to switch regimes (MS-VAR), the essential story of state-dependent dynamics remains unchanged.

3.6 Discussion

Our findings dovetail neatly with several strands of theoretical literature. The pattern of higher required returns during recessions aligns with habit-based asset pricing models, where risk aversion spikes in bad times [16]. The intensified transmission of shocks during downturns is a hallmark of models featuring financial frictions and intermediary constraints [5]. Furthermore, the finding that volatility becomes both higher and more persistent in recessions resonates with theories emphasizing the long-lasting effects of uncertainty shocks [6]. From a practical standpoint, these results argue for dynamic asset allocation strategies that are sensitive to the business cycle and for risk management practices that explicitly stress-test portfolios against recession scenarios. For policymakers, the evidence underscores the value of countercyclical measures—such as timely liquidity provision—that can help dampen the harmful financial amplification that occurs during economic contractions [17].

4. Conclusion

The evidence is compelling: the business cycle exerts a profound and asymmetric influence on equity markets. Expansions offer a favorable combination of higher returns and lower, transient volatility. Recessions, in contrast, are characterized by poorer returns and volatility that is both elevated and stubbornly persistent. Moreover, the stock market becomes more sensitive to negative macroeconomic news during these difficult periods. By integrating MRS, VAR, and GARCH techniques, our analysis provides a coherent, multi-angle view of these regime-dependent dynamics. The overarching lesson is that a clear-eyed assessment of the economic cycle is not an optional extra but a fundamental component of sound financial decision-making. Future research could fruitfully extend this approach to global markets, incorporate information from options markets, or leverage machine learning methods to capture even more complex, nonlinear relationships.

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