The Anatomy of Lost Stock Market Decades*

Todd Feldman† Brian Yang‡

August 22, 2025

Abstract

This paper explores the existence and implications of long-term stock market cycles, characterized by alternating periods of growth and lost performance, in the U.S. and global markets. Using historical data spanning over 150 years, we define growth periods as intervals of sustained positive returns lasting ten years or more and lost periods as phases of near-zero returns lasting a decade or longer. Our findings confirm the persistence of these cycles in the U.S. market, with growth periods typically generating an average annual return of 10% and lost periods yielding zero returns. The implications for asset allocation are significant.

Keywords: Financial markets, Investments **JEL codes:** G10, G11

*We retain sole responsibility for remaining idiosyncrasies and errors.

†Finance Department, 1600 Holloway Avenue, San Francisco State University, San Francisco, CA, 94132, USA. *tfeldman@sfsu.edu*

‡Finance Department, 1600 Holloway Avenue, San Francisco State University, San Francisco, CA, 94132, USA. *brianyang@sfsu.edu*

1 Introduction

Academic literature extensively explores stock market cycles in conjunction with the business cycle, focusing mainly on bull and bear markets. In contrast, we examine longer-term stock market cycles, periods exceeding ten years, and hypothesize that high-return growth phases and near-zero-return lost phases alternate in a repeating pattern. This approach draws on the idea that natural economic rhythms unfold over decades, beyond normal perception, and thus require a century-long perspective. Our goal is to identify recurring patterns in long-term stock market cycles and assess their implications for investment strategies.

We distinguish between bull/bear markets and long-term growth and stagnation phases, what we term lost periods. This distinction matters because a bear market can occur within a broader growth phase. For instance, the COVID-19 crash of 2020 took place during a growth period, as indicated by the subsequent doubling of the S&P500. Conversely, bull markets can occur within lost periods; the strong performance from 2004 to 2007 occurred during a broader lost phase.

Investors should first determine whether the market is in a growth or lost phase, as this choice guides decisions during corrections and momentum shifts. In a growth phase, a correction typically signals a buying opportunity, whereas a correction at the end of a growth phase may warrant caution or selling. The opposite applies during a lost period.

The study is motivated by two aims. First, we re frame stock market analysis by focusing on long-term movements rather than short-term events. Table 1 illustrates a historical pattern of alternating growth and lost phases; the 1980–2000 growth market saw the S&P500 rise from 100 to 1500 despite numerous disruptions, and it was followed by a lost period from 2000 to 2013. We investigate this pattern's statistical significance and practical implications.

Second, we explore the rarity and significance of lost periods, intervals of ten or more years with no net market return. Examples include Japan after 1989 and the United States from 2000 to 2013, when the S&P500 did not regain its 2000 peak until 2013. Lost periods are contrasted with growth phases such as 1980–2000, which saw consistent market gains despite short-term volatility. During growth periods recessions have limited impact on long-term investors, whereas during lost periods they can materially influence asset allocation. We aim to determine whether such long-term cycles exist and to develop methods for identifying

the market's current phase. This classification has important implications: investors may increase equity exposure during growth phases and shift toward safer assets during lost phases. For example, the current U.S. growth cycle began in 2013 and may extend into the 2030s; technological disruptions from AI, blockchain and robotics could foreshadow the next lost period.

We also examine whether technological innovation and demographic trends influence the formation of growth and lost periods. Evidence suggests that innovations often emerge during lost periods and mature during subsequent growth phases. Finally, we apply these definitions across multiple markets to detect recurring patterns over century-long horizons. Initial findings reveal significant alternation between growth and lost periods across markets: U.S. cycles average about 22 years for growth and 16 years for lost phases, while other markets, such as Canada, exhibit longer durations. Exponential-loss metrics provide a practical tool for identifying whether the market is in a growth or lost phase.

2 Literature Review

Empirical studies of U.S. stock market cycles use a wide range of methodologies, including time-series analysis, econometric modeling, wavelet analysis and regime-switching models. These approaches leverage historical market data to uncover cyclical patterns, estimate key parameters and evaluate theoretical models. Findings regarding the characteristics of U.S. stock market cycles, such as duration, amplitude and synchronization, vary among studies due to differences in data sources, sample periods and analytical methods (Hamilton, 1989; Diebold and Yilmaz, 2012; Tse and Tsui, 2002). Despite these variations, there is broad agreement that stock market cycles exhibit non-random behavior shaped by both internal market dynamics and external influences.

The interplay between stock market cycles and broader economic cycles, such as business cycles, remains a debated topic. Some researchers argue that stock market movements align closely with macroeconomic indicators like GDP growth, unemployment rates and inflation, reflecting a strong connection between financial markets and the real economy (Jorda et al., 2013). Others suggest that stock market cycles may lead or lag business cycles, influenced by factors such as investor sentiment, corporate earnings and policy interventions (Bernanke

and Gertler, 1995; Shiller, 2000).

Various theoretical frameworks have been applied to analyze stock market dynamics. For instance, Elliott Wave Theory, introduced by Ralph Nelson Elliott in the 1930s, suggests that stock prices follow repetitive wave patterns driven by investor psychology. Prechter and Frost (1978) expanded on Elliott's principles, identifying five-wave structures during upward trends and three-wave structures during downward trends. Similarly, Kondratiev waves, based on Nikolai Kondratiev's theory, propose that capitalist economies experience long cycles of expansion and contraction lasting 50–60 years, driven by technological innovation and eventual saturation. Empirical evidence supporting Kondratiev waves has been explored in various economic indicators, including stock market indices (Grinin et al., 2018).

Empirical investigations of long-term cycles also include Kuznets swings, introduced by Simon Kuznets, which describe sinusoidal economic patterns spanning 15–25 years. Abramovitz (1986) analyzed historical economic data to identify these swings and their relationship to stock market performance.

Strauss–Howe generational theory, developed by William Strauss and Neil Howe, describes recurring generational cycles tied to social, political and economic climates. Each cycle, or "saeculum," spans roughly 80–100 years and consists of four generational eras (turnings), each lasting 20–25 years. The theory posits that crises recur predictably within each saeculum, followed by recovery periods. This framework, outlined in *Generations* (1991) and expanded in *The Fourth Turning* (1997), has been applied to the United States and other developed nations to describe generational trends and societal cycles.

Additional studies have examined historical stock market returns over extended periods. Bunn and Shiller (2014), for example, reconstructed historical price, dividend and earnings data for the Industrials, Utilities and Railroads sectors from the 1870s to 2013. They assessed the predictive capabilities of the cyclically adjusted price-earnings (CAPE) ratio, adjusting for inflation and corporate payout changes. Their findings suggest that the CAPE ratio is a reliable predictor of long-term returns across sectors. They also proposed a sector-rotation strategy using CAPE-derived valuation signals, which generated an inflation-adjusted annualized excess return of approximately 1.09 per cent over the market benchmark during a 110-year period.

3 Data & Lost Period Definition

This study requires a comprehensive data set of stock market prices spanning over a century. We use monthly data from Global Financial Data (GFD) for Canada, Japan, Australia, Germany and France, markets chosen for their century-long price records. For the United States we rely on data from Robert Shiller (2005), which extend back to 1871 and are also monthly. We also use S&P500 dividend data to compute a valuation of the U.S. stock market through the dividend-discount model.

We define a "lost period" as a time frame of approximately ten years or more during which stock market returns are near zero. While this definition may appear arbitrary, its validity depends on whether testing reveals a recurring pattern. The approach is somewhat retrospective: we look for a consistent cycle in decades of stock market returns. If such a pattern is found, it warrants further investigation because it suggests an underlying rhythm in long-term stock market movements.

4 Empirical Model

The empirical model has two purposes: (i) to statistically validate the existence of growth and lost periods and their transitions, and (ii) to identify metrics that signal whether the market is in a growth or lost phase. The initial regression addresses the first goal by testing the relationship between S&P500 returns and a binary variable identifying lost periods:

$$S\&P_{\text{return}} = \beta_0 + \beta_1 \cdot \textit{lost_period} + \epsilon,$$

where $S\&P_{\text{return}}$ represents the monthly return on the S&P500, and *lost_period* is a binary variable equal to 1 for a lost period and 0 otherwise. A lost period is defined as an extended phase of approximately zero returns lasting over ten years. The null hypothesis is that there is no statistically significant difference in returns between growth and lost periods.

Subsequent regressions explore whether specific metrics can differentiate between growth and lost periods. Two metrics are used: the ratio of the S&P500 index level to its valua-

tion derived from the dividend-discount model (DDM) and a standardized exponential-loss function. The regression for the DDM metric is:

$$S\&P_{\text{DDM}} = \beta_0 + \beta_1 \cdot \textit{lost_period} + \epsilon,$$

where $S\&P_{\text{DDM}}$ is the ratio of the S&P500 index level to its DDM valuation. The DDM valuation V_0 is calculated as:

$$V_0 = \frac{DIV_0\,(1+g)}{r-g},$$

with DIV_0 the current dividend per share (from Shiller's data), g the long-term average dividend-growth rate and r a six percent discount rate, representing the long-term risk premium. We hypothesize that the DDM valuation ratio will be higher during lost periods and lower during growth periods.

The second metric, the exponential-loss function, captures the cumulative effect of negative S&P500 returns, weighting recent losses more heavily than past ones. During growth phases losses remain small for extended periods, whereas losses increase sharply at the onset of a lost period. The loss function is calculated as follows:

1. Compute monthly returns (R_{SP}) for the S&P500.

2. Extract negative returns, setting positive values to zero:

$$L_{\text{SP}} = \max\{0, -R_{\text{SP}}\}.$$

3. Calculate the exponential average of L_{SP}, denoted as $\hat{L}_{\text{SP}(t)}$.

4. Normalize the exponential-loss index by dividing it by its 20-year moving average:

$$\textit{exp_loss_stand} = \frac{\hat{L}_{\text{SP}(t)}}{\hat{L}_{\text{SP}(20\,\text{yr avg})}},$$

   where $\hat{L}_{\text{SP}(t)}$ is the exponential-loss function and $\hat{L}_{\text{SP}(20\,\text{yr avg})}$ its 20-year moving average. This standardized metric helps identify transitions between growth and lost

periods: values below 1 indicate losses below the historical average, and values above 1 indicate elevated losses.

The regression for the standardized exponential-loss function is:

$$exp_loss_stand = \beta_0 + \beta_1 \cdot lost_period + \epsilon,$$

where *exp_loss_stand* is the standardized exponential-loss index.

Finally, a logit regression evaluates the probability of a lost period based on the standardized exponential-loss function:

$$lost_period = \beta_0 + \beta_1 \cdot exp_loss_stand + \epsilon,$$

where *lost_period* = 1 if the period is classified as lost, and *exp_loss_stand* is the standardized loss variable. This approach aims to estimate the likelihood that a given month belongs to a lost phase based on the behavior of cumulative losses in the S&P500, providing a probabilistic measure of market regime.

4.1 Robustness Results

We recognize that some of the lost period definitions and cycle identification is objective. Therefore, we perform a series of robustness tests to verify our results. First, we repeat the cycle work using real (inflation-adjusted) S&P500 index levels rather than nominal levels to test whether the results persist. Similar results would help confirm that the cycle work has substance; divergent results would suggest the patterns may not be real.

Second, we re-estimate the results for the U.S. stock market using alternative definitions of a lost period, eight and twelve years instead of ten, to test the sensitivity of our findings to the chosen threshold.

Third, we estimate a two-state Markov-switching model for the standardized exponential-loss metric and, for comparison, for monthly S&P500 returns. Markov-switching models, originally developed by Hamilton and later extended to dynamic factor frameworks, treat

the observed series as being generated by distinct regimes (for example, "growth" and "lost") with transition probabilities estimated from the data. We use the standardized exponential-loss metric because it captures the cumulative impact of negative returns and spikes at the onset of lost periods. The model allows the intercept (mean) and variance to differ across regimes and estimates the probabilities of remaining in each state. This approach reduces researcher judgment by letting the data determine when the economy switches between high-loss and low-loss states, akin to the objective dating methods used in the business-cycle literature.

5 Results

Table 1 summaries the returns for the growth and lost periods of the U.S. stock market from 1871 to 2024. Growth phases yielded annualized returns of 8.33 per cent from 1954–1968, 14.02 per cent from 1980–2013 and 12.00 per cent from 2013–2024, producing a time-weighted average return of 12.24 per cent across these three periods. As of the latest data, the U.S. market remains in a growth phase.

Table 2 reports the average duration of growth and lost phases. Lost periods have lasted between twelve and twenty-six years, with a time-weighted average of roughly nineteen years; notably, the two most recent lost periods were shorter, at about twelve years each. Growth phases have ranged from fifteen to thirty-two years, with an average duration of twenty-two years from 1872–2024. Extrapolating from this pattern, the current growth phase could extend to around 2028–2032 if growth phases continue to span between fifteen and twenty years.

Figure 1 plots the S&P500 price index with the delineated lost and growth periods from 1871 to 2024. The chart reveals a clear cyclical pattern, with alternating phases of limited returns and high returns that align with the definitions used in this study.

To test whether switching between growth and lost phases is statistically significant, we estimate regressions that compare returns across regimes. The first regression (Table 3) shows that returns average about 1 per cent during lost periods and roughly 9 per cent during growth periods; this difference is significant at the 1 per cent level, providing strong

evidence of meaningful regime shifts.

Table 4 presents results from the second and third regressions, which evaluate two metrics for distinguishing between growth and lost periods. Both metrics can differentiate the two phases, but the DDM (Dividend Discount Model) ratio is significant only at the 5 per cent level, whereas the exponential-loss metric is significant at the 1 per cent level. On average the DDM ratio is 0.53 during lost periods and 0.81 during growth periods, even though one would expect it to exceed 1 in growth phases. Figure 2 shows the evolution of both metrics; the DDM ratio generally stays below 1 but tends to rise above 1 ahead of a lost phase.

The exponential-loss metric is more reliable. Table 4 indicates that it averages 1.30 in lost periods and 0.82 in growth periods, and its threshold value of 1 cleanly separates the two regimes. Figure 2 demonstrates that values above 3 typically mark the onset of a lost phase, whereas values below 0.50 indicate a return to growth. This robustness makes the exponential-loss metric a more effective indicator of market cycles than the DDM ratio.

A logit regression (Table 5) further confirms that higher values of the exponential-loss metric are associated with a greater probability of being in a lost phase.

Table 6 compares the two metrics directly. The exponential-loss function consistently averages above 1 during lost periods and below 1 during growth periods, whereas the DDM ratio does not display the same consistency. For example, the exponential-loss function averages between 0.70 and 0.80 during growth phases and about 1.27 during lost phases.

Table 7 links the introduction of transformative technologies to market phases. Although this analysis is narrative, it suggests that breakthrough technologies not dependent on prior innovations tend to emerge during lost periods, while their widespread adoption occurs during subsequent growth phases. For instance, personal computers appeared in the 1970s (a lost phase), while the internet gained commercial importance in the 1990s (a growth phase). Smartphones were introduced in 2007, another lost phase, and later enabled massive data generation. That data laid the groundwork for artificial intelligence, which became mainstream with the release of ChatGPT in 2023, during a growth phase.

Because long-term innovation data are sparse, we complement the narrative in Table 7 with objective proxies such as patent applications and R&D spending. These proxies are available only annually and only from the mid-twentieth century, making it difficult to integrate them

fully with a 150-year monthly dataset. Nevertheless, Figure 3 plots R&D expenditure as a percentage of GDP from 1996–2024. The series rises ahead of the 2000–2013 lost phase, remains flat during the lost phase, and increases again afterwards, suggesting that R&D investment slows during lost periods and picks up during growth phases.

We also consider demographics. The middle-aged-to-young (MY) ratio measures the number of people aged 40–49 relative to those aged 20–29. We construct this ratio from United Nations population data by summing male and female populations in the 40–44 and 45–49 cohorts and dividing by the sum of the 20–24 and 25–29 cohorts. Geanakoplos, Magill and Quinzii (2004) show that U.S. stock valuations follow a roughly twenty-year demographic cycle; peaks in the MY ratio coincide with long bull markets, whereas troughs correspond to lower valuations. Figure 4 plots the MY ratio alongside the lost periods and exponential-loss metric. The MY ratio declines during lost phases and rises during growth phases.

To validate our definitions, we apply the same criteria to other markets. Tables 8–12 show that Canada, Germany, Australia, France and Japan also experience alternating growth and lost phases, though the durations and timings differ. For instance, Canada has undergone a 47-year lost phase and a 50-year growth phase and currently remains in a lost phase, while the U.S. has been in a growth phase since 2013. These differences likely reflect structural factors; Canada's reliance on energy and mining, for example, has delayed its recovery since the global financial crisis and the advent of fracking lowered energy costs. Rising demand for materials in chip and battery production may eventually push Canada into a new growth phase. Despite such variations, the evidence suggests that switching between growth and lost phases is a widespread phenomenon rather than a U.S.-specific pattern.

Regarding robustness, we recalculated Table 1 using real (inflation adjusted) returns. Table 13 displays similar patterns of growth followed by lost phases, except for the 1898–1929 period, supporting the main findings for the modern era. We also recomputed the lost-period indicator using 8-year and 12-year windows and reran the regressions (Table 14); the exponential-loss metric continued to distinguish regimes, and the return differential between growth and lost phases remained highly significant. Finally, Table 15 reports parameter estimates for Markov-switching models applied to the exponential loss metric and monthly returns. For the loss metric, regime 0 (low-loss) has a mean of 0.713 and variance 0.077, and regime 1 (high-loss) has a mean of 1.912 and variance 0.590, with persistence probabilities

of 0.982 and 0.950, respectively. In contrast, the return based model yields a growth regime with a mean monthly return of 0.8 per cent (variance 0.00084) and a lost regime with a mean of –1.66 per cent (variance 0.00623), with persistence probabilities of about 0.975 and 0.838. These models provide an objective identification of market phases that is consistent with the empirical findings above.

6 Conclusion

This study confirms that the U.S. stock market alternates between multi-decade growth and lost phases. A lost phase is characterized by near zero returns from the previous all-time high to the recovery point and lasts about ten years or more; varying the window length between eight and twelve years does not materially change the results. Growth phases last about twenty years on average and deliver roughly 10 per cent annual returns, whereas lost phases yield zero returns. Recognizing which phase the market is in is crucial for asset allocation, as recessions are less consequential in growth phases but can have prolonged effects in lost phases. The U.S. market currently appears to be in a growth phase; a future recession or crisis could trigger a transition, and spikes in the exponential-loss metric above three may provide an early warning.

Among the tools we evaluate, the exponential loss function stands out as a reliable indicator of market regime. It tracks current and historical losses, gives greater weight to recent losses and sharply delineates transitions between prolonged low-loss periods and episodes of significant losses. The function typically spikes to around three at the onset of a lost phase and falls below 0.50 when a growth phase begins (see Figure 2).

The typical durations we find, about twenty years for growth phases and twelve years for lost phases, echo long-wave theories such as Kuznets' 15–25 year investment cycles and Kondratiev's 50–60 year innovation waves. By anchoring our analysis in financial market data, returns, draw-downs and exponential-loss metrics, we provide empirical support for the existence of long-term rhythms in asset returns. Our evidence also refines these theories. First, modern growth and lost phases are shorter and more compressed than those in the nineteenth and early twentieth centuries, implying that faster technological diffusion and greater global capital mobility have accelerated the cycle. Second, cross country comparisons

reveal that while the general pattern of alternating phases is pervasive, the duration and timing vary by market; Japan and Germany, for instance, experience much longer lost phases, and Canada's current lost phase has yet to end. These findings suggest that long-wave frameworks remain useful for understanding market dynamics but must be recalibrated for the pace of 21st-century innovation and globalization.

Because growth and lost phases have such different return dynamics, identifying the market's phase should be the first step in strategic asset allocation. Investors who correctly distinguish between the two can adjust their portfolios accordingly, emphasizing equities in growth phases and shifting to safer assets in lost phases, and thereby improve their long-term risk-adjusted returns.

7 References

Bernanke, B. S., & Gertler, M. (1995). Inside the Black Box: The Credit Channel of Monetary Policy Transmission. The Journal of Economic Perspectives, 9(4), 27-48.

Bunn, A., & Shiller, R. J. (2014). Data Series for Historical Prices, Dividends, and Earnings: 1871-2013. Retrieved from https://www.econ.yale.edu/ shiller/data.htm

Comin, Diego, and Bart Hobijn. 2010. "An Exploration of Technology Diffusion." American Economic Review 100 (5): 2031–59. https://doi.org/10.1257/aer.100.5.2031.

Diebold, F. X., & Yilmaz, K. (2012). Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers. International Journal of Forecasting, 28(1), 57-66.

Geanakoplos, John, Michael Magill, & Martine Quinzii. (2004). Demography and the Long-Run Predictability of the Stock Market. Brookings Papers on Economic Activity, 2004 (1):241–325.

Grinin, L., Korotayev, A., & Tausch, A. (2018). Economic Cycles, Crises, and the Global Periphery. Springer.

Hamilton, J. D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. Econometrica, 57(2), 357-384.

Jaffe, Adam B., and Manuel Trajtenberg. 2002. Patents, Citations, and Innovations: A Window on the Knowledge Economy. Cambridge, MA: MIT Press.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2013). Sovereigns versus Banks: Credit, Crises, and Consequences. Journal of the European Economic Association, 11(1), 45-79.

Kondratiev, Nikolai D. 1935. "The Long Waves in Economic Life." Review of Economic Statistics 17 (6): 105–115. https://doi.org/10.2307/1928486.

Kuznets, Simon. 1930. Secular Movements in Production and Prices: Their Nature and Their Bearing upon Cyclical Fluctuations. Boston: Houghton Mifflin.

Prechter, R. R., & Frost, A. J. (1978). Elliott Wave Principle: Key to Market Behavior. New Classics Library.

Schumpeter, Joseph A. 1934. The Theory of Economic Development: An Inquiry into Profits,

Capital, Credit, Interest, and the Business Cycle. Cambridge, MA: Harvard University Press.

Shiller, R. J. (2005). Irrational Exuberance. (2nd ed.). Princeton University Press.

Shiller, R. J. (2000). Irrational Exuberance. Princeton University Press.

Strauss, W., & Howe, N. (1991). Generations: The History of America's Future, 1584 to 2069. William Morrow Company.

Strauss, W., & Howe, N. (1997). The Fourth Turning: An American Prophecy. Broadway Books.

Tse, Y. K., & Tsui, A. K. (2002). A Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model with Time-Varying Correlations. Journal of Business Economic Statistics, 20(3), 351-362.

8 Tables and Figures

Table 1: S&P 500 Bull & Lost Period Switching

Date Range	Annual Return	# of Years	Growth Factor	Beg. Level	Ending Level
1872-1898	0.07%	26.00	1.02	5.18	5.27
1898-1929	5.73%	32.00	5.94	5.27	31.30
1929-1954	0.02%	25.00	1.00	31.30	31.45
1954-1968	8.33%	15.00	3.39	31.45	106.50
1968-1980	0.10%	12.00	1.01	106.50	107.70
1980-2000	14.02%	20.00	13.79	107.70	1,485.46
2000-2013	-0.03%	13.00	1.00	1,485.46	1,480.40
2013-2024	12.00%	12.00	4.04	1,480.40	5,979.52

Table 1 displays the existence of the lost and growth periods for the US stock market. Shiller Data used. Annual return is the cumulative return annualized. # of years it he number of years total spent in either the lost or growth period. Growth Factor is the cumulative gain of one dollar from the beginning of the period to the end of the period. Beginning level is the level of the S&P 500 at the beginning of the period. Ending level is the ending level of the S&P at the end of the period. Frequency is monthly.

Table 2: S&P 500 Growth / Lost Period Summary

Period	Avg. Return	Avg. Duration	Avg. Growth Factor
Lost Period	0.04%	19.00 yrs	1.01
Growth Period	9.04%	22.00 yrs	7.04

Table 2 displays the average duration of the various lost and growth periods for the US stock market shown in Table 1. Time weighted averages were calculated based on the results from Table 1.

Table 3: S&P 500 Lost Period Detection

Variable	β_0	β_1
Lost_Period	0.10**(0.006)	-0.081**(0.008)

Table 3 displays estimates from running equation 1.

$$S\&P_return = \beta_0 + \beta_1 * lost_period + \epsilon, \tag{1}$$

lost_periodt equals one if the period is detected to be a lost period returning zero percent longer than ten years. It equals zero if the period is detected as a growth period. *S&P_return* is the annual return changing on a monthly basis. The data extends from 1871 to 2024. *significant at 5%; **significant at 1%.

Table 4: Metrics of Lost Period Detection for US Stock Market

Dep_Variable	**Indep_Variable**	β_0	β_1
S&P_DDM	Lost_Period	0.81**(0.009)	-0.28*(0.014)
exp_loss_stand	Lost_Period	0.48**(0.033)	0.82**(0.022)

Table 4 displays estimates from running equation 2 and 3.

$$S\&P_DDM = \beta_0 + \beta_1 * lost_period + \epsilon, \tag{2}$$

$$exp_loss_stand = \beta_0 + \beta_1 * lost_period + \epsilon, \tag{3}$$

lost_periodt equals one if the period is detected to be a lost period returning zero percent longer than ten years. It equals zero if the period is detected as a growth period. *S&P_DDM* equals the level of the S&P 500 index relative to the S&P 500 valuation using the dividend discount model. *exp_loss_stand* is a cumulative loss metric with current losses weighted more than previous losses divided by the twenty year average of the loss metric. *significant at 5%; **significant at 1%.

Table 5: Logit Regression: S&P 500 Lost Period vs. Growth Period

Variable	β_0	β_1
Exp_Loss	1.21**(0.101)	-1.52**(0.112)

Table 5 displays estimates from running equation 4.

$$lost_period = \beta_0 + \beta_1 * exp_loss_stand + \epsilon, \tag{4}$$

lost_periodt equals one if the period is detected to be a lost period returning zero percent longer than ten years. It equals zero if the period is detected as a growth period. *exp_loss_stand* is a cumulative loss metric with current losses weighted more than previous losses divided by the twenty year average of the loss metric. *significant at 5%; **significant at 1%.

Table 6: S&P 500 Growth / Lost Period Switching

Dates	Annual Return	S&P/DDM	Exponential Loss
1898-1929	5.73%	0.80	**0.95**
1929-1954	0.02%	0.66	1.14
1954-1968	8.47%	0.81	**0.82**
1968-1980	0.09%	0.67	1.37
1980-2000	14.02%	0.77	**0.72**
2000-2013	-0.03%	1.11	1.62
2013-2024	12.34%	0.93	**0.70**

Table 6 displays two metrics that could help identify growth versus lost periods. Shiller Data used. Frequency is monthly.

Table 7: Innovation & Growth / Lost Period Switching

Innovation	Date of First Production	Lost Period	Exponential Loss
Telephone, Light Bulb	1880	Yes	1.56
ModelT	1908	No	0.42
Personal Computer	1975	Yes	2.37
Internet	1991	No	0.73
Smart Phone	2007	Yes	1.50
AI	2024	No	0.86

Table 7 displays the year of first available distribution to the public relative to the identification of a lost period. Date of first production is when a product is produced for distribution for the first time. For example, the iphone was available in 2007. The first Model T occurred in 1908.

Table 8: Canadian Growth / Lost Period Switching

Date Range	Annual Return	Duration	Growth Factor	Beg. Level	Ending Level
1829-1865	14.50%	36	130.93	0.71	92.78
1865-1908	-0.03%	43	0.99	92.78	91.54
1908-1929	7.46%	21	4.53	91.54	414.52
1929-1957	0.23%	25	1.06	414.52	439.09
1957-2007	7.39%	50	35.30	439.09	15,499.15
2007-2023	0.21%	16	1.03	15,499.15	16,025.50

Table 8 displays GFD data used. Frequency is monthly.

Table 9: Germany Growth / Lost Period Switching

Date Range	Annual Return	Duration	Growth Factor	Beg. Level	Ending Level
1835-1849	-0.32%	14	0.96	6.36	6.08
1849-1872	6.01%	23	3.82	6.08	23.25
1872-1977	-0.01%	105	0.99	23.25	23.03
1977-2007	12.06%	30	30.47	23.03	701.69
2007-2023	0.21%	16	1.03	701.69	725.11

Note. GFD Data used. Frequency is monthly.

Table 10: Australia Growth / Lost Period Switching

Date Range	Annual Return	Duration	Growth Factor	Beg. Level	Ending Level
1825-1848	0.09%	23	1.02	7.50	7.65
1848-1864	12.41%	16	6.50	7.65	49.71
1864-1921	-0.04%	47	0.98	49.71	48.73
1921-1929	12.64%	8	2.59	48.73	126.27
1929-1956	-0.02%	27	0.99	126.27	125.59
1956-1973	8.97%	17	4.31	125.59	541.17
1973-1985	0.51%	12	1.06	541.17	575.44
1985-2007	11.51%	22	10.98	575.44	6,319.07
2007-2023	-1.41%	16	0.80	6,319.07	5,033.63

Note. GFD Data used. Frequency is monthly.

Table 11: France Growth / Lost Period Switching

Date Range	Annual Return	Duration	Growth Factor	Beg. Level	Ending Level
1801-1820	0.43%	19	1.08	13.64	14.80
1820-1893	3.73%	73	14.47	14.80	214.07
1864-1977	-0.03%	113	0.98	214.07	209.78
1977-2023	4.74%	46	29.42	209.78	6,171.90

Note. GFD Data used. Frequency is monthly.

Table 12: Japan Growth / Lost Period Switching

Date Range	Annual Return	Duration	Growth Factor	Beg. Level	Ending Level
1901-1972	-0.02%	71	1.02	0.78	0.79
1972-1989	20.91%	17	25.21	0.79	20.03
1989-2023	-0.71%	24	0.84	20.03	16.88

Note. GFD Data used. Frequency is monthly.

Figure 1: Lost vs. Growth

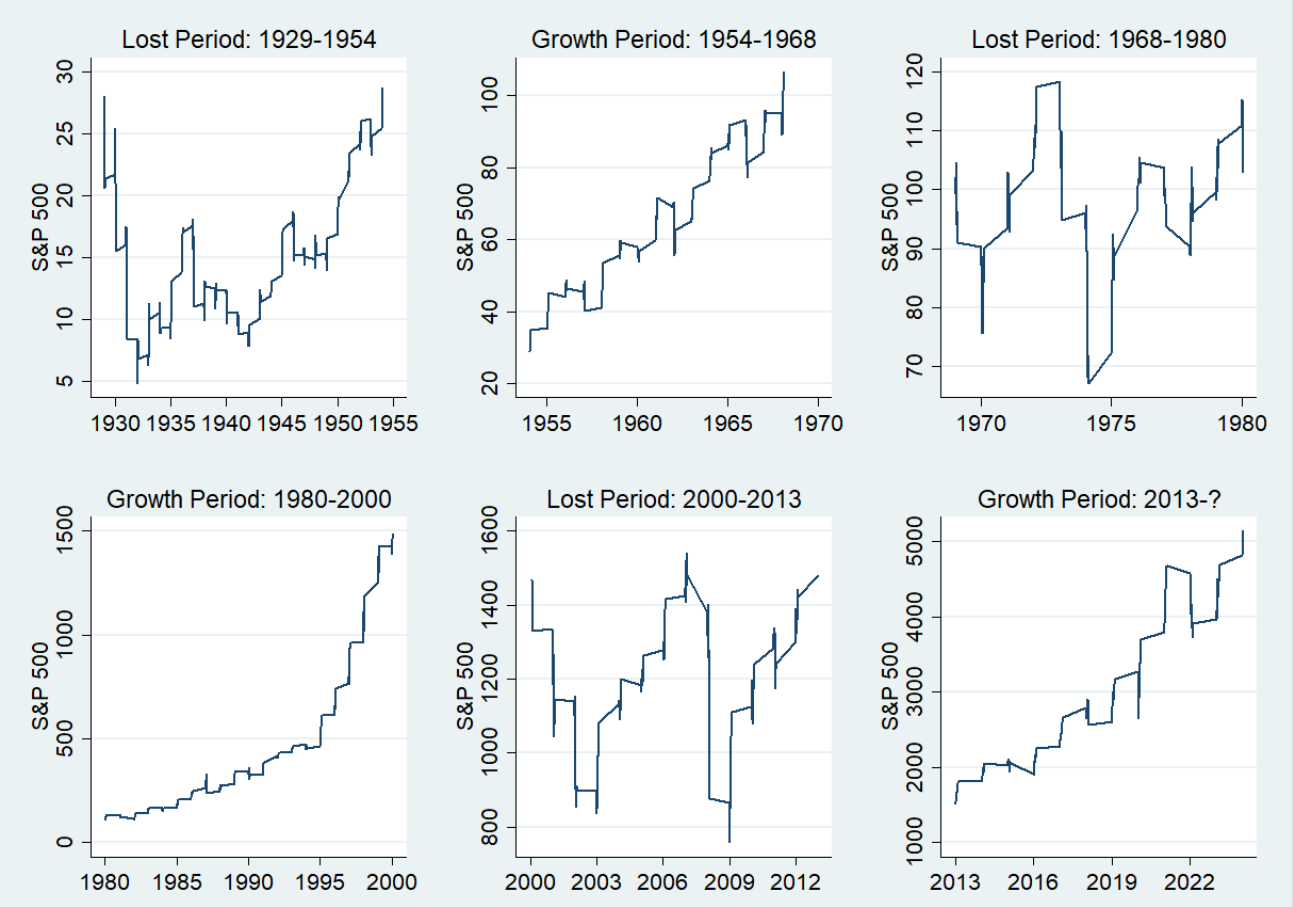


Figure 1 displays lost vs. growth periods of the S&P 500 from 1880 to 2024, nominal levels.

Figure 2: DDM and Exponential Loss

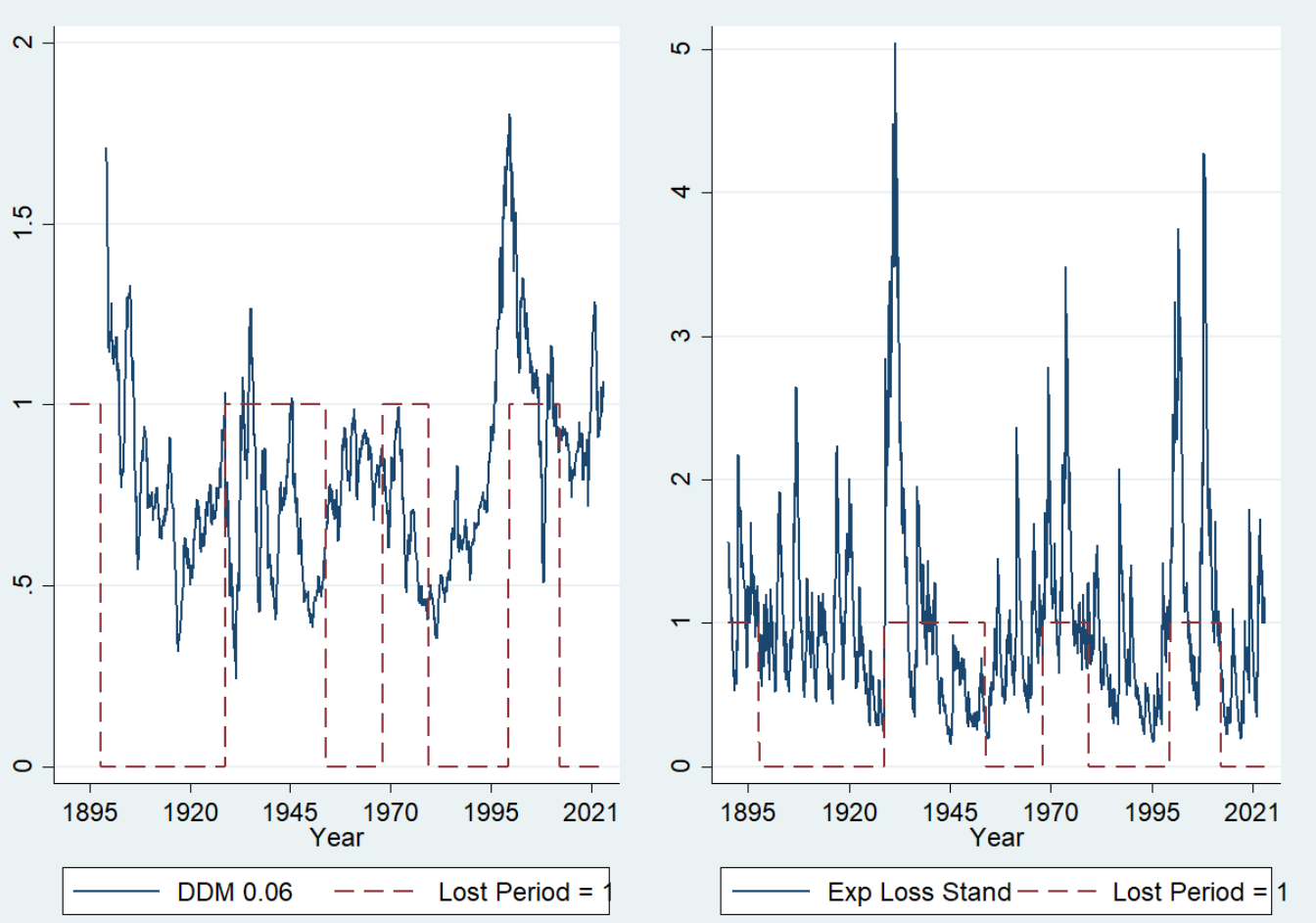


Figure 2 displays the exponential-loss and dividend discount model metrics to evaluate whether these metrics can help pinpoint which period the US stock market lies, lost or growth period.

Figure 3: R&D / GDP vs. Lost Periods

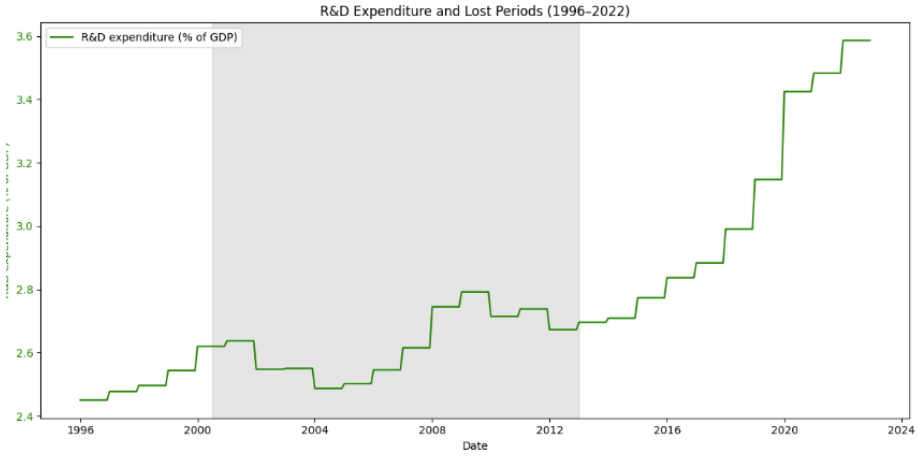


Figure 3 displays R&D as a percent of GDP relative the lost and growth periods. The lost period is the shaded region.

Figure 4: MY Ratio vs. Lost Periods

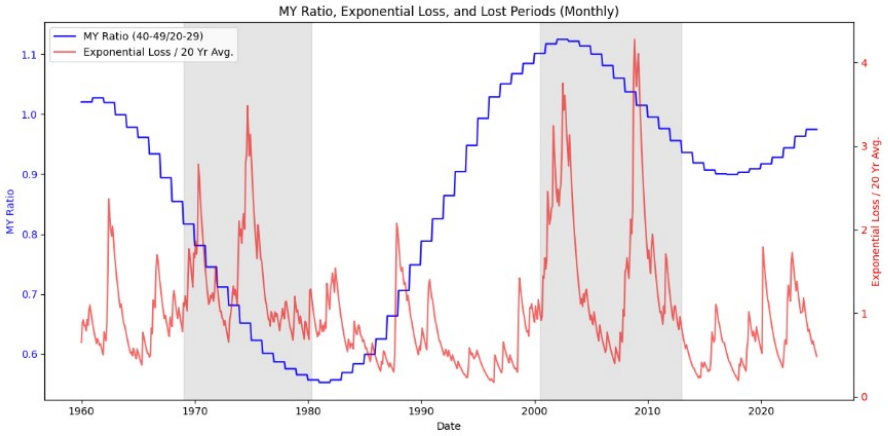


Figure 4 displays young to middle age ratio demographic relative to the exponential-loss metric and the growth and lost periods. as a percent of GDP relative the lost and growth periods. The lost periods are the shaded regions.

Table 13: Real S&P 500 Bull & Lost Period Switching

Date Range	Annual Return	# of Years	Growth Factor	Beg. Level	Ending Level
1872-1898	0.03	26.33	1.02	99.11	198.79
1898-1929	0.03	32.00	5.94	198.79	454.54
1929-1954	-0.02	25.00	1.00	454.54	294.82
1954-1968	0.06	15.00	3.39	294.82	753.70
1968-1980	-0.07	12.00	1.01	753.70	330.78
1980-2000	0.10	20.00	13.79	330.78	2159.70
2000-2013	-0.02	13.00	1.00	2159.70	1615.10
2013-2024	0.09	12.00	4.04	1615.10	4728.95
Bear	-1.06%	19.08	1.01		
Bull	6.20%	22.33	7.15		

Table 13 displays the existence of lost and growth periods for the U.S. stock market in real terms. Shiller data used. Annual return is the cumulative return annualized. # of years is the total time spent in either the lost or growth period. Growth Factor is the cumulative gain of one dollar from the beginning of the period to the end of the period. Beginning and ending S&P 500 levels are inflation-adjusted. Frequency is monthly.

Table 14: Alternate Lost Windows and S&P/DDM Ratio and Exponential Loss Metrics

Cycle length (years)	S&P/DDM (growth)	S&P/DDM (lost)	Exp. loss (growth)	Exp. loss (lost)
8	0.936	0.643	1.139	0.868
10	0.910	0.636	1.171	0.773
12	0.885	0.634	1.165	0.706

Table 14 displays results from examining different lost windows of 8, 10, and 12 years of no returns to considerend a lost period.

Table 15: Lost / Growth Period Markov Switching Identification

Series	**Regime**	**Mean**	**Variance**	p_{stay}	p_{switch}
Standardized exponential loss	0 (low loss)	0.713	0.077	0.982	0.018
	1 (high loss)	1.912	0.590	0.950	0.050
Monthly S&P 500 return	0 (growth)	0.008	0.00084	0.975	0.025
	1 (lost)	–0.0166	0.00623	0.838	0.162

Table 15 displays parameter estimates from two-state Markov switching models. Regime 0 corresponds to the low loss (growth) state for the exponential loss metric and the positive return state for monthly returns. Regime 1 corresponds to the high loss (lost) state.