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Bubbles Through the Years: An Examination of Unique and Analogous Characteristics among Financial Manias from the South Sea Bubble to the Great Financial Crisis

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Abstract

Throughout history, financial bubbles have been shrouded in fear and misunderstanding, with hope, greed, and hearsay fueling inane degrees of risk-taking amongst financial powerhouses and the common retail investor alike. While many studies have been conducted to delve into the unique attributes, causes, effects, and consequences of almost every crisis since adequate data could be recorded and preserved, it is not common for the varying types of crises to be directly compared in their core attributes and price movements. This paper conducts such an examination, with a look into ten different crises across the equity, real estate, and oil markets to compare volatility trends, key bubble statistical indicators, and sensitivity to common economic measuring points. It will be shown that while great differences do exist among many catastrophic collapses, several interesting points of significance emerge across both time and asset class that may inform greater research into investor psychology and what motivates the beginning and end of a financial bubble.

"Men, it has been well said, think in herds; it will be seen that they go mad in herds, while they only recover their senses slowly, and one by one." -Charles Mackay, Extraordinary Popular Delusions and the Madness of Crowds (1841)

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1. Introduction

The exact definition of a financial bubble is difficult to pin down. It is commonly used as an inexact term to describe a rapid acceleration and subsequent plummet in an asset's price, usually facilitated by the idea that some new phenomenon or temporary economic condition has achieved permanence, followed by the eventual realization that the shift was transient, which results in investors shifting their attitudes and allocations to recorrect. However, such a broad summarization fails to exactly benchmark or delineate the idea of a bubble. It is different from a market pullback, correction, or bear market, which are respectively defined as market drops of 5-10%, 10-20%, and more than 20% (CME Group). It sometimes can coincide with, cause, or result from an economic recession, but this is not a prerequisite feature, as captured by crises in more niche markets. It is paradoxically difficult to see when it is forming, yet obvious in its presence with hindsight, making market timing all but impossible. If such a phenomenon is so difficult to adequately understand explicitly, how then can we hope to properly study it across time? Perhaps in struggling to precisely define what a bubble is, it is important to understand what it is not.

A financial bubble is not rational. Investors usually do not use their normal methods, analysis, or diligence processes when caught up in the cloud of a bubble. This can be seen in several recent examples with Ark Invest's $1 million price target on Bitcoin for 2030 (Ark Investment Management LLC), WeWork's much maligned use of "community adjusted EBITDA" before their collapse (Axios), or Reddit-fueled retail investing hordes' chants of "to the moon" when facing down institutional investors like Melvin Capital in the GameStop meme saga (WSJ). A financial bubble is not always short in duration. As seen in this study, crises have a variety of lengths and different measurement points, including the bubble buildup, the bubble burst, and the total bubble periods. Within this study's sample, the average buildup lasts for 1,379 days, with a minimum of 174 days and a maximum of 2,933 days; the average bust lasts for 970 days, with a minimum of 176 days and a maximum of 2,435 days; the average total bubble lasts for 2,348 days, with a minimum of 455 days and a maximum of 3,969 days. A financial bubble is not (adding in one more criterion here with example, modeled the same as previous two). A financial bubble does not just affect the profits of influential elites on Wall Street. A common theme in the aftermath of crises is to lay blame solely at the feet of the financial markets and its "sophisticated" players. They are neither the single guilty party nor the most egregious source of risk-taking in the financial framework. Though it is certain the origins, packaging, and liquidity of the volatile assets are facilitated by financial markets, it is the wider economic willingness to believe in the story that is "too good to be true" that creates a catalyst for adoption and a fear of missing out that fuels the entire volatility architecture of a bubble. As will be displayed in this paper's results, volatility and momentum are the primary drivers of almost every financial bubble.

The relevance of the crisis categories examined for this study, as well as each individual crisis, is important to note, especially in terms of the market dynamics that other researchers have identified and studied in their own work that can lend to a cross-sectional analysis. It is this paper's goal to understand the broad market relationship that volatility and certain economic indicators have with asset prices during a financial bubble. While the result of higher market volatility lending to the speed and size of a bubble makes clear intuitive sense, it is of greater significance to understand how the lagged price and volatility significances vary and change between crisis types and time periods, as well as any pertinent relationships found with other economic covariates. The contribution of this study lies not in its statistical complexity or economic invention, but rather in its aggregation of many segregated market types and time periods to create a broader understanding for triggers that are "market-moving."

There will be three main market categories studied in this paper: equities, real estate, and oil. The first category, stocks, includes The South Sea Bubble (1719-1720), the Roaring Twenties (1921-1932), the Asian Financial Crisis (1992-1998), the Dot Com Crash (1995-2002), and the Chinese Stock Bubble (2005-2008). The South Sea Bubble data will examine an aggregated index of seven companies in Great Britain affiliated with trans-Atlantic trade, with exuberance in the companies pushed by the creation of insurance corporations that alleviated risk concerns for some investors. The Roaring Twenties data will study indexed equity prices compiled by The Cowles Commission for Research in Economics during the 1920s and early 1930s (Cowles, 2022), which captures the speculative fever that enveloped the U.S. before adequate securities regulations were introduced. The Asian Financial Crisis data utilizes the Korean index KOSPI to model the surge in financial markets throughout Asia in this period that resulted largely from massive inflows and outflows of foreign investment. The Dot Com Crash data will investigate the dramatic fall of the S&P 500 Information Technology Index, after a large run-up in early Internet companies at the end of the 20th century created a significant gap between market expectations and realities for companies with virtually no sales. The Chinese Stock Bubble data will examine the Shanghai SE Index during a runup in equity prices coinciding with the onslaught of the Great Financial Crisis. Based on typical investor practices for pricing and modeling equities with free cash flows and discount rates, it is expected that central bank interest rates and industrial growth will be significant covariates for these crises, with the additional expectation that, as with all the crises studied, lagged prices will create meaningful momentum to continuously drive existing prices up during the bubble periods.

The South Sea Bubble was one of the first episodes of wild speculation in recorded financial market history, involving three interwoven crises, the Mississippi Bubble, the South Sea

Bubble, and the Dutch Windhandel (Frehen, R.G.P., Goetzmann, W.N., Rouwenhorst, K.G., 2009). The main driver of the crisis was perceived innovation in the insurance and Atlantic shipping trade, the first such instance with data where human progress in an area became overblown by expected financial gains, resulting in the formation of a market bubble in stocks of the affiliated companies (Pastor and Veronesi, 2009). While insider trading and arbitraging have been found to be significant contributing factors to other early crises before the implementation of stronger regulatory rules, it is unlikely that such causes contributed to this crisis, as a great deal of the financial collapse was driven by an inability to meaningfully deliver on expectations of shipping from the New World (Frehen et al.). The data used to study this crisis in this paper comes from Frehen et al., which is publicly available.

A classic look at the Roaring Twenties bubble is that of an economy-wide credit bubble, (Eichengreen, B., Mitchener, K., 2003). Such a view, which has ties in its formation to the Dot Com Crisis to be discussed further later, focuses on the role runaway credit markets played in facilitating a competitive environment amongst lenders that led to decreased diligence and massive risk undertaking. Financial innovation can be seen to be a great contributor to the exuberance of the time, with hype surrounding emerging network technologies that were not yet ready for mass deployment and failure at the nascent Federal Reserve to properly monitor and steer financial markets with their existing power. It should not be said that the credit market was the sole, or even the main contributing factor to the Great Depression, but an exploration of this bubble is important to understand how much of it may have been driven by credit-related factors, other economic drivers, or its own generated momentum.

An exploration of the Asian Financial Crisis yields existing structural weaknesses in the economic conditions of many emerging markets in the Asian continent, including discrepancies in current account balances, the composition of capital flows into and out of countries, credit overleverage, and banking issues (Corsetti, G., Pesenti, P., Roubini, N., 1999). Both policy and structural changes in Asian countries that suffered from the bubble may have played an inordinate role in investor crowding and market sentiment that generated real economic gains and losses at this time. This bubble provides an opportunity to explore how surging asset prices in an export-driven economy can drive or be driven by real economic factors that create an environment for industrial development and foreign investor risk appetite, which can be seen to subsequently recede as expanded expectations for these developing economies implode.

An examination of the Dot Com Crisis offers a differentiated perspective on financial bubbles through the introduction of stock lockups and insider selling as important factors to consider (Ofek, E., Richardson M., 2003). The Dot Com era was hallmarked by the surge in significant and unprecedented block holdings, with subsequent trades of such massive stakes greatly affecting the bubble's steep rise and swift fall. It can be seen that the fall of the Dot Com era was precipitated by an unprecedented lockup expiration that flooded the markets with insiders looking to liquidate their richly valued positions. Once the selling intensified with enough expirations, confidence eroded in the Internet companies where so much stock was being sold by insiders, leading the wider market to sense weakness or overvaluation and flood out as well. This insider-driven bubble is distinct in its attributes from other bubbles to be studied that are driven more by outside investors who do not have a majority of their income coming from the company they may be invested in.

Corporate earnings, measures for an equity risk premium, and the risk-free interest rate are all important factors for the sharp rise in Chinese stock valuations from April 1999 through September 2009 (Bondt, G.J., Peltonen, T.A., Santabárbara, D., 2010). Evidence exists for price misallocations resulting from several sources during booms and busts in Chinese markets, including equity market reform pursued by the authoritarian government, excessive available capital from both foreign and domestic sources, and changes in deposit rates enacted by Chinese regulators and central bankers. A fundamentals-based approach to model equity values can be seen to be successful, through implementing both a dynamic present value model and empirical valuation techniques (Campbell and Shiller, 1988 and de Bondt, 2008). The idea that traditional fundamentals-based valuation could be used to properly model and allocate capital within Chinese equity markets is a novel one to researchers, with previous ideas centering on Chinese equities trading on sentiment and diverging in their financial valuation from more mature equity markets that thought to be more founded on business fundamentals and financial results.

The second market category, real estate, includes the Japanese Real Estate Crash (1984-1992) and the U.S. Housing Crisis (2002-2009). The Japanese Real Estate Crash will investigate the ramifications of emerging financial institutions in a foreign market, with a heavy emphasis on urban redevelopment and the domination of property markets by investor capital. The U.S. Housing Crisis will assess the extent of financial derivatives' impact on a market poised for growth, but with a financial system that extended borrowing and building beyond the limits of owners' ability to absorb rising financing costs. It is expected that nominal interest rates and monetary growth will be the most significant covariates for the real estate market due to the direct impact rates have on mortgage lending and the economic boost that strong monetary growth usually facilitates, which often manifests for average citizens in increased home purchases, and subsequently inflating prices.

A deep dive into the property boom and bust in the Japanese market during the 1980s and early 1990s finds a significant role is played by financial institutions in exacerbating the formation of a financial asset and real estate bubble, with requisite property finance infrastructure arising to meet the increased levels of demand and speculation (Oizumi, E., 1993). Specifically, tightening monetary policy from the Bank of Japan can be seen to act as a catalyst to cool the exuberant market at the end of 1989, which led to a series of so-called "bubble bankruptcies." Interestingly, the land domination that began to rise during the bubble actually increased as a result of the crash, rather than collapsing like so much of the finance capital that fled Japan at this time. Evidence for this can be found in observances of consolidation among capital providers, domestic policies geared at restoring faith in the property market, and the increased risk of real estate investment, which can often only be taken on after the crisis by large institutional players.

An exploration of the Great Financial Crisis requires a multi-geographical analysis of the housing bust, as real estate in the United States is an extremely regional market (Cohen, J.P., Coughlin, C.C., and Lopez D.A., 2012). A pricing survey finds that the bubble became most volatile in metropolitan areas, with 7 of 19 identified areas having experienced real declines over the course of the eventual bust. Pricing differences between houses of varying starting prices can be seen to exist, with lower-priced homes increasing by significantly more during the boom, while higher-priced homes performed better through the duration of the crisis. Additionally, appreciation in land values was more significant to the overall bubble than the price of the actual housing structures being built, implying that the financial bubble may not have been as linked to factors such as industrial production growth as one might think when studying a real estate bubble.

The third category, oil, includes the Stagflation Oil Crisis (1978-1986), the 2008 Oil Shock (2003-2008), and the 2010s Oil Collapse (2009-2016). The Stagflation Oil Crisis will examine the market trajectory of oil following the impacts of a staggering U.S. economy through a majority of the 1970s with the dual threat of rising inflation and unemployment, which was finally wrangled into submission in part by subduing rapid commodity inflation. The 2008 Oil Shock will investigate market dynamics of a commodity crisis in the throes of a recession, as the global economy was the collapse coincides with the Great Recession. The 2010s Oil Collapse will assess the dynamics of the back half of a double dip in oil following the 2008 price bubble, which is interesting to consider given the relatively smooth transition from bubble to crash twice over. When considering what variables are most likely to impact commodities, inflation and unemployment seem like the two most likely, as both factors help to inform consumer demand for main use cases of oil, such as gas used in family road trips or petroleum used to create plastic products flying off consumer shelves.

A focus on the Stagflation Oil Crisis finds both the inherent difficulties of attempting to assign a significant role to oil in such a far-reaching crisis, as well as the exogenous nature of oil price movements when crises in the market do occur (Barsky, R., Kilian, L, 2004). It can be argued that widespread perceptions about the causality of oil prices on macroeconomic factors are actually reversed, with macroeconomic factors creating oil price shifts rather than vice versa. Under such a premise, claims that the 1970s stagflation may have been the result of an oil crisis would be ill-informed and incorrect.

When examining the 2007-08 oil price shock relative to previous oil crises one of the significant differences may be found in the occurrence of inflation (Hamilton, J.D., 2009). Whereas previous oil bubbles throughout recorded history are driven mostly by supply disruptions alone, the 2007-08 case presented a dual shock in the form of spiking demand and lagging supply. Similarities exist in the eventual effects of the bubble, with consumer spending and automobile purchases both taking significant hits as gasoline prices ate more into consumers' wallets. The effects of the commodity crisis are important in the context of the global recession during this same time period, which may or may not have been extended or worsened by the existence of such energy market shocks.

The 2010s Oil Collapse is quite more interesting upon a second glance, with its connection to a so-called commodities super-cycle carrying over from the 2008 Oil Shock (Baffes, J., Kose, M.A., Ohnsorge, F., Stocker, M., 2015). Several proximate causes for the price collapse can be identified, including innovations in the oil production space that led to unexpected supply increases, a downtrend in global oil demand, easing of geopolitical tensions, and an upswing in the U.S. currency. Overall, the effects of the bubble appear to be largely positive for the global economy, as a downward trajectory for oil prices allows for an easier flow of international trade and all kinds of economic activities that directly and indirectly benefit from the tailwind. However, it should be noted that while there are numerous benefits to oil prices falling, oil exporters experience a significant decline in their business that is immediately realized, while the previously mentioned benefits take months, or even years, to properly materialize.

2. Literature Review

In beginning to place this research in the context of wider economic literature, a few important questions arise with respect to the idea and definition of a "bubble." What exactly constitutes a bubble? How can one be identified for study? Why is an understanding of bubble characteristics and dynamics an important area of academic research? What are the consequences of proper versus misinformed understandings of bubbles? While this paper does not attempt to create a model or new avenue of understanding for how to examine bubbles, it does take a unique perspective in examining bubble dynamics across time and asset class. This kind of cross-sectional analysis has not been previously studied, as it is often neater and more cogent for theoretical work to make an argument using a single market example, if a practical market at all, rather than a theoretical one. Based on the body of existing literature, there appears to be a gap between theorists who use niche market scenarios, or even manufactured market settings, to study their proposed theories and practitioners who deal in dynamic, "messy" market conditions every day. This research proposes to offer the first layer of bridging such a gap, as a theoretical framework brought to analyze the patterns of important, historical market bubbles that are often the subject of much financial commentary, but not academic research. The "mess" of many confounding factors present in the real world's bubbles will be parsed to understand if certain time and market-specific factors affect the trading patterns that are seen in bubbles, comparing such results with existing theoretical frameworks to discover which ideas merit further development for particular market regimes.

The definition of a market bubble can most aptly be described theoretically by Evanoff, Kaufman, Malliaris (2012), who state that a bubble "exists when the market price of an asset exceeds its price determined by fundamental factors by a significant amount for a prolonged period of time." While this is not the hard and fast definition that might be hoped for in a statistical examination of bubbles, every bubble is different. As will be demonstrated in the bubbles studied in this research, assets vary widely in terms of relative price volatility and trading frequency. What may constitute bubble-like behavior for a traditional asset like real estate may be normal volatility for a distinct asset, like Bitcoin. It is important to understand the relevance of such nuances in developing an appropriate labeling of bubbles, especially as this research reaches across asset classes for comparison purposes. With regard to the importance of understanding bubbles, Evanoff, et al. (2012) captures the essence of public interest in terms of being able to properly gauge and respond to market bubble behavior. In crises that can affect an entire country's, or even the world's, economic stability, policy interventions during or after market bubbles can be the difference between a correction in a particular asset class and the total collapse of a critical market or economic system. Proper bubble frameworks that match the reality of bubble dynamics must be utilized by monetary policy makers to inform decisions and generate beneficial, yet realistic, policy proposals.

Despite their importance to broad economic conditions and the public welfare, bubbles are not universally accepted as a phenomenon by all economists and financial academics. Various explanations have been offered over time for explaining bubble behavior, including purely rational mathematical models that explain large price and transaction volume swings, to investors' hedging needs for other investments, agency problems within institutions, and even investor gambling behavior. These particular explanations are put forward and dismissed by Xiong and Yu (2011), who examined a bubble in over a dozen Chinese warrants between 2005-2008 that were essentially worthless due to being deeply out of the money but traded frequently above their theoretical value. This paper finds that particularly important drivers of bubbles are short-sales constraints and heterogeneous beliefs on price, in addition to the inflow of new investors contributing to the prolonging of such formed bubbles. The paper provides direct evidence of feedback effects in the warrant returns and indirect evidence of "smart" investors, who are said to "ride" the bubble and its elevated returns. The ideas of investor beliefs and the flow of new investors is seen in other research as well, providing credence that such ideas may be pervasive across various bubble types.

Another study of interest in the Chinese market explores the combination of extrapolative beliefs and a disposition effect, which are demonstrated to be contributory factors to the investor belief and new investor inflow ideas proposed in Xiong and Yu (2011). Liao and Peng (2019) examine the 2014-2015 Chinese stock market bubble and meshe together the mechanics involved with high prices paired with high transaction volume, a difficult phenomenon to explain when taken in conjunction with extrapolative beliefs. Essentially the problem this paper confronts is that investors with extrapolative beliefs will want to buy a stock because it has recently gone, but also seem to be exiting into and out of the assets quickly, which is counterintuitive to their extrapolative beliefs. Disposition effects, or the tendency for investors to sell stocks trading at a gain while holding on to those trading at a loss, are offered as an explanation for the odd trading patterns. It is demonstrated that investors motivated by extrapolation and disposition effects increase their trading volume by about 800% at bubble peaks, offering an important glimpse into the kinds of investors moving markets during a bubble formation. The realization utility of such investors, paired with the modern ability to margin trade, appear to be strong factors in the market behavior seen in bubble conditions.

Finally, Weitzal, et al. (2019) contribute a meaningful market consideration in their research's comparisons of bubble formation in student, professional, and intermixed groups within an experimental market setting. It is worth noting in its own right that this study demonstrates a unique aspect of some research niches in this topic area, which is the introduction of lab-based market environments to study particular hypotheses about market reactions or isolate distinct variables pertinent to certain market participants. While such experiments obviously create a large abstraction from the real-world market environment, the results of this research are striking in the realization of persistent bubble formations across groups with varying "professional" dynamics. Bubbles are clearly displayed to be a relatively ordinary phenomenon, as 25% of professional market groups generated bubbles, while 58% of student groups generated bubbles. Importantly, it is demonstrated that professionals play a kind of stabilizing role in markets, as intermixed market groups achieved bubble formation rates almost identical to the professional-only groups, indicating that there is a relative scale in the likelihood of a bubble, proportional to the makeup of a market's participants. Additionally, heterogeneous beliefs about future prices are seen to be a strong predictor of price inefficiencies and bubble conditions, further supporting findings from the papers previously discussed that bubbles are a kind of expectations game fueled by investor psychology.

3. Methods and Data

The main methods used to analyze crisis data over the varying crisis periods are OLS regressions to study covariate relationships and GARCH analyses to study volatilities. Several different regression equations are constructed for analysis, with variations in the models including different covariates and different time periods over which to examine the reaction of price data. The dependent variable for all regression equations is the difference in asset returns between data point measures, described below by equation (1)

(1) $Diff_t = Return_t - Return_{t-1}$

Covariates for the regressions include a variety of economic indicators and their lagged values. The source and importance of each covariate will be described in detail below, but as a brief synopsis the covariates include: lagged dependent variable ($Diff_{t-1}$), nominal interest rates (i_t), lagged nominal interest rates (i_{t-1}), inflation rates (π_t), lagged inflation rates (π_{t-1}), unemployment rates (u_t), lagged unemployment rates (u_{t-1}), industrial production growth rates (id_t), lagged industrial production growth (id_{t-1}), growth in the money supply (m_t), and lagged growth in the money supply (m_{t-1}).

Five regression analyses are conducted for this study including:

- A regression through the entire period of interest with only variables at time *t* (Regression 1)
- A regression through the entire period of interest with variables at time *t* and lagged variables at time *t-1* (Regression 2)
- A regression through the rise of the asset price from the beginning of the study period until its peak price with variables at time *t* (Regression 3)

- A regression through the crash of the asset price from the peak price to the end of the study period with variables at time *t* (Regression 4)
- A regression through the most intense volatility of the asset price, which is defined to be the year of the asset price peak, beginning five months before the peak price and ending six months after the peak price for a total of only twelve months of data with variables at time *t* (Regression 5)

The equation used for Regressions 1 and 3-5, as well as the equation for Regression 2 are detailed below in equations (2) and (3) respectively:

(2) $Diff_t = \beta_1 Diff_{t-1} + \beta_2 i_t + \beta_3 \pi_t + \beta_4 u_t + \beta_5 id_t + \beta_6 m_t + \varepsilon_t$

(3) $Diff_t = \beta_1 Diff_{t-1} + \beta_2 i_t + \beta_3 i_{t-1} + \beta_4 \pi_t + \beta_5 \pi_{t-1} + \beta_6 u_t + \beta_7 u_{t-1} + \beta_8 id_t + \beta_9 id_{t-1} + \beta_{10} m_t + \beta_{11} m_{t-1} + \varepsilon_t$

Interest rates are captured on a nominal basis from the market country's respective central bank discount rate. These government-set rates give an idea of the underlying economic environment as they are a primary monetary policy tool used to manage economic crises when present in a country. This variable will give an indication as to how interconnected these bubbles are with economic crises that require a central bank response.

Inflation is captured by growth in the market country's CPI index, a key relatively uniform measure of inflation across different times and countries. The CPI measure could coincide with asset price inflation, while also seemingly acting counter to some assets as increasing overall prices reduces the capacity of individuals to speculate, which could cut a market runup short. This variable is of interest for this very dichotomy and understanding how the factor impacts different kinds of bubbles.

Unemployment data is pulled from market countries' official unemployment statistics reported monthly by the government. This factor would intuitively be linked to business cycles and indicate strength or weakness in the labor market, can contribute to stock bubble patterns. The variable could also be seen to make an impact on bubbles for similar reasons as inflation, in pulling speculators away from the market because they no longer have the risk appetite to push more money into certain high-price sectors.

Industrial production growth figures are calculated from market countries' industrial production volume figures published monthly. This indicator would be directly indicative of robust or weak health in the overall economy for a given period and could also be constructive if bubbles seem to coincide with a lull in output activity. Such an outcome might imply that greater production was expected at a certain time, but never materialized, resulting in a runup in asset prices, followed by a subsequent collapse.

Monetary growth is calculated from a market country's M2 money supply with respect to month over month changes. The money supply is a useful variable as it can directly be funneled into growing asset prices through its distribution coming from the banks, flowing to asset appreciation rather than real inflation in the economy and possibly fueling bubble growth. The factor could also be indicative of government economic support flowing from increased stimulus as hard times begin to emerge in the throes of a market crash.

An additional analysis to specifically study the volatility associated with the ten bubbles was conducted in the form of a GARCH model. GARCH models effectively provide an analysis of conditional volatility for a time series dataset where current values could be a function of previous values via a kind of volatility clustering. In the context of this study, the GARCH analysis is used to understand trends in the volatility of asset prices through the bubble periods, with the particular purpose of understanding if the rising and subsequent falling nature of prices themselves acts to enforce the runup and drawdown effects that are seen in bubbles.

There are several pertinent tests in a GARCH reading that this study relies on. The Weighted Ljung-Box Test examines a series' autocorrelation within a model's standard residuals, with a null hypothesis that there is no auto-correlation present. Similarly, the Weighted ARCH LM Tests check the data series for serial dependence, or autocorrelation, again with a null hypothesis that autocorrelation is not present. Statistical significance in both the Ljung-Box and ARCH LM tests indicates that the data series has a self-dependent component to it that is impacting its forward trajectory, which could otherwise be interpreted as the bubble growing itself. The Nyblom Stability Test assesses the data for significant changes in the series across time, which would mean that the relationships between variables are changing over time, which would be expected over the course of a bubble as the market begins to shift expectations. Next, the Sign Bias Test determines if specific biases are significantly affecting the model through both positive and negative shocks, or one particular kind of shock, with the null hypothesis being that such shocks do not have an effect. Finally, the Adjusted Pearson Goodness-of-Fit Test is creating a comparison between the data's distribution and a selected theoretical model to determine if there is overlap, with the null hypothesis being that the empirical and theoretical models are the same and no interesting divergences from a predicted distribution exist. Full readouts of the GARCH tests referenced in the results section are available for examination in the Appendix.

4. Results

Initial results from the price analyses are quite telling in a number of areas. Beginning with the individual bubble results, detailed below in Table 1, the South Sea Bubble stands out as a crisis of particular note, with the shortest buildup time, the shortest bubble duration, the greatest total bubble return (TBR), the greatest annualized TBR, and the highest daily change in price. There are several other crises worth mentioning in the context of these results. The Asian Financial Crisis had the smallest bubble peak, the lowest TBR, the lowest annualized TBR, and the lowest daily change in price maximum. The Roaring Twenties had the longest buildup time, the longest bubble duration, and the largest peak to trough price drawdown. The Stagflation Oil Crisis had the longest bust period and the shortest build-to-bust ratio. The 2008 Oil Shock had the shortest bust period and the highest build-to-bust ratio. The Dot Com Crisis had the highest bubble peak. The Chinese Stock Bubble had the smallest bubble drawdown.

Table 1: Individual Price Analysis Highlights

Bubbles	Buildup (days)	Bust (days)	Total Bubble (days)	Bubble Peak	Bubble Drawdown	Total Bubble Return (TBR)	TBR Annualized	Highest Daily Change	Build/Bust Ratio
South Sea Bubble	174	281	455	655.77%	-73.33%	101.59%	75.48%	42.32%	0.62x
Roaring Twenties	2,933	1,036	3,969	410.00%	-86.03%	-28.77%	-3.07%	18.60%	2.83x
Dot Com Crash	1,910	917	2,827	915.22%	-81.69%	85.84%	8.33%	22.30%	2.08x
Chinese Stock Bubble	827	385	1,212	502.28%	-71.98%	68.73%	17.06%	9.46%	2.15x
Asian Financial Crisis	809	1,316	2,125	148.06%	-75.41%	-39.01%	-8.14%	8.50%	0.61x
Japanese Real Estate Crash	1,958	988	2,946	523.15%	-76.20%	48.29%	5.00%	12.40%	1.98x
US Housing Crisis	1,582	758	2,340	166.69%	-76.92%	-38.45%	-7.29%	18.82%	2.09x
2008 Oil Shock	1,892	176	2,068	519.67%	-76.57%	45.20%	6.80%	19.88%	10.75x
2010s Oil Collapse	1,119	1,408	2,527	225.15%	-79.70%	-34.00%	-5.83%	11.29%	0.79x
Stagflation Oil Crisis	579	2,435	3,014	203.69%	-77.24%	-30.87%	-4.37%	40.90%	0.24x
Average	1,378	970	2,348	426.97%	-77.51%	17.85%	8.40%	20.45%	2.41x
Max	2,933	2,435	3,969	915.22%	-86.03%	101.59%	75.48%	42.32%	10.75x
Crisis	Roaring Twenties	Stagflation	Roaring Twenties	Dot Com	Roaring Twenties	South Sea Bubble	South Sea Bubble	South Sea Bubble	2008 Oil
Min	174	176	455	148.06%	-71.98%	-39.01%	-8.14%	8.50%	0.24x
Crisis	South Sea Bubble	2008 Oil	South Sea Bubble	AFC	Chinese Stocks	AFC	AFC	AFC	Stagflation

The pricing analyses also revealed some interesting trends between crises, as highlighted in Table 2 below, with the best performing averaged market statistics highlighted in green and the worst highlighted in red. It is striking to see, from a general overview, equity crises tend to be better on average than real estate or oil crises, with shorter bubble periods, higher TBRs, and the shortest build-to-bust ratio, though they do have the highest bubble peaks, making them extremely risky. Oil crises on the other hand tend to be very painful for investors, with the longest bust periods, the lowest TBRs, the greatest volatility captured by high daily change in price, and the longest build-to bust ratio. However, oil crises do benefit from having the shortest buildup periods and the smallest bubble peaks, making them somewhat less likely to catch investors in the thralls of intense speculation. Real estate crises are more neutral, though they do have the poor characteristics of having the longest buildup periods, the longest total bubble durations, and the lowest annualized TBR, although they do have the lowest volatility captured by high daily change, making the asset more stable.

Table 2: Market-Segmented Price Analysis Highlights

Sector Stats	Buildup (days)	Bust (days)	Total Bubble (days)	Bubble Peak	Bubble Drawdown	Total Bubble Return (TBR)	TBR Annualized	Highest Daily Change	Build/Bust Ratio
Equities	1,331	787	2,118	526.26%	-77.69%	37.68%	17.93%	20.23%	1.66x
Real Estate	1,770	873	2,643	344.92%	-76.56%	4.92%	-1.14%	15.61%	2.03x
Oil	1,197	1,340	2,536	316.17%	-77.84%	-6.56%	-1.13%	24.02%	3.93x

Moving on to the regression analysis presented in Figure 1 below for Regression 1, it is clear that the lagged dependent variable is the most significant factor for the movement of asset prices, as it is statistically significant for all of the bubbles studied, apart from the Stagflation Oil Crisis. This finding is more accentuated when viewed in the context of the GARCH analysis results, presented later. Interest rates and unemployment are all found to be insignificant factors across all bubbles. Inflation is positively statistically significant at the 5% level for the Asian Financial Crisis, corresponding with increasing prices in the real economy along with the appreciation of financial assets from increasing foreign investor capital, and vice versa during the bubble's precipitous fall. Industrial production growth is found to be statistically significantly negative at the 5% level for the 2010s Oil Collapse and the Dot Com Crisis, while being statistically significantly positive at the 0.1% level for the Japanese Real Estate Bubble. The connection between industrial production growth and declining oil value in the 2010s most likely results from the negative shock oil spikes and crashes produce for the rest of the economy, as it was observed during this crisis that industrial and transportation companies benefited from falling oil prices to increase their own production at lower costs. On a different track, the Dot Com Crisis most likely reinforces a focus on real assets and the industrial economy in its crash, with much of this bubble being caught in the emerging tech and software industries that had drawn attention away from traditionally more profitable industrials businesses. Opposite from these, industrial production greatly benefited from the investor capital asset price appreciation brought into Japan during the time of its real estate boom, as the economy became inextricably linked with asset price growth that afforded the overall economy a runway for growth. Finally, monetary growth is statistically significantly negative and positive at the 5% level for the Dot Com Crisis and U.S. Housing Crisis respectively. Such a dynamic falls in line with the previous reasoning for industrial production being negatively related to the technology company price swings, with monetary growth in the real economy acting as a similar measure on economic activity that receives more attention with the fall of the Dot Com era, while the U.S. Housing bubble is directly linked with the physical economy, as people push whatever money they have into real estate and homebuilding or home buying.

Figure 1: Regression 1 Results

	AFC	2008 Oil	2010s Oil	China	Dot Com	Japan	Roaring Twenties	Stagflation	US Housing
(Intercept)	-16.132	49.636	-6.746	-1.625	6.111	4.334	0.019	-0.602	0.325
	(21.881)	(44.736)	(5.965)	(136.145)	(14.335)	(14.730)	(0.802)	(6.032)	(16.737)
Lag_Dependent	-0.481 ***	-0.396 **	-0.448 ***	-0.623 ***	-0.528 ***	-0.536 ***	-0.354 ***	-0.181	-0.418 ***
	(0.116)	(0.118)	(0.093)	(0.153)	(0.089)	(0.081)	(0.088)	(0.103)	(0.110)
Interest_Rate	2.738	-2.409	-12.566	-4.054	-0.167	0.864		-0.052	-0.087
	(3.101)	(2.436)	(23.392)	(6.820)	(0.978)	(1.203)		(0.285)	(1.130)
Inflation	668.016 *	-4.361	-1.539	1.344	2.342	-1.301	-1.325	0.221	-0.804
	(266.224)	(3.440)	(3.804)	(3.291)	(5.887)	(2.616)	(1.113)	(2.564)	(2.059)
Unemployment	-1.188	-8.126	0.875	3.381	-0.155	-3.595		0.115	-0.566
	(2.565)	(7.151)	(0.807)	(29.465)	(2.224)	(4.883)		(0.700)	(2.540)
Industrial_Growth	-43.054	1.082	-4.412 *	1.267	-4.792 *	0.709 ***	-0.356	0.643	-1.017
	(588.569)	(2.189)	(2.171)	(4.484)	(2.404)	(0.184)	(0.326)	(0.969)	(1.533)
Money_Growth	157.769	1.867	3.757	-0.028	-7.513 *	155.609		-0.134	6.195 *
	(170.325)	(3.913)	(2.565)	(28.260)	(3.559)	(117.942)		(1.801)	(2.678)
N obs.	71	69	84	41	93	98	132	100	78
P vlue	0.004	0.010	0.000	0.011	0.000	0.000	0.000	0.727	0.002

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

The next regression results from Regression 2, presented in Figure 2 below, exhibit the robustness of the lagged dependent variable's effect, as even incorporating lagged economic variables does not change the significance or sign of the results. All bubbles, except for the Stagflation Oil Crisis again, are shown to be statistically significantly negative, often at the 1% level. Unemployment and lagged unemployment are both found to be insignificant factors for all of the bubbles. Interest rates and lagged interest rates were significantly negative and positive respectively for the Dot Com Crisis at the 5% level. This would seem to be indicative of a lagging policy response by the central bank to respond to the bubbly economy through raising interest rates as the economy begins to overheat from the bubble. Another significant result from the Chinese Stock Bubble reflects the same dynamic for lagged interest rates, with a positive statistically significant coefficient at the 5% level. Inflation is statistically significantly positive at the 1% level for the Asian Financial Crisis, while lagged inflation is statistically significantly negative at the 0.1% level for the 2008 Oil Shock and at the 1% level for the 2010s Oil Collapse. Inflation corresponding with the Asian Financial Crisis makes sense, as part of the bubble involved rapid appreciation of countries' currencies, which would naturally lead to rapid price appreciation in the real economy. Lagged inflation would seem to follow with these two oil bubbles from a commodities impact perspective, as the previous inflation reflects the increasing costs to industry for usages of oil, such as in gas for transportation or petroleum for plastics. Industrial growth is statistically significantly negative and positive respectively at 5% and 1% for the 2010s Oil Collapse and the Japanese Real Estate Bubble, while lagged industrial growth is statistically significantly positive at the 0.1% level for the U.S. Housing Crisis. The 2010s negative industrial growth most likely arises from the previously mentioned negative impact of rising oil prices on industry and the positive effect in Japan aligns with the explanation from Figure 1's result, that saw financial inflows from the bubble directly benefit the Japanese economy through real production growth. The positive effect through the U.S. Housing Crisis bubble years most likely stems from the growth of construction related industries that were pouring in investment at the time to meet rising demand for new housing. Monetary growth is statistically significantly positive during the U.S. Housing Crisis at the 1% level and statistically significantly negative during the Dot Com Crisis at the 5% level. The impact during the Housing Crisis likely reflects the underlying accelerating, then sudden decelerating economy that was pushed and pulled along by the housing boom through its direct impact on bank lending and government-backed mortgage loans. The identical effect on the Dot Com Crisis from Regression 1 for this variable points to the same real economy versus digital economy dynamic previously proposed for this relationship.

Finally, lagged monetary growth is statistically significantly negative at the 5% level for the Asian Financial Crisis, which most likely reflects an alteration in the monetary flows present within Asian countries at this time as a result of surging foreign investor capital. A closer study of such monetary flows is warranted to fully understand this relationship.

Figure 2: Regression 2 Results

	AFC	2008 Oil	2010s Oil	China	Dot Com	Japan	Roaring Twenties	Stagflation	US Housing
(Intercept)	-0.448	75.085	-8.934	-56.924	0.707	8.495	-0.012	2.138	-31.216
	(22.975)	(47.542)	(6.557)	(158.348)	(16.083)	(14.722)	(0.822)	(6.272)	(18.622)
Lag_Dependent	-0.511 ***	-0.638 ***	-0.584 ***	-0.389 *	-0.533 ***	-0.500 ***	-0.379 ***	-0.192	-0.271 *
	(0.117)	(0.123)	(0.102)	(0.164)	(0.092)	(0.085)	(0.090)	(0.107)	(0.106)
Interest_Rate	7.320	1.145	-3.640	-21.895	-5.153 *	-1.359		-0.452	-2.695
	(6.506)	(4.686)	(27.596)	(11.809)	(2.247)	(5.873)		(0.499)	(3.149)
Lag_Interest_Rate	-4.600	-4.482	-30.888	25.762 *	5.749 *	1.430		0.659	3.868
	(5.951)	(4.919)	(30.399)	(11.663)	(2.270)	(5.848)		(0.531)	(3.341)
Inflation	788.720 **	4.113	6.433	6.720	6.753	-0.119	-0.958	2.801	0.153
	(286.056)	(4.109)	(4.410)	(4.515)	(6.225)	(2.654)	(1.167)	(3.375)	(2.232)
Lag_Inflation	-24.598	-15.336 ***	-14.144 **	-4.918	-6.313	-1.409	-0.573	-5.645	-0.045
	(300.759)	(4.042)	(4.136)	(3.268)	(5.923)	(2.942)	(1.151)	(3.289)	(2.384)
Unemployment	6.100	1.519	1.964	-55.661	12.547	23.295		-0.358	10.412
	(7.242)	(11.019)	(6.678)	(55.252)	(10.191)	(16.219)		(4.735)	(7.204)
Lag_Unemployment	-9.317	-12.803	-0.289	65.364	-12.500	-26.424		-0.067	-5.798
	(7.932)	(12.222)	(6.925)	(62.051)	(10.261)	(16.159)		(4.735)	(8.144)
Industrial_Growth	857.469	2.931	-4.582 *	1.481	-3.632	0.621 **	-0.157	0.875	0.140
	(730.095)	(2.077)	(2.270)	(4.509)	(2.539)	(0.185)	(0.373)	(1.246)	(1.418)
Lag_Industrial_Growth	-1382.574	-1.289	-1.118	1.068	1.609	-0.317	-0.398	-0.507	6.390 ***
	(728.452)	(2.176)	(2.321)	(4.527)	(2.559)	(0.200)	(0.383)	(1.085)	(1.419)
Money_Growth	38.276	-0.860	3.802	-10.875	-8.671 *	62.648		-0.418	8.234 **
	(173.156)	(3.829)	(2.445)	(32.202)	(3.597)	(138.978)		(1.830)	(2.584)
Lag_Money_Growth	-394.875 *	-7.022	-1.089	-12.515	1.058	-172.707		0.538	-2.416
	(177.491)	(3.953)	(2.526)	(35.906)	(3.725)	(127.325)		(1.844)	(2.649)
N obs.	71	69	84	41	93	98	132	100	78
P vlue	0.004	0.000	0.000	0.011	0.000	0.000	0.001	0.598	0.000

*** p < 0.001; ** p < 0.01; * p < 0.05.

Results from Regressions 3, 4, and 5 are best analyzed in concert, as the comparison between them is quite meaningful from an interpretative perspective. Figures 3, 4, and 5 display results from the correspondingly numbered regression models. Notably, the lagged dependent variable is by far the most significant covariate in Regressions 3 and 4, with a statistically significantly negative coefficient for seven and five of the nine and eight crises analyzed respectively between the two regression models. In fact, the lagged dependent variable is the only significant covariate for Regression 3, outside of 5% statistically significantly positive coefficient for monetary growth in the Japanese Real Estate Crash. The significance of the lagged dependent variable captures the buildup of the bubbles studied, which seems to indicate that the buildup of bubbles is a self-perpetuating process that can exist outside the trends of traditionally significant economic indicators. There are two other significant covariates for Regression 4, including inflation, which is statistically significantly positive at the 1% level for the Asian Financial Crisis, and industrial growth, which is statistically significantly positive at the 0.1% level for the Japanese Real Estate Bubble. The positive inflation covariate for the Asian Financial Crisis in this regression emphasizes the negative effects the crash had on Asian economies at large, as the positive relationship with falling prices indicates that deflation was created in the wake of investor capital pulling out of Asian financial markets. The positive industrial growth covariate for the Japanese Real Estate Bubble reflects similarly to the Asian Financial Crisis, with the drawdown of the crash dragging industrial production with it as a result of the importance of foreign capital in the production economy that had benefited from the boom times. Finally, in inspecting the results from Figure 5 for Regression 5, there is only one instance of a significant covariate, including the previously steady lagged dependent variable. The one statistically significant result is for industrial growth at the 5% level during the Japanese Real Estate Bubble, displaying the strong positive relationship between financial assets and industrial production in Japan discussed previously. This lack of other statistically significant covariates appears to display the true unpredictable nature present in the heart of every bubble, as volatility reigns supreme above all possible predictable variables. The lack of other significant covariates may also arise from the fact that a mere twelve data points are analyzed for each crisis due to the desired emphasis on close timing to the crisis event and the use of monthly data in this study. Perhaps if weekly or daily data were utilized for the same crises and covariates, additional significant relationships may emerge to shed light on if other factors are effectual in the midst of such financial turmoil.

Figure 3: Regression 3 Results

	AFC	2008 Oil	2010s Oil	China	Dot Com	Japan	Roaring Twenties	Stagflation	US Housing
(Intercept)	-2.095	30.479	-17.714	22.236	17.093	0.294	0.355	113.248	-9.149
	(24.678)	(51.167)	(34.447)	(141.169)	(14.917)	(21.220)	(0.497)	(164.432)	(26.821)
Lag_Dependent	-0.749 ***	-0.432 ***	-0.315 *	-0.182	-0.587 ***	-0.585 ***	-0.495 ***	-0.382	-0.716 ***
	(0.175)	(0.119)	(0.137)	(0.218)	(0.122)	(0.102)	(0.087)	(0.240)	(0.126)
Interest_Rate	2.798	-1.756	-23.944		-2.011	1.424		-0.567	0.488
	(2.612)	(2.665)	(35.385)		(2.317)	(1.666)		(1.836)	(1.437)
Inflation	-594.080	-4.021	-6.960	2.568	-1.563	-2.184	-0.569	2.899	-2.665
	(393.800)	(4.032)	(6.279)	(4.956)	(7.363)	(3.283)	(0.703)	(13.791)	(2.076)
Unemployment	-1.088	-4.738	2.364	-6.395	-0.102	-3.103		-15.017	1.745
	(6.232)	(8.309)	(3.804)	(34.188)	(2.529)	(7.770)		(24.877)	(4.322)
Industrial_Growth	292.659	2.278	-5.361	2.800	-4.759	0.462	-0.307	1.933	-2.071
	(599.748)	(3.055)	(2.834)	(4.675)	(2.493)	(0.376)	(0.214)	(5.032)	(1.580)
Money_Growth	-516.008	1.677	3.710	0.725	-5.980	310.872 *		-33.763	-0.660
	(248.245)	(4.443)	(3.226)	(32.284)	(5.996)	(152.720)		(18.817)	(2.524)
N obs.	27	63	37	27	62	65	97	19	52
P vlue	0.016	0.009	0.019	0.901	0.000	0.000	0.000	0.445	0.000

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Figure 4: Regression 4 Results

	AFC	2010s Oil	China	Dot Com	Japan	Roaring Twenties	Stagflation	US Housing
(Intercept)	-6.588	-7.216	-236.199	-64.024	98.912	-5.697	-2.810	-26.406
	(15.437)	(10.897)	(411.389)	(121.454)	(74.221)	(5.395)	(6.354)	(36.986)
Lag_Dependent	-0.573 ***	-0.534 ***	-1.110 *	-0.591 **	-0.456 **	-0.255	-0.113	-0.317
	(0.154)	(0.141)	(0.342)	(0.175)	(0.136)	(0.192)	(0.120)	(0.227)
Interest_Rate		-14.593	0.984	2.897	-3.860		-0.030	2.073
		(37.546)	(14.653)	(7.197)	(2.283)		(0.285)	(3.335)
Inflation	1021.211 **	2.912	-3.347	7.097	2.609	-4.732	-0.052	-0.231
	(359.942)	(5.421)	(5.977)	(12.129)	(4.083)	(4.554)	(2.606)	(4.762)
Unemployment	-1.092	0.845	53.603	11.432	-36.852		0.283	2.356
	(3.748)	(1.636)	(93.848)	(19.141)	(33.083)		(0.691)	(5.112)
Industrial_Growth	-80.412	-5.206	13.446	-16.856	0.952 ***	-1.632	0.148	-0.478
	(931.246)	(4.111)	(16.311)	(8.777)	(0.199)	(1.617)	(0.897)	(3.881)
Money_Growth	303.288	5.108	44.032	-9.786	126.632		0.700	10.925
	(216.486)	(4.640)	(77.751)	(6.492)	(234.769)		(1.597)	(6.059)
N obs.	43	46	13	30	32	34	80	25
P vlue	0.006	0.016	0.139	0.063	0.000	0.198	0.957	0.298

*** p < 0.001; ** p < 0.01; * p < 0.05.

Figure 5: Regression 5 Results

	AFC	2008 Oil	2010s Oil	China	Dot Com	Japan	Roaring Twenties	Stagflation	US Housing
(Intercept)	28.104	145.605	-166.123	66.241	-353.964	5.554	-0.509	-65.923	178.257
	(55.471)	(117.874)	(162.330)	(831.947)	(325.588)	(220.743)	(3.513)	(63.055)	(198.982)
Lag_Dependent	0.355	0.302	0.131	-0.845	-0.608	-0.793	0.070	-0.287	-0.138
	(0.473)	(0.673)	(0.468)	(0.353)	(0.423)	(0.335)	(0.373)	(0.186)	(0.410)
Interest_Rate		-5.218	22.002	3.687	-4.313	0.359		0.878	-29.024
		(11.692)	(95.833)	(14.677)	(10.062)	(6.351)		(1.883)	(30.936)
Inflation	214.511	-15.166	-10.322	1.813	9.764	10.171	-2.125	-12.039	2.429
	(487.636)	(11.810)	(10.660)	(6.813)	(21.444)	(7.523)	(6.319)	(17.997)	(5.423)
Unemployment	-0.592	-23.501	18.279	-15.013	93.706	-2.880		11.663	-5.869
	(17.687)	(17.380)	(18.866)	(205.583)	(71.975)	(91.248)		(10.653)	(21.666)
Industrial_Growth	-2348.977	-6.542	2.964	-19.825	-4.297	1.606 *	-1.419	3.918	-9.467
	(1971.388)	(5.333)	(13.080)	(23.228)	(16.214)	(0.610)	(1.855)	(6.081)	(5.992)
Money_Growth	-344.453	-9.881	25.781	0.275	3.668	-401.496		-11.290	4.729
	(301.632)	(11.776)	(13.736)	(74.625)	(16.821)	(495.433)		(18.847)	(10.248)
N obs.	12	12	12	12	12	12	12	12	12
P vlue	0.711	0.677	0.468	0.302	0.415	0.179	0.779	0.411	0.385

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

The final results to understand are from the GARCH analyses conducted for each of the ten bubbles covered in this study. The readouts of each individual analysis can be found in the Appendix. The main tests of interest for the GARCH analysis are the Nyblom Stability Test, the Sign Bias Test, and the Adjusted Pearson Goodness-of-Fit Test. The Nyblom and Adjusted Pearson tests inform the degree to which the time series data fluctuates from what would normally be expected for time series data, whereas the Sign Bias Test detects the outsized influence of positive and negative shocks to the dataset, which would be very informative when examining the rise and fall of bubbles. As far as the Nyblom test, all bubbles were significant at the 1% level, except for the Stagflation Oil Crisis which was significant at the 5% level. This indicates that all of the crises had significant shifts in their volatility as time progressed, which would be expected for the kinds of extreme price movements present during these crises. It is significant to note that such an outcome also indicates that the extremity of the volatility within the crises changes as the bubbles form and eventually pop, which is demonstrated in the various forms of positive or negative sign bias that the Sign Bias Test reveals. There are four crises that have no significant results from the Sign Bias Test, including the Roaring Twenties, the Japanese Real Estate Crash, the 2010s Oil Collapse, and the Stagflation Oil Crisis. Negative sign bias is exhibited by the South Sea Bubble at the 5% level and the Chinese Stock Bubble at the 10% level. Positive sign bias is exhibited by the Dot Com Crisis at the 1% level, the Asian Financial Crisis at the 5% level, the U.S. Housing Crisis at the 5% level, and the South Sea Bubble at the 10% level. Regular sign bias, which signals the effect of positive and negative shocks is exhibited by the Dot Com Crisis at the 1% level, the Asian Financial Crisis at the 1% level, and the 2008 Oil Shock at the 5% level. Negative sign bias would tend to be exhibited by crises that had more erratic changes in volatility when prices were decreasing, as opposed to positive sign bias being exhibited in crises that had more erratic changes in volatility when prices were increasing. Regular sign bias is seen in crises that had rapid changes in volatility regardless of the direction and could be seen as an indicator for the most extreme and unpredictable bubbles. All of these bias results provide a more accurate picture for which aspects of particular bubbles were most significant from a volatility perspective. Finally, the Adjusted Pearson Goodness-of-Fit test was found to be significant for all the crises, serving as one final emphasis on the unpredictable nature of the bubbles' volatility, as none of the volatility models matched up against the theoretical ones tested against them. While not surprising in its outcome, this test serves to reinforce the findings of the Nyblom Test for the irregularity of the volatility within these bubbles.

5. Conclusions

Overall, the findings of this study are concentrated on the dramatic impact outsized and varying levels of volatility have on a variety of bubbles over time. Based on different markets' price analysis, it seems relatively clear that equity bubbles are the least damaging overall for investors caught in them, while oil bubbles have many nasty components and real estate bubbles are a mixed bag. Turning to regression evidence, majority of bubbles seem primarily driven by their own volatility and momentum, though a few crises exhibit significant relationships with important economic factors, such as the Asian Financial Crisis with inflation, the Japanese Real Estate Bubble with industrial production growth, and the 2010s Oil Collapse with industrial production growth as well. Finally, the evidence supporting volatility itself as a primary driver of bubbles is bolstered by results from the GARCH analyses that detect significant variations from normal time series patterns for all of the bubbles, with quite a few also displaying sign biases during bubble growth or decline that help to influence the unpredictable nature of bubbles' volatility.

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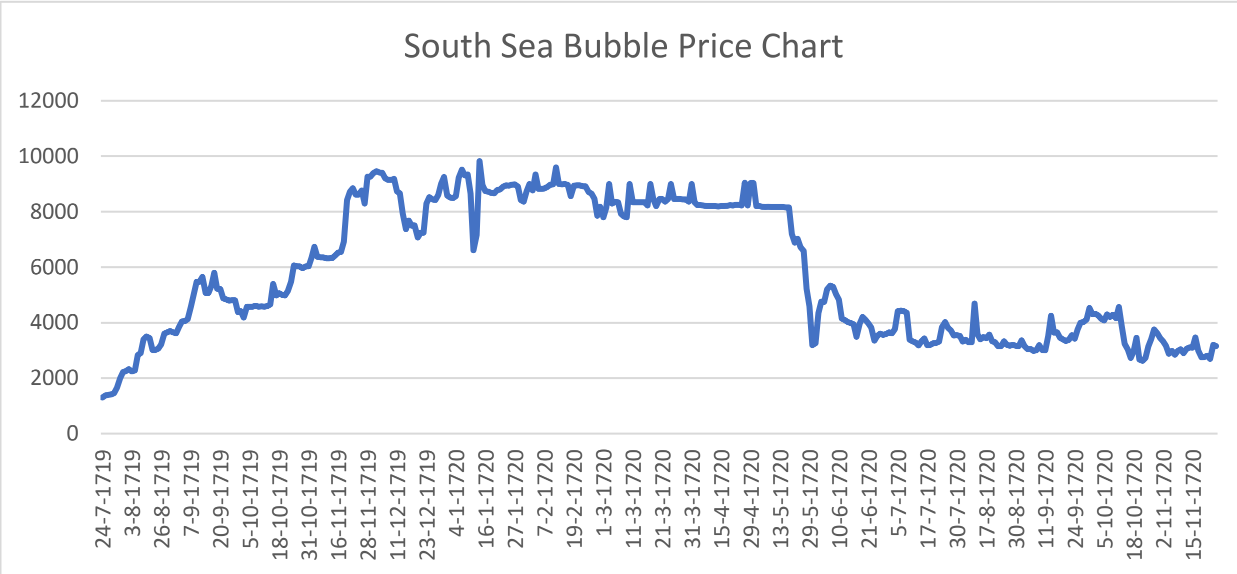
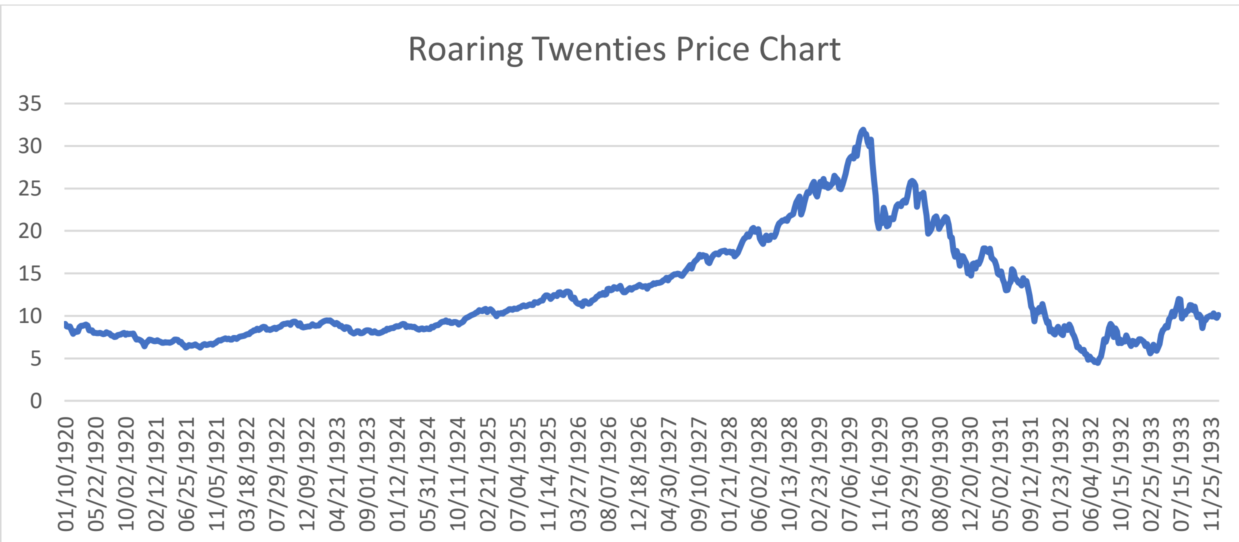
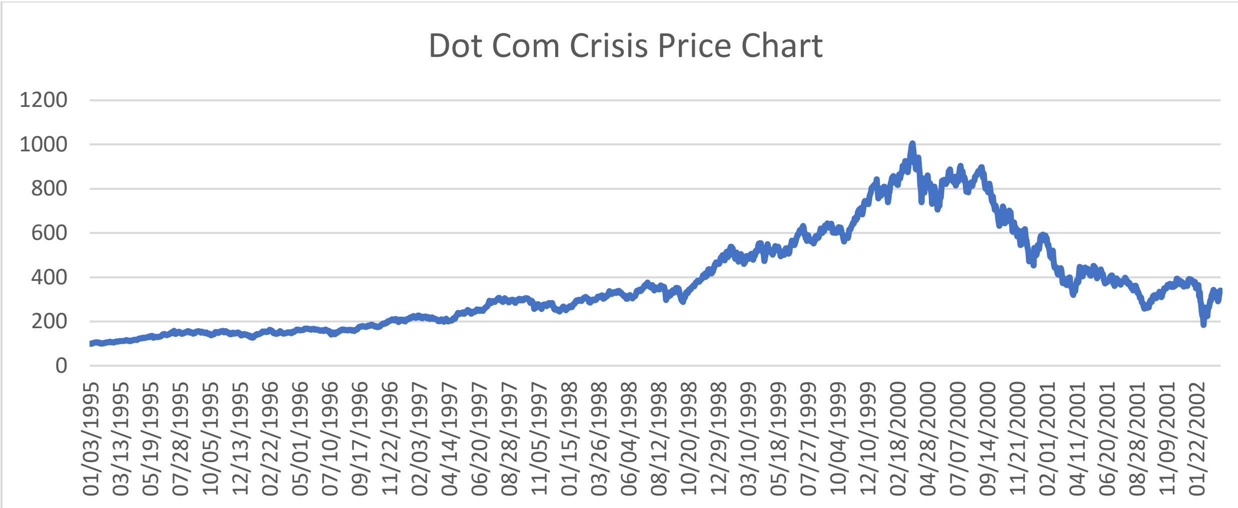
7. Appendix

I. Price Charts for Individual Bubbles



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1000
800
600
400
200
0
01/03/1995
03/13/1995
05/19/1995
07/28/1995
10/05/1995
12/13/1995
02/22/1996
05/01/1996
07/10/1996
09/17/1996
11/22/1996
02/03/1997
04/14/1997
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06/04/1998
08/12/1998
10/20/1998
12/29/1998
03/10/1999
05/18/1999
07/27/1999
10/04/1999
12/10/1999
02/18/2000
04/28/2000
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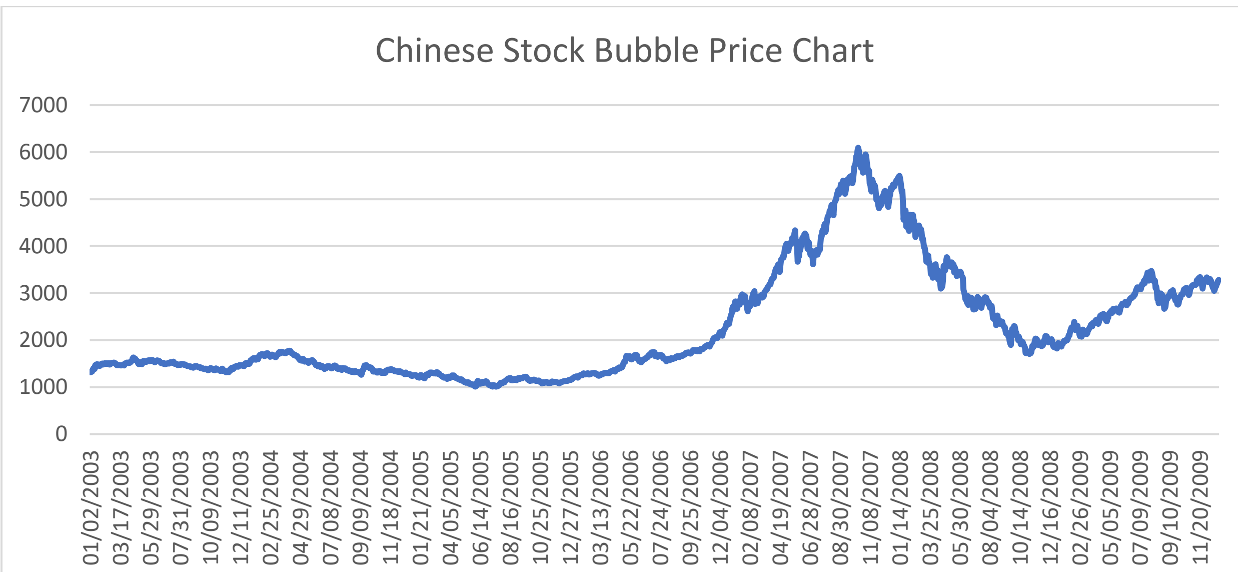
11/09/2001
01/22/2002


Chinese Stock Bubble Price Chart
7000
6000
5000
4000
3000
2000
1000
0
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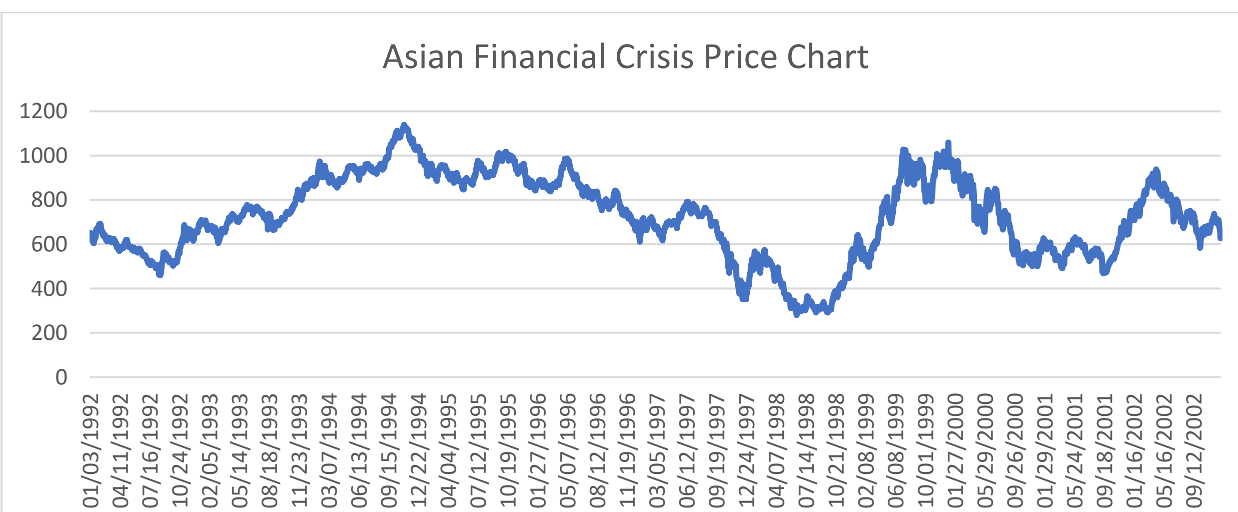
03/17/2003
05/29/2003
07/31/2003
10/09/2003
12/11/2003
02/25/2004
04/29/2004
07/08/2004
09/09/2004
11/18/2004
01/21/2005
04/05/2005
06/14/2005
08/16/2005
10/25/2005
12/27/2005
03/13/2006
05/22/2006
07/24/2006
09/25/2006
12/04/2006
02/08/2007
04/19/2007
06/28/2007
08/30/2007
11/08/2007
01/14/2008
03/25/2008
05/30/2008
08/04/2008
10/14/2008
12/16/2008
02/26/2009
05/05/2009
07/09/2009
09/10/2009
11/20/2009


Asian Financial Crisis Price Chart
1200
1000
800
600
400
200
0
01/03/1992
04/11/1992
07/16/1992
10/24/1992
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05/14/1993
08/18/1993
11/23/1993
03/07/1994
06/13/1994
09/15/1994
12/22/1994
04/04/1995
07/12/1995
10/19/1995
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05/07/1996
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03/05/1997
06/12/1997
09/19/1997
12/24/1997
04/07/1998
07/14/1998
10/21/1998
02/08/1999
06/08/1999
10/01/1999
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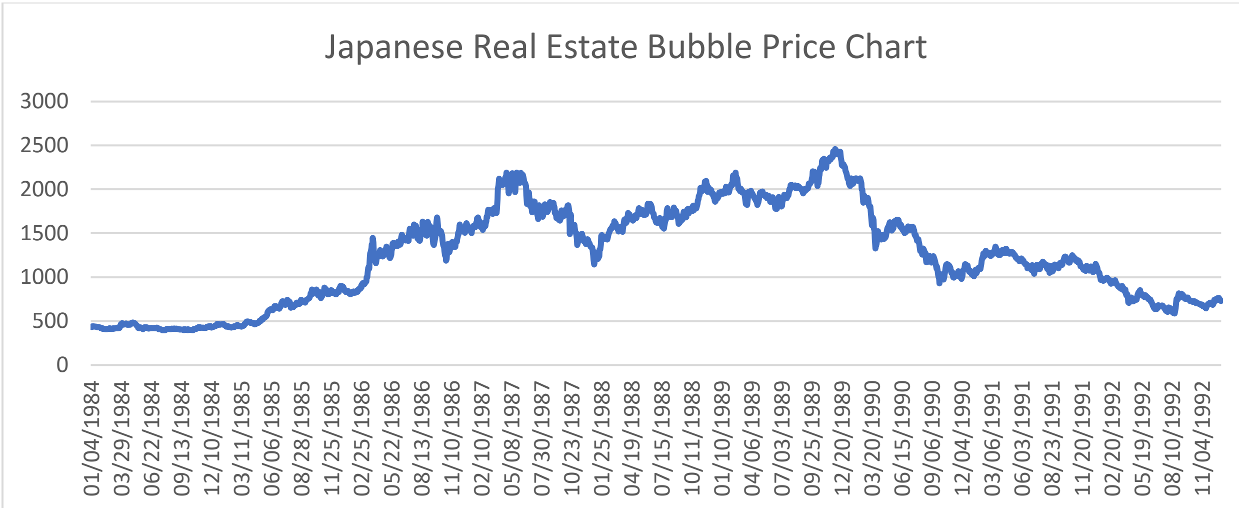
05/16/2002
09/12/2002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2500
2000
1500
1000
500
0
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03/29/1984
06/22/1984
09/13/1984
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06/06/1985
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02/25/1986
05/22/1986
08/13/1986
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02/10/1987
05/08/1987
07/30/1987
10/23/1987
01/25/1988
04/19/1988
07/15/1988
10/11/1988
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04/06/1989
07/03/1989
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12/20/1989
03/20/1990
06/15/1990
09/06/1990
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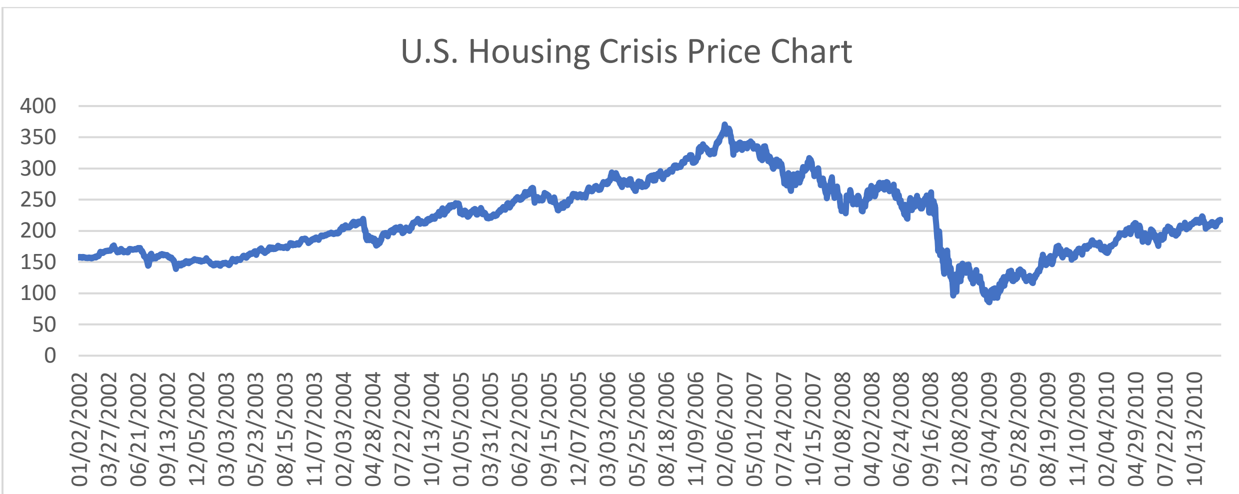
08/10/1992
11/04/1992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300
250
200
150
100
50
0
01/02/2002
03/27/2002
06/21/2002
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12/05/2002
03/03/2003
05/23/2003
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11/07/2003
02/03/2004
04/28/2004
07/22/2004
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09/15/2005
12/07/2005
03/03/2006
05/25/2006
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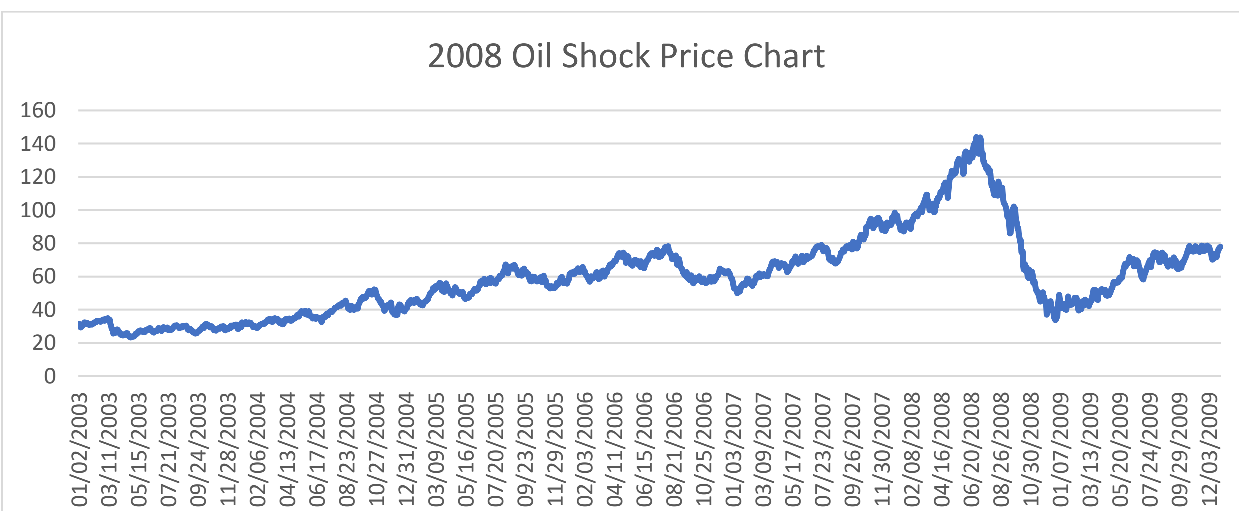
11/09/2006
02/06/2007
05/01/2007
07/24/2007
10/15/2007
01/08/2008
04/02/2008
06/24/2008
09/16/2008
12/08/2008
03/04/2009
05/28/2009
08/19/2009
11/10/2009
02/04/2010
04/29/2010
07/22/2010
10/13/2010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160
140
120
100
80
60
40
20
0
01/02/2003
03/11/2003
05/15/2003
07/21/2003
09/24/2003
11/28/2003
02/06/2004
04/13/2004
06/17/2004
08/23/2004
10/27/2004
12/31/2004
03/09/2005
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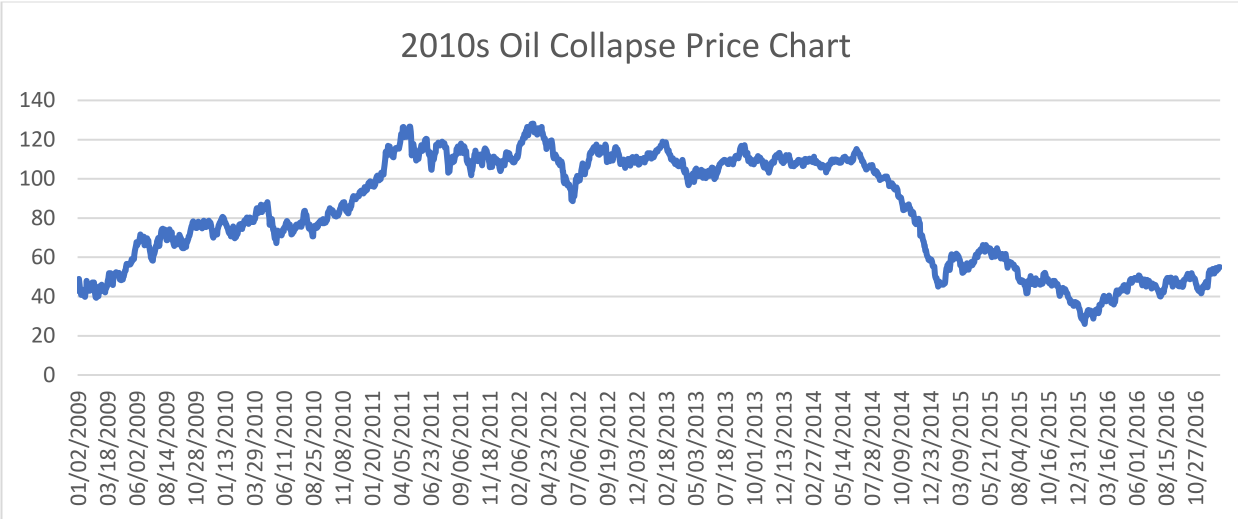
11/29/2005
02/03/2006
04/11/2006
06/15/2006
08/21/2006
10/25/2006
01/03/2007
03/09/2007
05/17/2007
07/23/2007
09/26/2007
11/30/2007
02/08/2008
04/16/2008
06/20/2008
08/26/2008
10/30/2008
01/07/2009
03/13/2009
05/20/2009
07/24/2009
09/29/2009
12/03/2009


2010s Oil Collapse Price Chart
140
120
100
80
60
40
20
0
01/02/2009
03/18/2009
06/02/2009
08/14/2009
10/28/2009
01/13/2010
03/29/2010
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12/13/2013
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05/14/2014
07/28/2014
10/09/2014
12/23/2014
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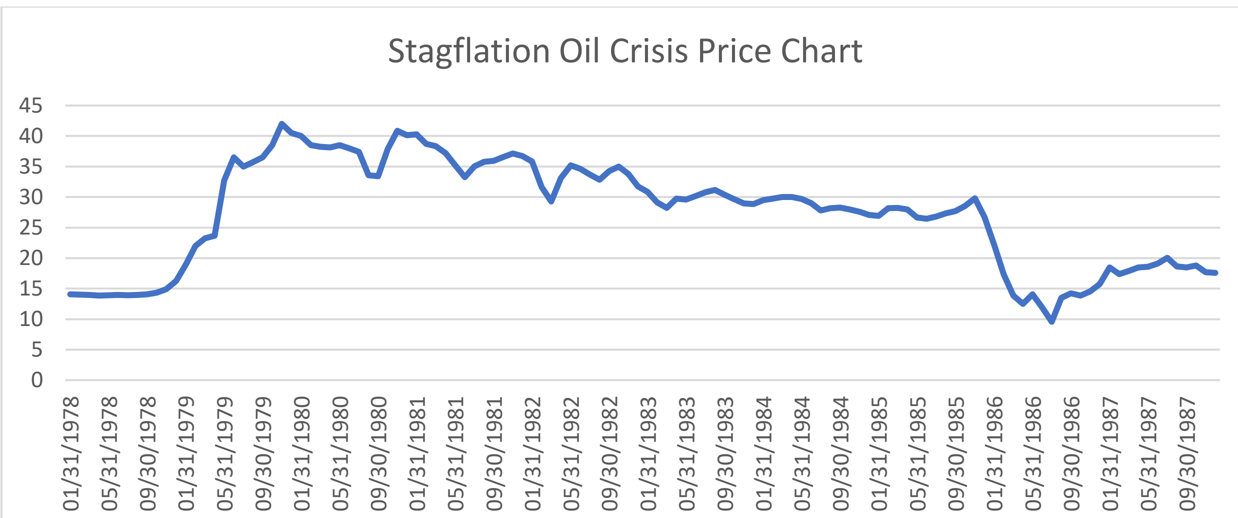
08/15/2016
10/27/2016


Stagflation Oil Crisis Price Chart
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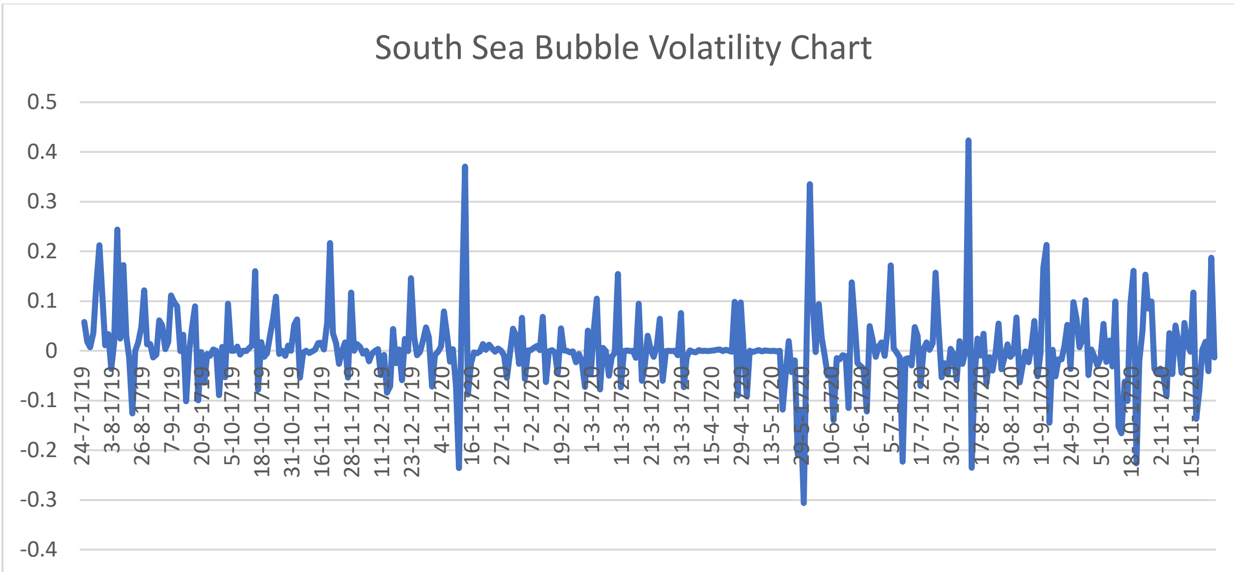
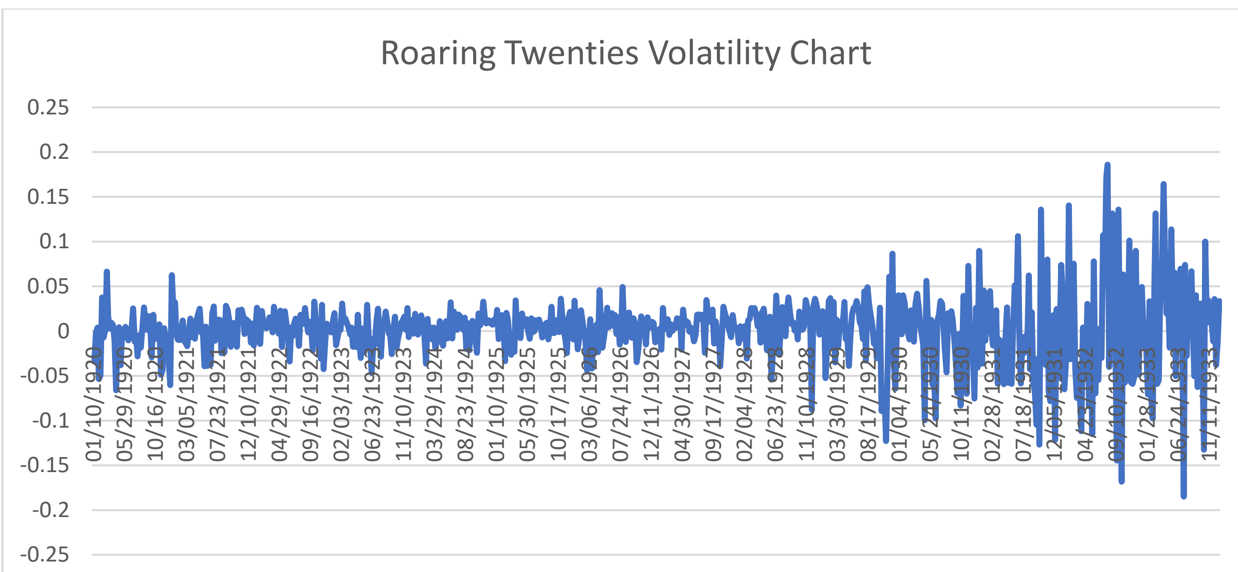
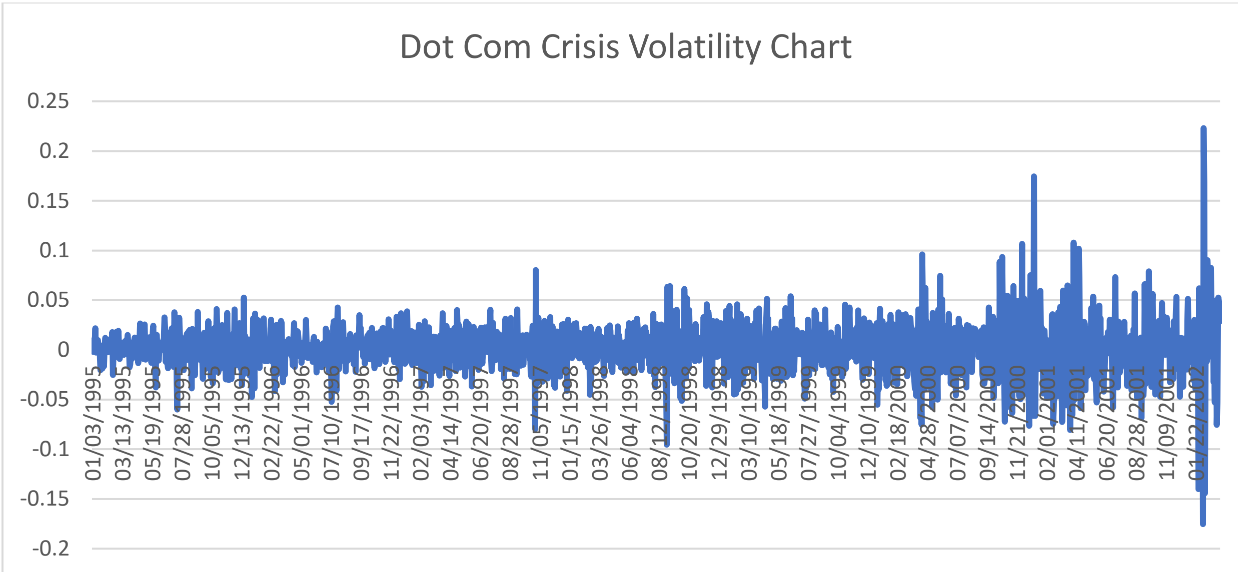
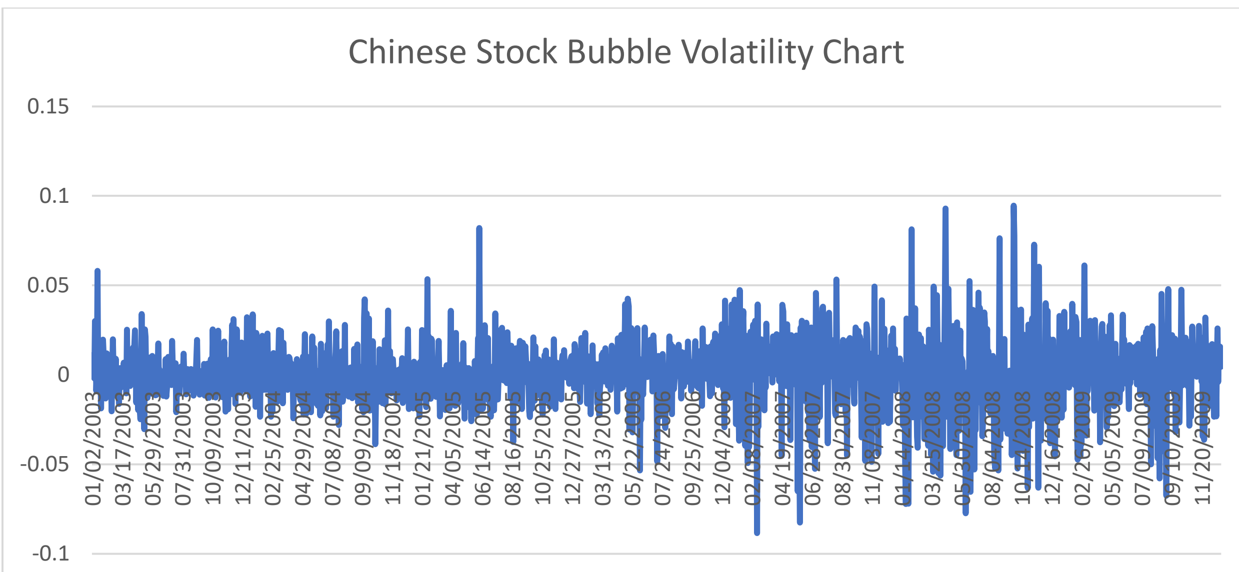
40
35
30
25
20
15
10
5
0
01/31/1978
05/31/1978
09/30/1978
01/31/1979
05/31/1979
09/30/1979
01/31/1980
05/31/1980
09/30/1980
01/31/1981
05/31/1981
09/30/1981
01/31/1982
05/31/1982
09/30/1982
01/31/1983
05/31/1983
09/30/1983
01/31/1984
05/31/1984
09/30/1984
01/31/1985
05/31/1985
09/30/1985
01/31/1986
05/31/1986
09/30/1986
01/31/1987
05/31/1987
09/30/1987

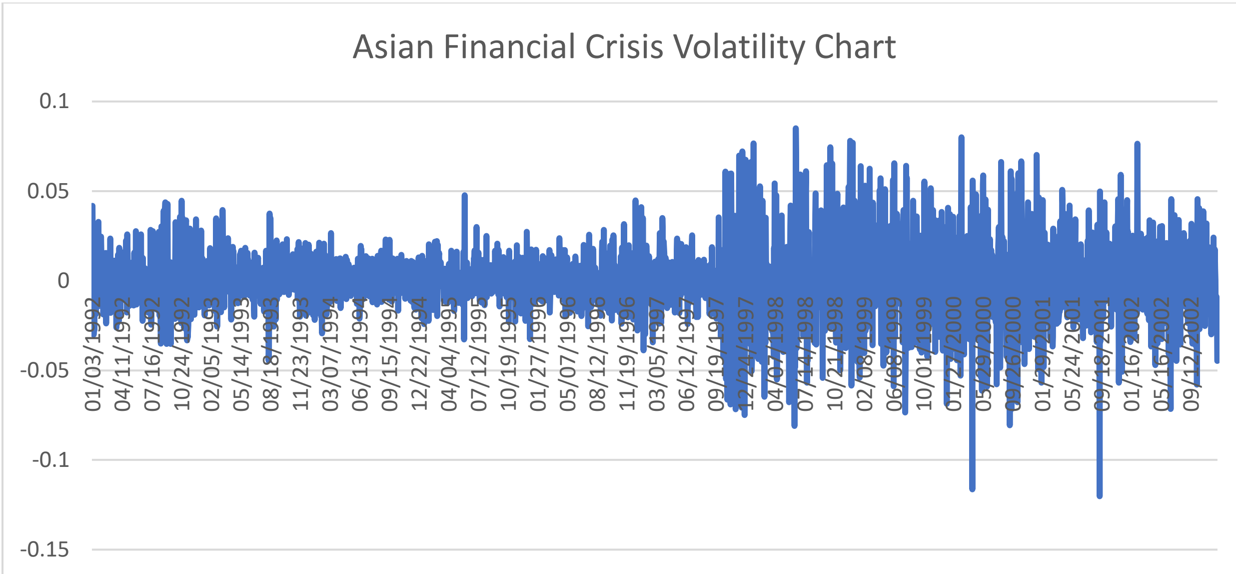
II. Volatility Charts for Individual Bubbles

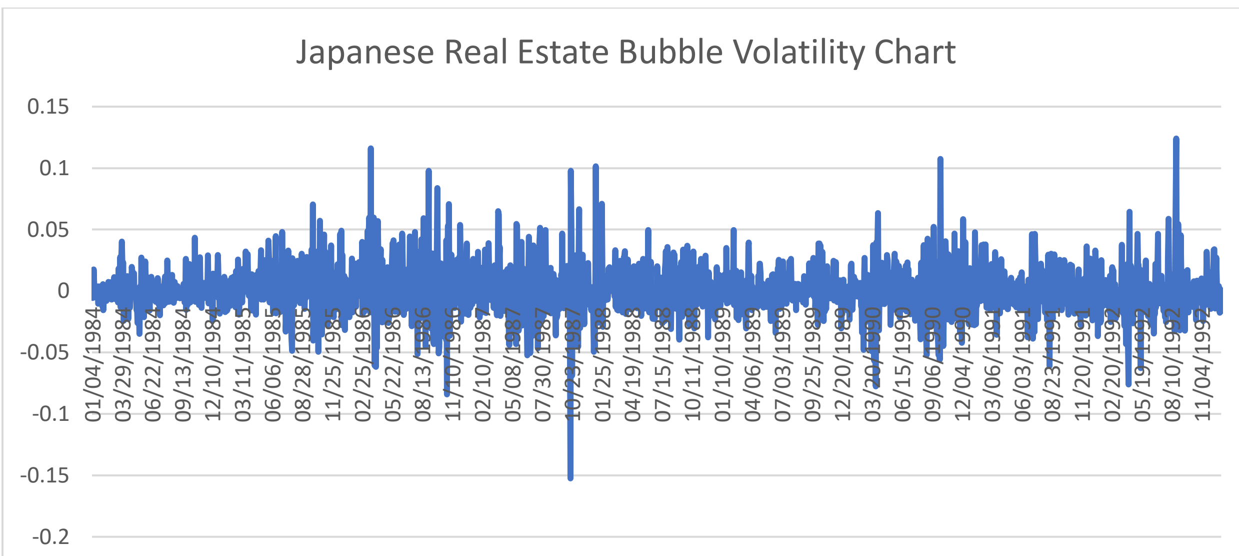





Dot Com Crisis Volatility Chart
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2


Chinese Stock Bubble Volatility Chart
0.15
0.1
0.05
0
-0.05
-0.1


Asian Financial Crisis Volatility Chart
0.1
0.05
0
-0.05
-0.1
-0.15


Japanese Real Estate Bubble Volatility Chart
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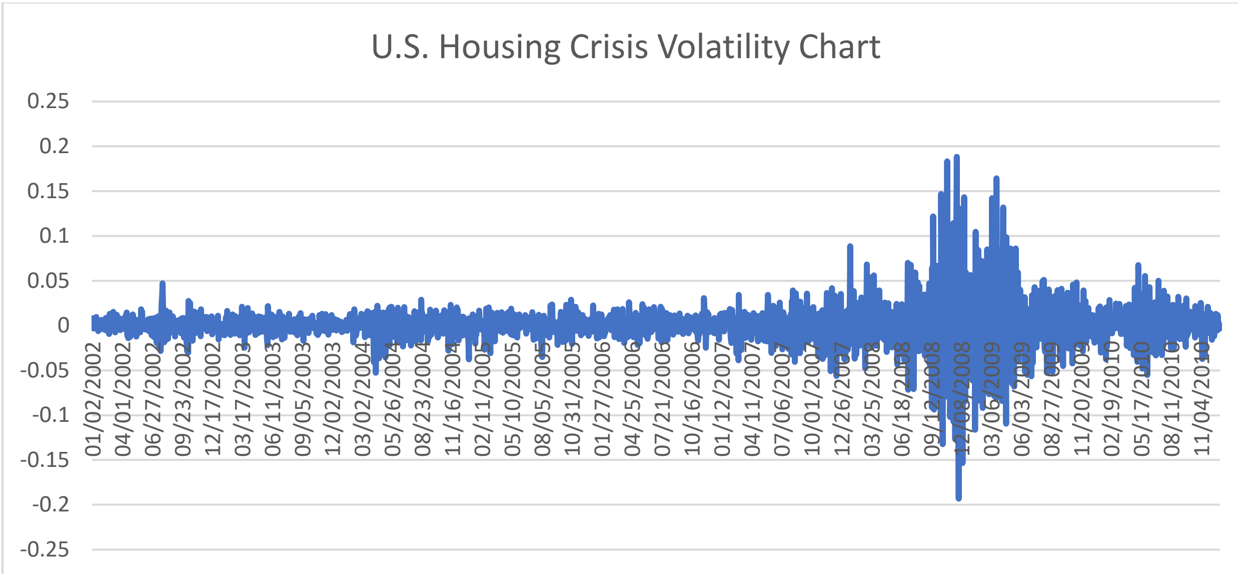
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2


U.S. Housing Crisis Volatility Chart
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
01/02/2002
04/01/2002
06/27/2002
09/23/2002
12/17/2002
03/17/2003
06/11/2003
09/05/2003
12/02/2003
03/02/2004
05/26/2004
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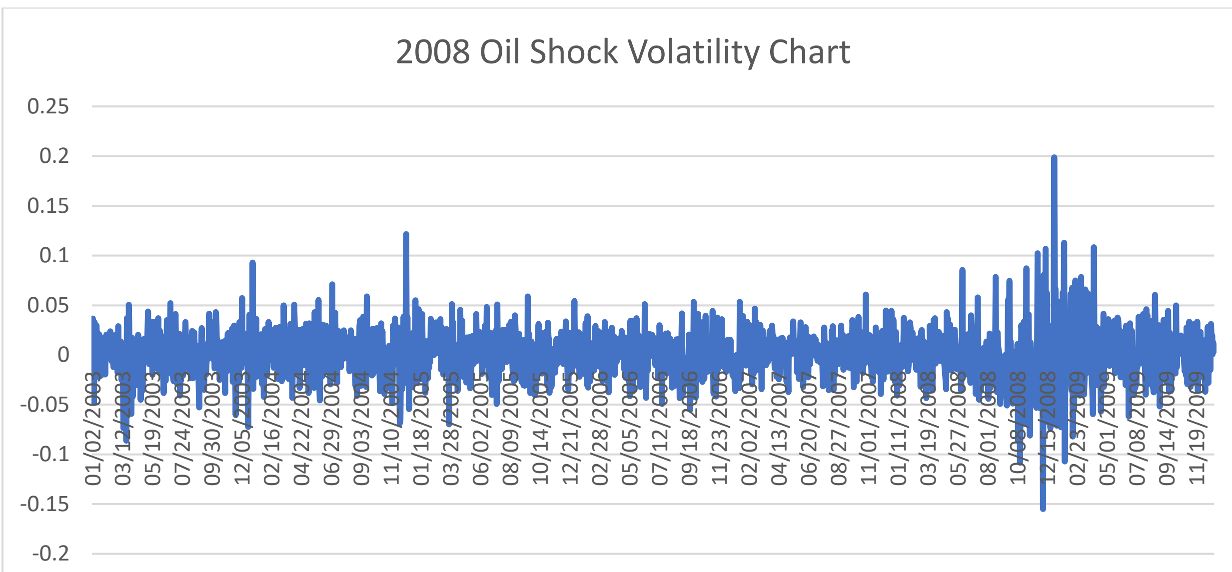
11/16/2004
02/11/2005
05/10/2005
08/05/2005
10/31/2005
01/27/2006
04/25/2006
07/21/2006
10/16/2006
01/12/2007
04/11/2007
07/06/2007
10/01/2007
12/26/2007
03/25/2008
06/18/2008
03/06/2009
06/03/2009
08/27/2009
11/20/2009
02/19/2010
05/17/2010
08/11/2010
11/04/2010


2008 Oil Shock Volatility Chart
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
01/02/2003
05/19/2003
07/24/2003
09/30/2003
02/16/2004
04/22/2004
06/29/2004
09/03/2004
01/18/2005
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12/21/2005
02/28/2006
05/05/2006
07/12/2006
09/18/2006
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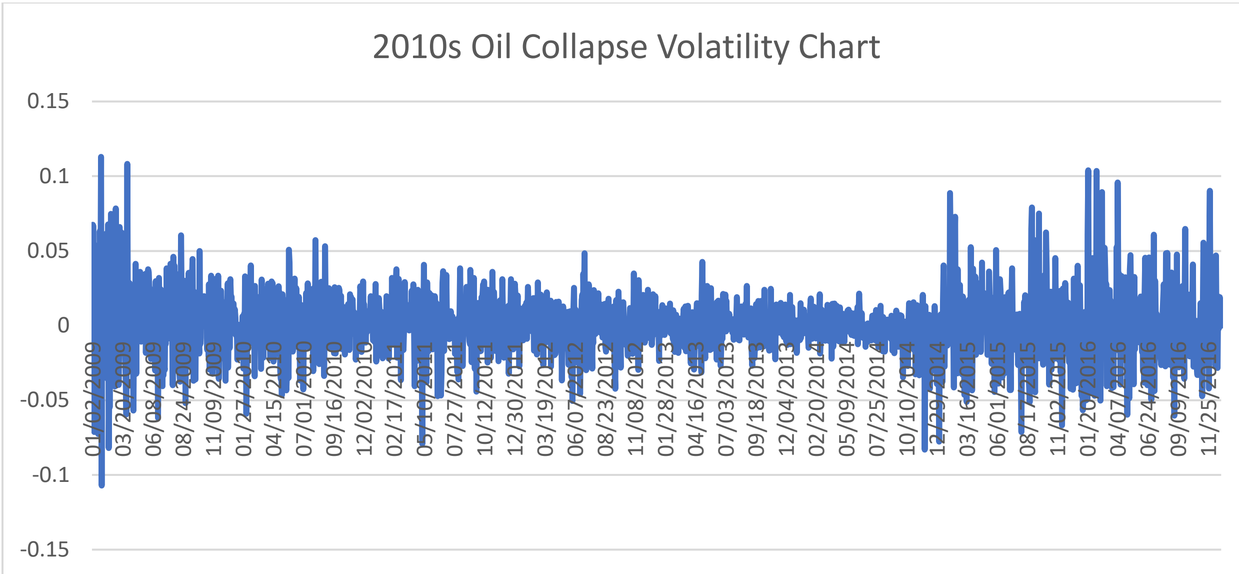
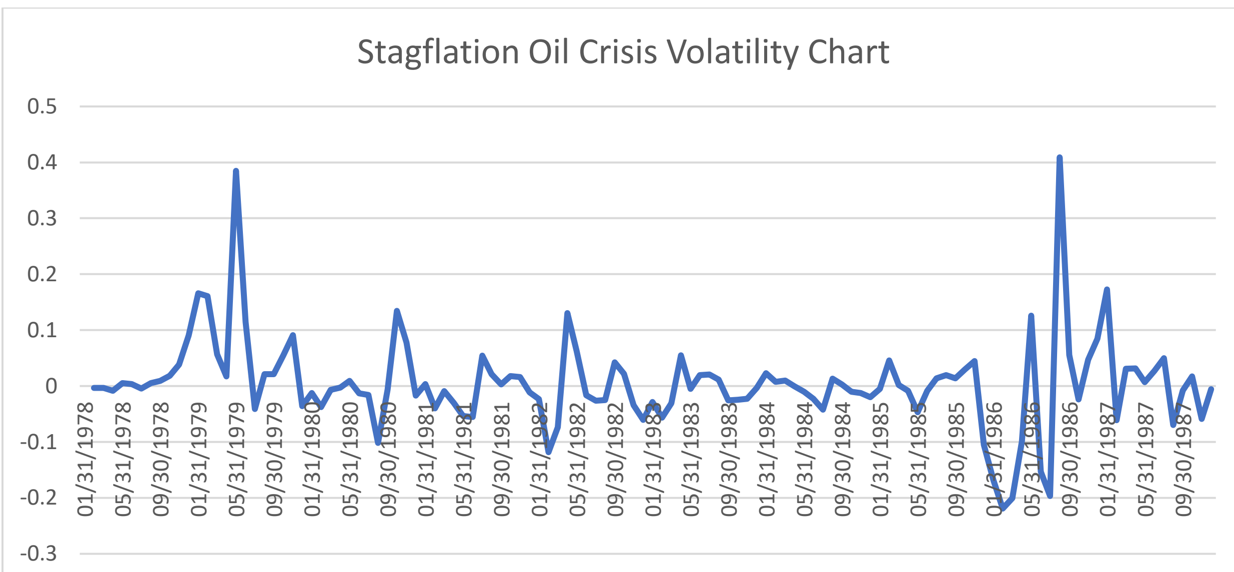
02/02/2007
04/13/2007
06/20/2007
08/27/2007
11/01/2007
01/11/2008
03/19/2008
05/27/2008
08/01/2008
05/01/2009
07/08/2009
09/14/2009
11/19/2009


2010s Oil Collapse Volatility Chart
0.15
0.1
0.05
0
-0.05
-0.1
-0.15


Stagflation Oil Crisis Volatility Chart
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0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
01/31/1978
05/31/1978
09/30/1978
01/31/1979
05/31/1979
09/30/1979
05/31/1980
01/31/1981
09/30/1981
05/31/1982
09/30/1982
05/31/1983
09/30/1983
01/31/1984
05/31/1984
09/30/1984
01/31/1985
09/30/1985
09/30/1986
01/31/1987
05/31/1987

III. Price Statistics for Individual Bubbles

South Sea Bubble	
Bubble Start Price	1,300.00
Bubble Start Date	07/24/1719
Bubble Peak Price	9,825.00
Bubble Peak Date	01/14/1720
Bubble Trough Price	2,620.63
Bubble Trough Date	10/22/1720
Time to Climb	174 days
Time to Decline	281 days
Bubble	655.77%
Drawdown	-73.33%
Bubble Start to End Return	101.59%
Bubble Start to End Annualized Return	75.48%
Highest Daily Change	42.32%
Bubble Build/Burst (Time to Climb/Decline)	0.62x

Roaring Twenties	
Bubble Start Price	6.26
Bubble Start Date	08/27/1921
Bubble Peak Price	31.92
Bubble Peak Date	09/07/1929
Bubble Trough Price	4.46
Bubble Trough Date	07/09/1932
Time to Climb	2,933 days
Time to Decline	1,036 days
Bubble	410.00%
Drawdown	-86.03%
Bubble Start to End Return	-28.77%
Bubble Start to End Annualized Return	-3.07%
Highest Weekly Change	18.60%
Bubble Build/Burst (Time to Climb/Decline)	2.83x

Dot Com Crisis	
Bubble Start Price	99.04
Bubble Start Date	01/03/1995
Bubble Peak Price	1,005.49
Bubble Peak Date	03/27/2000
Bubble Trough Price	184.06
Bubble Trough Date	09/30/2002
Time to Climb	1,910 days
Time to Decline	917 days
Bubble	915.22%
Drawdown	-81.69%
Bubble Start to End Return	85.84%
Bubble Start to End Annualized Return	8.33%
Highest Daily Change	22.30%
Bubble Build/Burst (Time to Climb/Decline)	2.08x

Chinese Stock Bubble	
Bubble Start Price	1,011.50
Bubble Start Date	07/11/2005
Bubble Peak Price	6,092.06
Bubble Peak Date	10/16/2007
Bubble Trough Price	1,706.70
Bubble Trough Date	11/04/2008
Time to Climb	827 days
Time to Decline	385 days
Bubble	502.28%
Drawdown	-71.98%
Bubble Start to End Return	68.73%
Bubble Start to End Annualized Return	17.06%
Highest Daily Change	9.46%
Bubble Build/Burst (Time to Climb/Decline)	2.15x

Asian Financial Crisis	
Bubble Start Price	459.07
Bubble Start Date	08/21/1992
Bubble Peak Price	1,138.75
Bubble Peak Date	11/08/1994
Bubble Trough Price	280.00
Bubble Trough Date	06/16/1998
Time to Climb	809 days
Time to Decline	1,316 days
Bubble	148.06%
Drawdown	-75.41%
Bubble Start to End Return	-39.01%
Bubble Start to End Annualized Return	-8.14%
Highest Daily Change	8.50%
Bubble Build/Burst (Time to Climb/Decline)	0.61x

Japanese Real Estate Bubble	
Bubble Start Price	394.56
Bubble Start Date	07/25/1984
Bubble Peak Price	2,458.70
Bubble Peak Date	12/04/1989
Bubble Trough Price	585.09
Bubble Trough Date	08/18/1992
Time to Climb	1,958 days
Time to Decline	988 days
Bubble	523.15%
Drawdown	-76.20%
Bubble Start to End Return	48.29%
Bubble Start to End Annualized Return	5.00%
Highest Daily Change	12.40%
Bubble Build/Burst (Time to Climb/Decline)	1.98x

U.S. Housing Crisis	
Bubble Start Price	138.95
Bubble Start Date	10/09/2002
Bubble Peak Price	370.57
Bubble Peak Date	02/07/2007
Bubble Trough Price	85.52
Bubble Trough Date	03/06/2009
Time to Climb	1,582 days
Time to Decline	758 days
Bubble	166.69%
Drawdown	-76.92%
Bubble Start to End Return	-38.45%
Bubble Start to End Annualized Return	-7.29%
Highest Daily Change	18.82%
Bubble Build/Burst (Time to Climb/Decline)	2.09x

2008 Oil Shock	
Bubble Start Price	23.23
Bubble Start Date	04/29/2003
Bubble Peak Price	143.95
Bubble Peak Date	07/03/2008
Bubble Trough Price	33.73
Bubble Trough Date	12/26/2008
Time to Climb	1,892 days
Time to Decline	176 days
Bubble	519.67%
Drawdown	-76.57%
Bubble Start to End Return	45.20%
Bubble Start to End Annualized Return	6.80%
Highest Daily Change	19.88%
Bubble Build/Burst (Time to Climb/Decline)	10.75x

2010s Oil Collapse	
Bubble Start Price	39.41
Bubble Start Date	02/18/2009
Bubble Peak Price	128.14
Bubble Peak Date	03/13/2012
Bubble Trough Price	26.01
Bubble Trough Date	01/20/2016
Time to Climb	1,119 days
Time to Decline	1,408 days
Bubble	225.15%
Drawdown	-79.70%
Bubble Start to End Return	-34.00%
Bubble Start to End Annualized Return	-5.83%
Highest Daily Change	11.29%
Bubble Build/Burst (Time to Climb/Decline)	0.79x

Stagflation Oil Crisis	
Bubble Start Price	13.83
Bubble Start Date	04/30/1978
Bubble Peak Price	42.00
Bubble Peak Date	11/30/1979
Bubble Trough Price	9.56
Bubble Trough Date	07/31/1986
Time to Climb	579 days
Time to Decline	2,435 days
Bubble	203.69%
Drawdown	-77.24%
Bubble Start to End Return	-30.87%
Bubble Start to End Annualized Return	-4.37%
Highest Monthly Change	40.90%
Bubble Build/Burst (Time to Climb/Decline)	0.24x

IV. GARCH Analysis Results for South Sea Bubble


```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     3784.34292  1.0132e+02 37.35110 0.000000
## omega  5940.49401  1.0972e+04  0.54141 0.588222
## alpha1    0.56262  1.0295e-01  5.46520 0.000000
## beta1     0.43638  1.2725e-01  3.42920 0.000605
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     3784.34292  6.7199e+01 5.631540 0.000000
## omega  5940.49401  6.7401e+04 0.088136 0.929760
## alpha1    0.56262  3.1246e-01 1.800605 0.071765
## beta1     0.43638  6.2652e-01 0.696506 0.486112
##
## LogLikelihood : -3335.42
##
## Information Criteria
## ------------------------------------
##
## Akaike       17.622
## Bayes        17.664
## Shibata      17.622
## Hannan-Quinn 17.639
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                      274.0       0
## Lag[2*(p+q)+(p+q)-1][2]     384.7       0
## Lag[4*(p+q)+(p+q)-1][5]     650.8       0
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                      2.680  0.1011
## Lag[2*(p+q)+(p+q)-1][5]     4.416  0.2065
## Lag[4*(p+q)+(p+q)-1][9]     7.701  0.1421
## d.o.f=2
```

```
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]    0.2357 0.500 2.000  0.6274
## ARCH Lag[5]    3.1735 1.440 1.667  0.2656
## ARCH Lag[7]    4.4554 2.315 1.543  0.2856
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  4.9032
## Individual Statistics:
## mu     0.1026
## omega  0.4587
## alpha1 0.6631
## beta1  0.0942
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.07 1.24 1.6
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value    prob sig
## Sign Bias           0.3925 0.69480
## Negative Sign Bias  1.0989 0.03654  **
## Positive Sign Bias  1.6788 0.09402   *
## Joint Effect        7.2465 0.06444   *
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20      1168   5.137e-236
## 2    30      1266   2.940e-240
## 3    40      1661   9.881e-324
## 4    50      1407   1.105e-262
##
##
## Elapsed time : 0.2885609
```

V. GARCH Analysis Results for Roaring Twenties


```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu      8.549638    0.041482 206.5041 0.000000
## omega   0.012895    0.006606   1.9519 0.050946
## alpha1  0.625432    0.066100   9.4619 0.000000
## beta1   0.373560    0.058542   6.3812 0.000000
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu      8.549638    0.150163  56.9357 0.000000
## omega   0.012895    0.010817   1.1921 0.233224
## alpha1  0.625432    0.116140   5.3852 0.000000
## beta1   0.373560    0.122419   3.0516 0.002277
##
## LogLikelihood : -1658.327
##
## Information Criteria
## ------------------------------------
##
## Akaike       4.5660
## Bayes        4.5921
## Shibata      4.5660
## Hannan-Quinn 4.5766
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                      594.6       0
## Lag[2*(p+q)+(p+q)-1][2]     864.8       0
## Lag[4*(p+q)+(p+q)-1][5]    1619.7       0
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic   p-value
## Lag[1]                      10.41 1.256e-03
## Lag[2*(p+q)+(p+q)-1][5]     18.03 6.712e-05
## Lag[4*(p+q)+(p+q)-1][9]     19.95 2.071e-04
## d.o.f=2
```

```
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]     5.896 0.500 2.000 0.01518
## ARCH Lag[5]     6.217 1.440 1.667 0.05341
## ARCH Lag[7]     6.291 2.315 1.543 0.12286
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  2.6541
## Individual Statistics:
## mu     0.6594
## omega  0.6260
## alpha1 0.1641
## beta1  0.4856
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.07 1.24 1.6
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           1.1991 0.2309
## Negative Sign Bias  0.6192 0.5294
## Positive Sign Bias  1.0558 0.2914
## Joint Effect        1.8654 0.6008
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20      1932            0
## 2    30      3205            0
## 3    40      2933            0
## 4    50      3692            0
##
##
## Elapsed time : 0.1166868
```

VI. GARCH Analysis Results for Asian Financial Crisis


```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     704.28493    2.329507 302.3322 0.000000
## omega   86.27712   22.236422   3.8798 0.000104
## alpha1   0.87097    0.061786  14.0965 0.000000
## beta1    0.12802    0.060148   2.1287 0.033282
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     704.28493    19.34268 36.41109  0.00000
## omega   86.27712    89.28585  0.96630  0.33389
## alpha1   0.87097     0.14725  5.91487  0.00000
## beta1    0.12802     0.17067  0.75011  0.45319
##
## LogLikelihood : -18584.54
##
## Information Criteria
## ------------------------------------
##
## Akaike       12.253
## Bayes        12.261
## Shibata      12.253
## Hannan-Quinn 12.256
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                       2723       0
## Lag[2*(p+q)+(p+q)-1][2]      4013       0
## Lag[4*(p+q)+(p+q)-1][5]      7738       0
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic   p-value
## Lag[1]                      19.83 8.463e-06
## Lag[2*(p+q)+(p+q)-1][5]     27.72 1.383e-07
## Lag[4*(p+q)+(p+q)-1][9]     33.40 5.076e-08
## d.o.f=2
```

```
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale  P-Value
## ARCH Lag[3]     4.197 0.500 2.000 0.040507
## ARCH Lag[5]    10.164 1.440 1.667 0.005995
## ARCH Lag[7]    10.075 2.315 1.543 0.011407
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  3.6354
## Individual Statistics:
## mu     1.4174
## omega  1.7329
## alpha1 0.3920
## beta1  0.7975
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.07 1.24 1.6
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value     prob sig
## Sign Bias           2.6194 0.008852 ***
## Negative Sign Bias  0.8396 0.401225
## Positive Sign Bias  2.1550 0.031243  **
## Joint Effect        7.5243 0.056937   *
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20      9264            0
## 2    30     11933            0
## 3    40     13741            0
## 4    50     13387            0
##
##
## Elapsed time : 0.375041
```

VII. GARCH Analysis Results for Dot Com Crisis


```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     297.14842    0.798368 372.1983 0.000000
## omega   11.05365    4.509734   2.4511 0.014243
## alpha1   0.70979    0.069155  10.2637 0.000000
## beta1    0.28921    0.066035   4.3797 0.000012
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     297.14842    1.232148 133.1127 0.000000
## omega   11.05365    6.270128   1.7687 0.076296
## alpha1   0.70979    0.069484  10.2269 0.000000
## beta1    0.28921    0.072559   3.9859 0.000067
##
## LogLikelihood : -11682.31
##
## Information Criteria
## ------------------------------------
##
## Akaike       12.210
## Bayes        12.222
## Shibata      12.210
## Hannan-Quinn 12.214
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                       1658       0
## Lag[2*(p+q)+(p+q)-1][2]      2444       0
## Lag[4*(p+q)+(p+q)-1][5]      4721       0
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic   p-value
## Lag[1]                      42.69 6.414e-11
## Lag[2*(p+q)+(p+q)-1][5]     51.88 1.921e-14
## Lag[4*(p+q)+(p+q)-1][9]     57.81 5.773e-15
## d.o.f=2
```

```
##
## Weighted ARCH LM Tests
## ------------------------------------
##              Statistic Shape Scale   P-Value
## ARCH Lag[3]     0.5446 0.500 2.000 0.4604608
## ARCH Lag[5]    14.9300 1.440 1.667 0.0003990
## ARCH Lag[7]    16.2176 2.315 1.543 0.0005754
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  7.6221
## Individual Statistics:
## mu     6.1432
## omega  0.5524
## alpha1 0.2560
## beta1  0.2795
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.07 1.24 1.6
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value     prob sig
## Sign Bias           2.8777 0.004052 ***
## Negative Sign Bias  0.6774 0.498209
## Positive Sign Bias  2.8406 0.004553 ***
## Joint Effect       13.5139 0.003647 ***
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20      7550            0
## 2    30      9959            0
## 3    40     12928            0
## 4    50     10065            0
##
##
## Elapsed time : 0.18257
```

VIII. GARCH Analysis Results for Chinese Stock Bubble


```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##          Estimate  Std. Error  t value Pr(>|t|)
## mu     1466.33786    3.805002 385.3711 0.000000
## omega   212.56663   58.410092   3.6392 0.000273
## alpha1    0.99899    0.038264  26.1048 0.000000
## beta1     0.00000    0.014458   0.0000 1.000000
##
## Robust Standard Errors:
##          Estimate  Std. Error   t value Pr(>|t|)
## mu     1466.33786   20.134981 71.465493  0.00000
## omega   212.56663   78.049636  2.723408  0.00646
## alpha1    0.99899    0.013166 75.875151  0.00000
## beta1     0.00000    0.007470  0.000001  1.00000
##
## LogLikelihood : -12533.88
##
## Information Criteria
## ------------------------------------
##
## Akaike       14.794
## Bayes        14.807
## Shibata      14.794
## Hannan-Quinn 14.799
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                       1558       0
## Lag[2*(p+q)+(p+q)-1][2]      2314       0
## Lag[4*(p+q)+(p+q)-1][5]      4577       0
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic   p-value
## Lag[1]                     0.2281 6.329e-01
## Lag[2*(p+q)+(p+q)-1][5]   12.8256 1.688e-03
## Lag[4*(p+q)+(p+q)-1][9]   21.4405 8.513e-05
## d.o.f=2
```

```
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale   P-Value
## ARCH Lag[3]     13.93 0.500 2.000 1.899e-04
## ARCH Lag[5]     19.87 1.440 1.667 2.306e-05
## ARCH Lag[7]     22.83 2.315 1.543 1.199e-05
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  5.3949
## Individual Statistics:
## mu     2.1798
## omega  0.1250
## alpha1 2.1681
## beta1  0.4459
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.07 1.24 1.6
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value    prob sig
## Sign Bias           0.9245 0.35533
## Negative Sign Bias  1.6790 0.09334   *
## Positive Sign Bias  0.9693 0.33254
## Joint Effect        3.7589 0.28878
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20      7640            0
## 2    30     18405            0
## 3    40     11986            0
## 4    50     11702            0
##
##
## Elapsed time : 0.270178
```

IX. GARCH Analysis Results for Japanese Real Estate Bubble


```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error   t value Pr(>|t|)
## mu     1.2579e+03    4.361317 288.42939  0.00000
## omega  4.9499e+02  193.961562   2.55202  0.01071
## alpha1 9.6101e-01    0.093055  10.32736  0.00000
## beta1  3.7984e-02    0.093763   0.40511  0.68540
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     1.2579e+03    19.78637 63.57567  0.00000
## omega  4.9499e+02   397.37155  1.24567  0.21289
## alpha1 9.6102e-01     0.17062  5.63239  0.00000
## beta1  3.7984e-02     0.18047  0.21047  0.83330
##
## LogLikelihood : -16232.09
##
## Information Criteria
## ------------------------------------
##
## Akaike       14.614
## Bayes        14.624
## Shibata      14.614
## Hannan-Quinn 14.618
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                       2064       0
## Lag[2*(p+q)+(p+q)-1][2]      3060       0
## Lag[4*(p+q)+(p+q)-1][5]      5064       0
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic   p-value
## Lag[1]                      13.59 2.270e-04
## Lag[2*(p+q)+(p+q)-1][5]     25.14 6.817e-07
## Lag[4*(p+q)+(p+q)-1][9]     32.90 6.960e-08
## d.o.f=2
```

```
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale   P-Value
## ARCH Lag[3]     11.16 0.500 2.000 8.252e-04
## ARCH Lag[5]     20.32 1.440 1.667 1.329e-05
## ARCH Lag[7]     23.03 2.315 1.543 1.065e-05
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  6.373
## Individual Statistics:
## mu     3.0046
## omega  0.0095
## alpha1 1.1156
## beta1  0.3787
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.07 1.24 1.6
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           1.5705 0.1146
## Negative Sign Bias  0.1609 0.8722
## Positive Sign Bias  1.6099 0.1076
## Joint Effect        3.6465 0.3023
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20      9951            0
## 2    30     13714            0
## 3    40     16977            0
## 4    50     15354            0
##
##
## Elapsed time : 0.3849709
```

X. GARCH Analysis Results for U.S. Housing Crisis


```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##          Estimate  Std. Error    t value Pr(>|t|)
## mu     195.891912    0.270031 725.442547 0.000000
## omega    4.858152    1.396555   3.478668 0.000504
## alpha1   0.998997    0.053191  18.781193 0.000000
## beta1    0.000003    0.045782   0.000067 0.999947
##
## Robust Standard Errors:
##          Estimate  Std. Error    t value Pr(>|t|)
## mu     195.891912    0.698509 280.442883  0.00000
## omega    4.858152    3.621565   1.341451  0.17977
## alpha1   0.998997    0.055729  17.925843  0.00000
## beta1    0.000003    0.064277   0.000048  0.99996
##
## LogLikelihood : -11331.72
##
## Information Criteria
## ------------------------------------
##
## Akaike       10.836
## Bayes        10.846
## Shibata      10.836
## Hannan-Quinn 10.840
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                       2016       0
## Lag[2*(p+q)+(p+q)-1][2]      2995       0
## Lag[4*(p+q)+(p+q)-1][5]      5879       0
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic   p-value
## Lag[1]                      3.689 5.470e-02
## Lag[2*(p+q)+(p+q)-1][5]    15.776 1.747e-04
## Lag[4*(p+q)+(p+q)-1][9]    39.326 1.121e-09
## d.o.f=2
```

```
## 
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale   P-Value
## ARCH Lag[3]     14.19 0.500 2.000 1.651e-04
## ARCH Lag[5]     21.17 1.440 1.667 1.008e-05
## ARCH Lag[7]     43.31 2.315 1.543 4.580e-11
## 
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  7.6321
## Individual Statistics:
## mu     2.0008
## omega  1.9112
## alpha1 1.0257
## beta1  0.1319
## 
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.07 1.24 1.6
## Individual Statistic:     0.35 0.47 0.75
## 
## Sign Bias Test
## ------------------------------------
##                    t-value    prob sig
## Sign Bias           0.6202 0.53520
## Negative Sign Bias  1.3100 0.18498
## Positive Sign Bias  2.3722 0.01777  **
## Joint Effect        7.5238 0.05695   *
## 
## 
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20      8857            0
## 2    30     11791            0
## 3    40     13744            0
## 4    50     12731            0
## 
## 
## Elapsed time : 0.1765089
```

XI. GARCH Analysis Results for 2008 Oil Shock


```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error    t value Pr(>|t|)
## mu     58.465763     0.23522 248.557564  0.0e+00
## omega   1.541383     0.36352   4.240206  2.2e-05
## alpha1  0.990774     0.15657   6.328206  0.0e+00
## beta1   0.000001     0.14884   0.000005  1.0e+00
##
## Robust Standard Errors:
##         Estimate  Std. Error   t value Pr(>|t|)
## mu     58.465763     1.20852 48.377934 0.000000
## omega   1.541383     0.70111  2.198502 0.027913
## alpha1  0.990774     0.24289  4.079166 0.000045
## beta1   0.000001     0.13991  0.000003 0.999997
##
## LogLikelihood : -7145.216
##
## Information Criteria
## ------------------------------------
##
## Akaike       7.9172
## Bayes        7.9294
## Shibata      7.9172
## Hannan-Quinn 7.9217
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                       1591       0
## Lag[2*(p+q)+(p+q)-1][2]      2361       0
## Lag[4*(p+q)+(p+q)-1][5]      4618       0
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic   p-value
## Lag[1]                     0.2007 6.541e-01
## Lag[2*(p+q)+(p+q)-1][5]   14.1618 7.451e-04
## Lag[4*(p+q)+(p+q)-1][9]   25.3433 7.937e-06
## d.o.f=2
```

```
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale   P-Value
## ARCH Lag[3]    0.1299 0.500 2.000 7.186e-01
## ARCH Lag[5]   25.2433 1.440 1.667 1.014e-05
## ARCH Lag[7]   27.6700 2.315 1.543 6.607e-07
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  6.8496
## Individual Statistics:
## mu     5.0593
## omega  0.1995
## alpha1 0.5614
## beta1  0.7891
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.07 1.24 1.6
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value    prob sig
## Sign Bias           1.9702 0.04886  **
## Negative Sign Bias  1.5742 0.11563
## Positive Sign Bias  0.3834 0.70145
## Joint Effect        4.1846 0.24220
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20      5441            0
## 2    30      7934            0
## 3    40      8679            0
## 4    50      8198            0
##
##
## Elapsed time : 0.2183828
```

XII. GARCH Analysis Results for 2010s Oil Collapse


```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error   t value Pr(>|t|)
## mu     109.11606    0.102546 1064.0686 0.000000
## omega    0.72716    0.154338    4.7115 0.000002
## alpha1   0.80873    0.063296   12.7770 0.000000
## beta1    0.19827    0.050478    3.2541 0.001137
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     109.11606    0.262901 415.0457 0.000000
## omega    0.72716    0.213095   3.4124 0.000644
## alpha1   0.80873    0.072766  11.1142 0.000000
## beta1    0.19827    0.075436   2.5123 0.011660
##
## LogLikelihood : -8386.323
##
## Information Criteria
## ------------------------------------
##
## Akaike       8.1459
## Bayes        8.1569
## Shibata      8.1459
## Hannan-Quinn 8.1500
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                       1551       0
## Lag[2*(p+q)+(p+q)-1][2]      2242       0
## Lag[4*(p+q)+(p+q)-1][5]      4120       0
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic  p-value
## Lag[1]                      9.602 0.001944
## Lag[2*(p+q)+(p+q)-1][5]    11.633 0.003475
## Lag[4*(p+q)+(p+q)-1][9]    13.360 0.008799
## d.o.f=2
```

```
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]    0.2335 0.500 2.000  0.6289
## ARCH Lag[5]    1.6864 1.440 1.667  0.5447
## ARCH Lag[7]    2.7754 2.315 1.543  0.5569
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  2.0014
## Individual Statistics:
## mu     0.6881
## omega  0.0814
## alpha1 0.0469
## beta1  0.7957
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:         1.07 1.24 1.6
## Individual Statistic:    0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           0.8832 0.3772
## Negative Sign Bias  0.1023 0.9185
## Positive Sign Bias  0.8877 0.3748
## Joint Effect        1.1991 0.7532
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     18359            0
## 2    30     13640            0
## 3    40     10986            0
## 4    50     15606            0
##
##
## Elapsed time : 0.1704901
```

XIII. GARCH Analysis Results for Stagflation Oil Crisis


```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu      29.04813    0.322583  90.0487 0.000000
## omega    0.52265    0.342881   1.5243 0.127440
## alpha1   0.81211    0.143806   5.6472 0.000000
## beta1    0.18689    0.085648   2.1821 0.029101
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu      29.04813     0.87565  33.1733 0.000000
## omega    0.52265     0.27458   1.9034 0.056984
## alpha1   0.81211     0.16801   4.8336 0.000001
## beta1    0.18689     0.13078   1.4291 0.152983
##
## LogLikelihood : -372.6625
##
## Information Criteria
## ------------------------------------
##
## Akaike       6.2777
## Bayes        6.3706
## Shibata      6.2756
## Hannan-Quinn 6.3154
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                      89.41       0
## Lag[2*(p+q)+(p+q)-1][2]    122.26       0
## Lag[4*(p+q)+(p+q)-1][5]    209.12       0
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic   p-value
## Lag[1]                      22.55 2.043e-06
## Lag[2*(p+q)+(p+q)-1][5]     23.58 1.092e-06
## Lag[4*(p+q)+(p+q)-1][9]     24.07 1.730e-05
## d.o.f=2
```

```
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]    0.9837 0.500 2.000  0.3213
## ARCH Lag[5]    1.5610 1.440 1.667  0.5764
## ARCH Lag[7]    1.6126 2.315 1.543  0.7985
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  1.2542
## Individual Statistics:
## mu     0.6955
## omega  0.1525
## alpha1 0.2148
## beta1  0.1318
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.07 1.24 1.6
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias          0.06055 0.9518
## Negative Sign Bias 0.53318 0.5949
## Positive Sign Bias 0.61473 0.5399
## Joint Effect       0.66293 0.8819
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     149.3    2.947e-22
## 2    30     147.5    8.098e-18
## 3    40     187.3    2.797e-21
## 4    50     175.0    4.672e-16
##
##
## Elapsed time : 0.04757207
```