Demographics as a Predictor of United States Equity Prices

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Abstract

In this paper, I find that the long-run, secular moves of the MY ratio, the ratio of middle-aged to young, is related to the long-run, secular moves of the S&P 500 from 1950 to 2020. I focus my research on the United States, but also find compelling evidence of the MY ratio's global importance through the case of Japan. Utilizing a vector error correction model (VECM), I project the ability of economic variables and the MY ratio to accurately predict S&P 500 growth. I then create forecasts of the S&P 500 and Nikkei 225 growth rates until 2050 using only medium-variant predictions of the MY ratio.

Acknowledgements

To my thesis advisor, Alberto Arredondo-Chavez, thank you for encouraging me and guiding me throughout this process. You are brilliant, and Haverford is lucky to have you. I also want to thank my family for always supporting me. Lastly, I would like to thank Joshua Jamner for inspiring the contents of this thesis and for being my mentor.

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I. Introduction

Demographics play a prominent role in the consumption and investment decisions made by individuals. As individuals earn more, they can spend and save more. By working longer, the purchasing power of mature workers is greater than the average young person who has spent fewer years working. Older individuals' incomes directly flow into certain sectors and markets through their purchases of goods, services, and investment instruments causing the economy to be further stimulated. Capital flows can have outsized effects on financial markets if there is a larger cohort of older workers in comparison to younger workers since high-skilled, high-paid individuals provide a large stream of capital into specific sectors and markets. This is why I hypothesize that demography is a significant indicator of equity market bear and bull cycles. Through my work, I hope to demonstrate demographics as an overlooked predictor of equity prices. Moreover, through this exploration, I provide a long-run prediction of S&P 500 price growth rate based on US Census Bureau predictions of United States population prospects in the coming decades.

The Pew Research Center estimates that the average United States generation lasts 16 to 20 years (Dimock, 2019). Generations are determined by a significant event or events that precedes the generation but directly shapes the social and economic environment in which the generation develops. These generation-defining events include World War II, the 1969 moon landing, the 1980s stock market crash, 9/11, and likely the 2020 coronavirus pandemic. Generations are not uniform in size. Birth rates historically fluctuate in response to economic and financial circumstances. For example, the baby boom generation, defined as those born from 1946 to 1964, is the largest generational cohort born in the United States. The first of the baby boomers were born at the end of World War II during a time when the US was

experiencing favorable housing and education conditions. These favorable conditions enabled young parents to have more children than in previous generations.

The baby boomers provide significant insight into the effects of a large cohort on the economy. The large mass of boomers entering the workforce had a chaotic impact on 1980s turbulent economic and social conditions. Subsequently, their entrance into their peak earning and spending years coincided with the 1990s asset price boom. This led economists to begin to wonder if cohort size may have large implications to financial markets. Thus, there began many predictions and literature in the late 1990s and early 2000s documenting how the boomers' mass exit from the workforce, starting approximately in the 2010s into the 2020s, could have extreme implications for asset market prices. However, since an asset bust has not played out, research highlighting the impact of generation size on capital markets has relatively gone out of fashion. Yet, the relationship between demographics and market returns has not ceased to be relevant.

By examining intergenerational relationships, I hope to discover whether a generation's size and, more importantly, the size of different age groups in the labor force can significantly affect financial markets. My main variable of interest is the proportion of middle-aged to young in the population, known as the MY ratio. The MY ratio (middle-aged to young) captures the relative proportion of the highly skilled and well-paid workforce in relation to younger, less experienced workers. I define the terms middle-aged and young in relative terms to the working-age population of 15 to 64. I label middle-aged as those between 35 and 49 years old and young as those aged 20 to 34 years old. Younger agents make relatively less income than their older counterparts, and, consequently, younger households require more of their income to make large purchases on housing and education. Upper-middle to upper-income class households of middle-aged adults typically have greater liquidity allowing them to engage in such costly

expenditures. Thus, financially stable middle-aged adults can partake in savings activities such as investing in stocks and bonds. That is why I conclude that the larger the number of middle-aged workers and citizens in comparison to less mature workers, the larger the expected flows will be into the capital markets.

Exploring the relationship between working-age fluctuations and the stock market is motivated by the cyclical flows evident in birth rates and stock returns that occur at similar times. Financial analysts and institutions estimate that the average secular bull and bear markets also last around the same length as a generation, approximately 16 to 20 years (Devulapally, 2019). I believe that the 16 to 20-year length of market cycles and generations is not merely coincidental. As discussed before, middle-aged agents are highly influential due to their higher purchasing power and their propensity to consume and save at higher levels than other age groups. In the 1960s and the 2000s, a large cohort of middle-aged agents concurred with record-high stock returns. The reverse situation occurred in the 1980s and currently in the 2020s in which young, less-skilled workers outnumber the amounts of experienced workers. These similar time periods 40 years apart are marked by their relative market instability. All four examples of concurring peak to trough movements of equity pricing and generation sizes provide the basis for which I believe there may be a wealth of knowledge to explore demographics as a reliable predictor of long-run stock market returns.

This thesis will provide an update to previous works exploring the effects of baby booms on capital accumulations and decumulations. The focus will be on generation sizes impacting equity prices as displayed through the aggregate prices of the S&P 500. Like other research, I will not explore the exact nature by which the rich have an outsized effect on capital returns, but this information will be implicit inside my model. My results depend on a vector error

correction model (VECM) to create coefficients to forecast S&P 500 annual growth rates based on realized and predicted population values. I also form a VECM utilizing the additional variables GDP, real interest rates, and foreign domestic investments to provide a fuller sense of the economic conditions that affect the stock market. Lastly, I make a country comparison of the US to Japan, a country infamous for its unfavorable aging population, to test my hypothesis that working-age demographics impact a nation's equity prices.

II. Literature Review

Since the late 1990s, there has been economic research on intergenerational cohorts' effects on asset prices due to concerns of asset sell-offs by baby boomers as they come into retirement. The majority of these papers utilize Franco Modigliani's 1986 life-cycle hypothesis (LCH) of saving theory to provide a basis for individuals' consumption decisions. The principle of LCH is that consumers are rational and utility-maximizing throughout their lives. According to LCH, a generational cohort earns more income as they work longer. The representative consumer chooses a relatively "stable rate" of consumption relative to their life resources at their age (Modigliani, 1986, p. 299). It is expected that the representative consumer then spends the remainder of his or her savings before death. The MY ratio I utilize builds off the LCH theory and previous researchers' models to formulate how having many individuals in their prime earnings period could in part lead to higher equity prices.

Schieber and Shoven (1997) discuss the baby boomers' sizeable impact on society since the generation's conception in post-World War II era America using statistics from the US Bureau of the Census. From 1950 to 1970, the number of students enrolled in primary school jumped from 21 to 34 million students—a staggering 162% increase attributable to the baby boom. From 1970 to 1986, the baby boomers joined the workforce, and the United States "labor

force grew at a compound rate of 2.6% per year" (Schieber and Shoven, 1997, p. 112). However, as the first batch of baby boomers began to retire in the 2000s it was unclear how the cost to support them through Social Security and Medicare payments would affect their smaller generation of successors, the Gen Xers. Additionally, it was unclear who would absorb their fiscal assets as boomers began to sell off assets to cover retirement costs. Peer papers of this time utilize econometric-based models to view how baby boomers retiring could potentially send shocks throughout the nation's asset markets.

In 1994, Yoo applied a multiperiod, overlapping generations (OLG) model of asset prices to see the relationship between cohort size and asset returns. Utilizing data from the Survey of Consumer Finances (SCF), Yoo breaks down average gross asset holdings for individuals 25 years and older and separates these individuals into age groups of 10 years. The SCF data identifies the age group of 45 to 54-year-olds as the largest holders of aggregate household wealth. He finds a strong, statistically significant relationship between 45 to 54-year-olds and net equity purchases. Yoo concludes that demographic variables can explain nearly 50% of the variance of the real annual returns of Treasury bills and a lower percent of the variance of real returns on other financial assets. Yoo suggests that the baby boomers' entrance into the 45 to 54 age group may result in a period of low real rates, which has since been realized as true.

Similar to Yoo (1994), Poterba (2001) builds a theoretical model using age-wealth profiles from the SCF to create simulated results for different age groups' asset holdings. In using the SCF data, Poterba is purposefully focusing on high-income individuals. He believes higher-income households hold the most considerable influence on asset shocks as they account for most domestic money flowing into the markets. Since investing in the stock market requires excess disposable income, the idea that high net worth individuals are primarily responsible for

most of the relationship between demographics and asset returns is likewise implicit in my model. Poterba finds a meaningful relation between demographics and returns on Treasury bills, long-term government bonds, and corporate stock in the US. However, he observes no significant pattern to link demographic structure and asset returns that would not be rationally anticipated and corrected in the markets. Thus, Poterba correctly rejects the prediction of an asset price meltdown.

In 2004, Geanakoplos, Magill, and Quinzii (GMQ) introduce the idea of the MY ratio. They define the MY ratio as the ratio of middle-aged (40 to 59) to young (20 to 39). GMQ utilize historical birth data to suggest there are cyclical fluctuations in US live births and generation sizes, causing the MY ratio to move in 20-year cycles from peak to trough. GMQ simulate 20-year cohorts fluctuating from large cohorts (N) to small cohorts (n) following each other in a stationary equilibrium model every 20 years. Due to favorable lifetime consumption streams for agents in a small cohort n, GMQ develop what they term the favored cohort effect (Geanakoplos, Magill, and Quinzii, 2004, p. 285). Because small cohorts experience more favorable gains from less competition in the labor market, large cohorts are expected to have less favorable lifetime consumption streams. They posit that this theory is partially responsible for the extreme cyclical nature of US birth rates, as small cohorts can birth large cohorts and large cohorts birth small cohorts due to less favorable consumption streams. GMQ add historical data on business cycle shocks, historical security prices, risk premia, and interest rates and found support for their favored cohort effect theory. The study's main findings display how demographics with controls on economic conditions and business shocks are powerful influencers and predictors for equity premiums, PE ratios, and dividends.

Favero, Gozluklu, and Tamoni (2011) support and further GMQ's study by examining the MY ratio's relation to the stochastic and slowly evolving portion of the dividend-price ratio and stock prices to make long-run stock market return predictions. Favero, Gozluklu, and Tamoni (FGT) utilize a vector error correction model (VECM) containing the change in dividend-prices, prices, and the MY ratio to obtain cointegration estimates forecasting long-run stock market returns. This method is the closest in literature to that of the VECM which I employ. FGT combines out-of-sample long-run forecasts of the MY ratio with the full sample cointegrating system to simulate projections for long-run equity premium, defined as the difference between S&P 500 returns and risk-free rates. Their simulation finds an average equity risk premium of about 5% projected from 2010 to 2050 (Favero, Gozluklu, and Tamoni, 2011, p. 1516). FGT compares their findings to previous research and determines that the MY ratio, more so than any other demographic ratio, is a strongly significant predictor of long-run real stock market returns.

Quayes and Jamal (2016) conduct a similar cointegration method to FGT to project the proportion of middle-aged and old effects on the price-dividend ratio. Quayes and Jamal include real GDP, population proportion between 45 to 64 (to represent prime earning age), population proportion of 65+, the budget deficit, and the real inflation rate into their model of determinants of the price-dividend ratio. They find a smaller significant relation than FGT between demographic change and stock market returns. I will be utilizing a very similar out-of-sample prediction method to these two studies. However, instead of predicting S&P 500 dividend-price ratios, I will be predicting S&P 500 annual price growth rates.

Keying in on the MY ratio rather than different demographics ratios, such as the dependency ratio (<15 and 65+ divided by 15 to 64-year-olds) and MO ratio (middle-aged to

old), allows some of the major current conflicts in the life-cycle hypothesis to diminish in importance. For example, Goodhart and Pradhan (2020) believe aging populaces have increased savings in advanced economies. The reality of households increasing savings past retirement is oppositional to the LCH belief that drives most previous demographics research. I believe the issues arising from an aging population are not as significantly displayed in the MY ratio as in the dependency ratio or the MO ratio, which is largely why I choose to examine the MY ratio over other demographic ratios.

Since most of the previous literature is over a decade old, I consult an updated demographics research paper from Kurz, Li, and Vine (2018). Kurz et al. document the spending behaviors of millennials in comparison to past generations. Millennials currently exceed baby boomers in size in the US, though the number of millennials born in the US is lower than that of the baby boomers born. This 2018 paper provides insights into whether the millennial generation and the current middle-aged cohort behave in ways abnormal to previous generations or conflicting with the LCH. Kurz et al. do not find evidence that recent cohorts differ in consumption and savings patterns of earlier decades. Thus, I feel the MY ratio remains a valid variable to study since its first adoption in 2004 by GMQ.

III. Data

My principal empirical model is created using two data sets to look at both population and equity returns. The MY ratio is my main independent variable of interest, and US stock market prices, shown using the S&P 500, are my outcome variable. The population data used to create a time series of United States MY ratios are obtained from the United Nations. Secondly, annual prices of the composite index of the S&P 500 are gathered from Thomson Reuters Eikon's database. I also include data from the Federal Reserve Bank of St. Louis for real interest

rates in annual percentage terms, year-end GDP, and real foreign direct investment data. Using all five data sets, I run a vector error correction model (VECM) to help estimate the growth rate of S&P 500 returns.

a. Population Data

The United Nations Population Division of the Department of Economic and Social Affairs released the *2019 Revision of World Population Prospects* (*WPP*). The WPP data set includes over 443 unique location identifiers for countries and continents. The focus of my population data is the United States of America. However, I keep Japan in an auxiliary data set as a point of comparison to the United States. The data for each country has 3,171 observations containing aggregate population counts of age groups from 0 to 100 broken into 5-year spans. The country and continent-level observations include historical population data from 1950 to 2020 and medium-ranged estimates for the population from 2021 to 2100. The United Nations' medium-range demographics predictions are based on historical fertility, migration, and mortality rates. To run my forecasts, I will use these medium-variant predictions for the United States, but for the realized MY ratio values, I only keep the years from 1950 to 2020.

The primary variable of interest is the ratio of middle-aged adults to young adults, known as the MY ratio. The middle-aged and young populations are defined in terms of the estimated years spent in the labor market from ages 15 to 64 (Goodhart and Pradhan, 2020, p. 3). In Geanakoplos, Magill, and Quinzii (2004), the MY ratio is defined as a middle-aged cohort 40 to 49 years old divided by a young cohort 20 to 29 years old. However, in my study, I choose to define the cohorts in two adjoining 15-year blocks of 35 to 49 and 20 to 34. I choose 15-year blocks because this is the closest I can get to the expected length of a generation (approximately

16 years) using the UN data. My variables, *middle* and *young*, roughly report two concurring generations, though they do not match up with actual generations in most years.

I define *MY* by dividing *middle* by *young*. There are 71 yearly MY ratio observations, as shown in Table 1, from 1950 to 2020. The mean MY ratio is .9, which means that, on average, there are approximately 90 Americans aged 35 to 49 in a year for every 100 Americans aged 20 to 34. Because of deadly diseases such as heart disease and cancer that primarily affect middle-aged and older populations, it is sensible that there are more young adults than middle-aged adults in the average year. However, there are years in which this ratio goes as low as around 62.4 middle-aged Americans per 100 young Americans. There are also years where the MY ratio shows the opposite situation in which there are more middle-aged Americans than young Americans. The maximum MY ratio is 1.12, where there are approximately 112 middle-aged Americans per 100 young Americans.

Table 1. Summary Statistics, MY Ratio

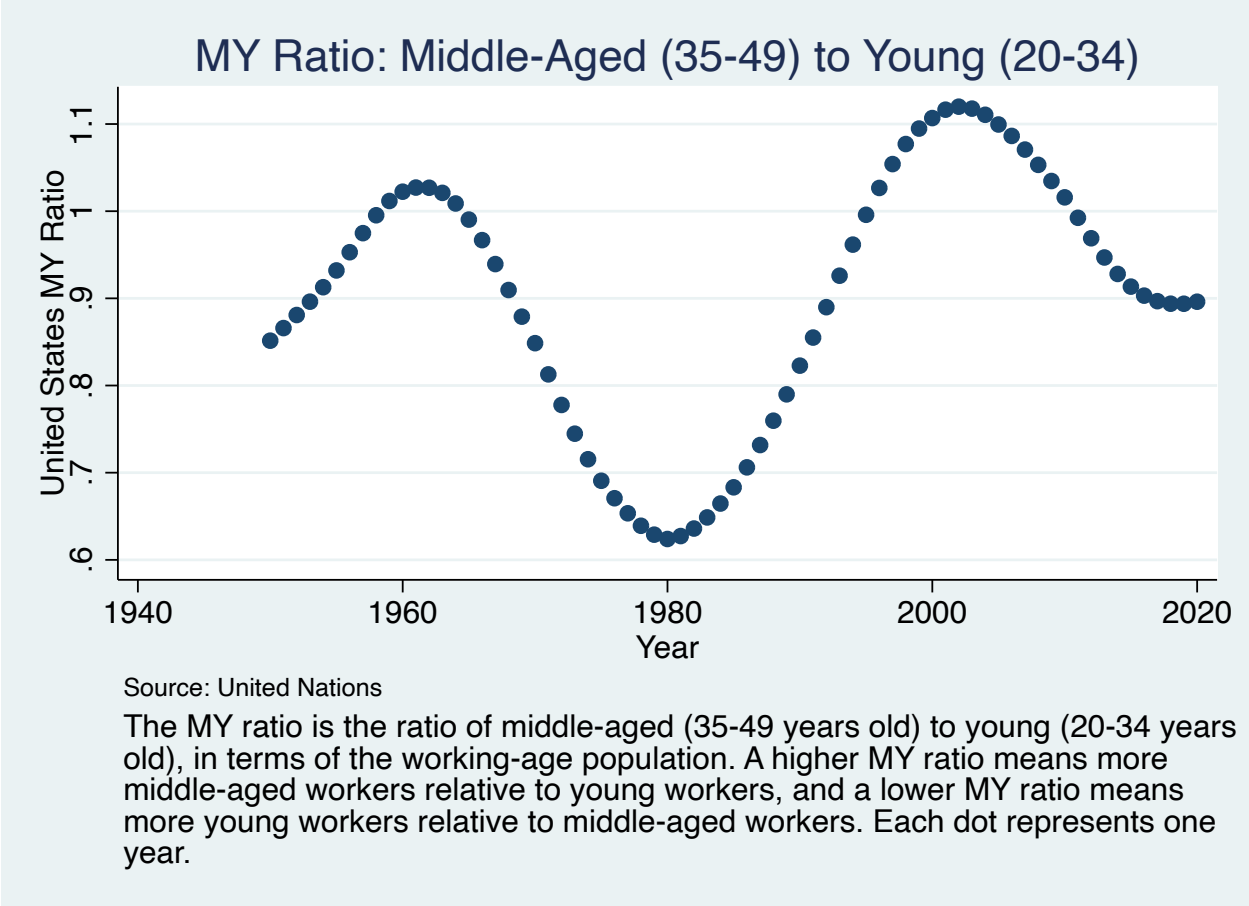
Variable	N	Mean	Std. Dev.	Min	Max
MY Ratio (Middle-Aged to Young)	71	0.9011823	0.1475951	0.6238878	1.11987

Source: United Nations

Figure 1 presents the United States MY ratio from 1950 to 2020. Each MY ratio-year observations are displayed as dots in the scatter plot. Peaks in the MY ratio seem to occur around 1960 and the early 2000s. The largest trough in the MY ratio occurs in 1980. A trough, or inflection point, appears to be happening 40 years later, in 2020. This suggests that a movement from peak to trough takes approximately 20 years and that a move from peak-to-peak lasts 40 years. This is extremely important. Twenty years is around the time it takes for a generation to grow up and enter the labor force, so the 20-year length it takes for expansion or contraction marks the years in which a young adult comes of age. When a young person reaches 20 years old, they are entered into the young cohort of the MY ratio to symbolize their entrance

into their labor market. Though it is often said that the working-age population is 15 to 64 years old, developed countries' working life cycle typically begins at 20 and ends a little past 67 years old (Goodhart and Pradhan, 2020, p. 3 & 67). Additionally, the cyclical fluctuations in the MY ratio shown in Figure 1 support Geanakoplos, Magill, and Quinzii's (2004) favored cohort effect.

Figure 1. MY Ratio, 1950-2020



I then create a variable named *chgMY* that captures the 16-year change in the MY ratio. The 16-year difference in time is because the average length of a generation is 16 (Pew Research Center, 2019). If we assume that there are cyclical flows in generation size that correspond to similarly sized flows in the stock market, taking 16-year changes makes the most logical sense to compare to 16-year percentage changes in stock market returns. The variable *chgMY* has its first observation in 1966, so going forward, the data only examines 1966 to 2020. Previous

researchers on relevant works start their data around 1950 due to the unpredictability of S&P 500 data previous to 1950, so the start in 1966 is only a little off from the hoped starting point. The new summary statistics for the population are shown in Table 2.

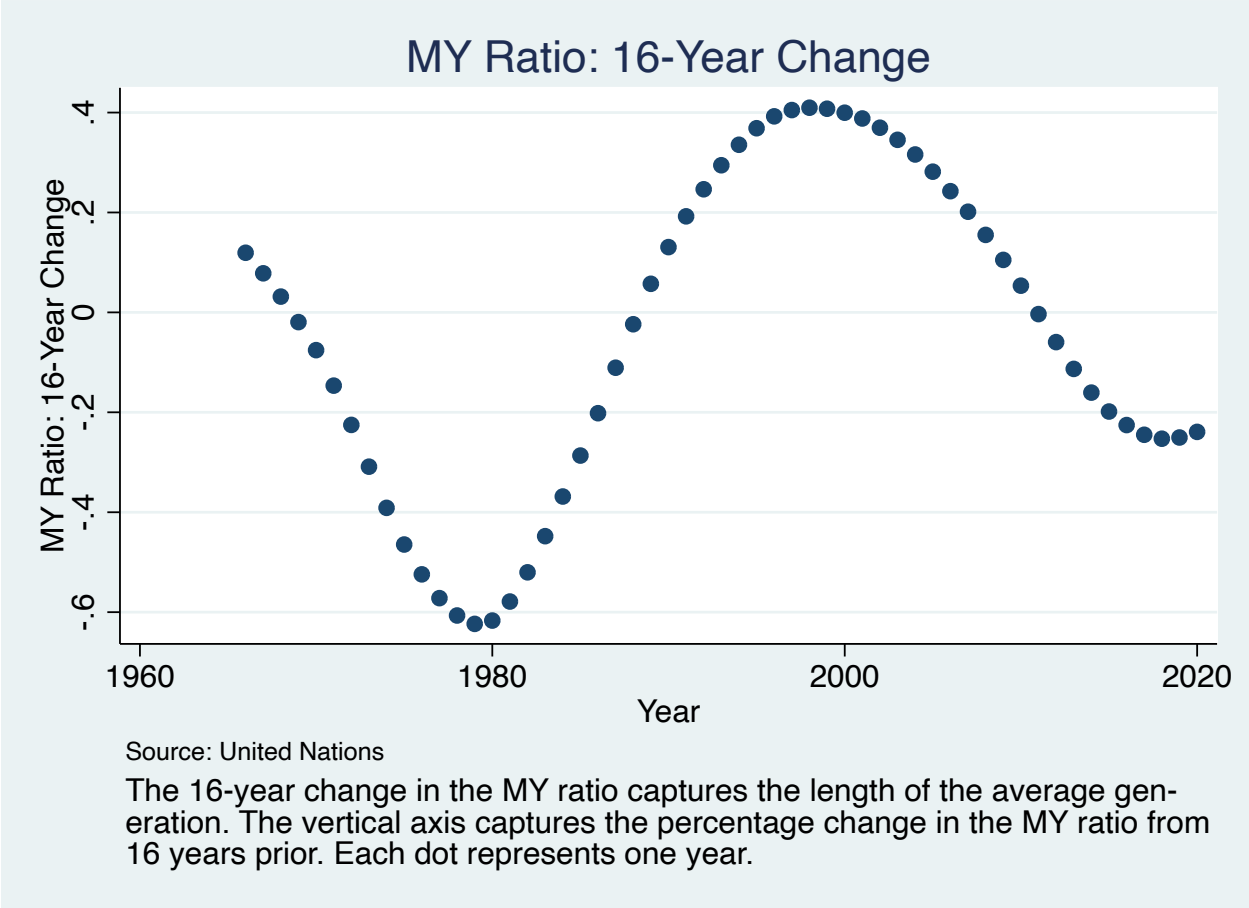
Table 2. Summary Statistics, MY Ratio

Variable	N	Mean	Std. Dev.	Min	Max
MY Ratio (Middle-Aged to Young)	55	0.8838919	0.1606632	0.6238878	1.11987
16-Year Changes in MY ratio	55	-0.0461477	0.322861	-0.6235682	0.4096163

Source: United Nations

Figure 2 displays the 16-year change in the MY ratio from 1966 to 2020. Figure 2 does not look very different from Figure 1. The similarity in the graphs furthers my belief in GMQ's theory that generations of small cohorts n and large cohorts N cycle every 16 years. The peak in the 16-year changes in the MY ratio occurs around the year 2000, with a percentage change of 41%. This implies that from 1986 to 2000, the size of the middle-aged cohort to the young cohort increased by nearly 41%. The mean of the 16-year change is -0.046, which can be interpreted that on average, the size of the middle-aged cohort is decreasing by about 4.6% relative to the size of the young cohort. This means the young typically outweigh the middle-aged, and the change in this ratio has either the middle-aged decreasing and/or the young increasing over 16 years. The trough occurs around 1980, with a change of -0.62. This suggests that from 1964 to 1980, there was a decrease in the middle-aged cohort relative to the young cohort of about 62%.

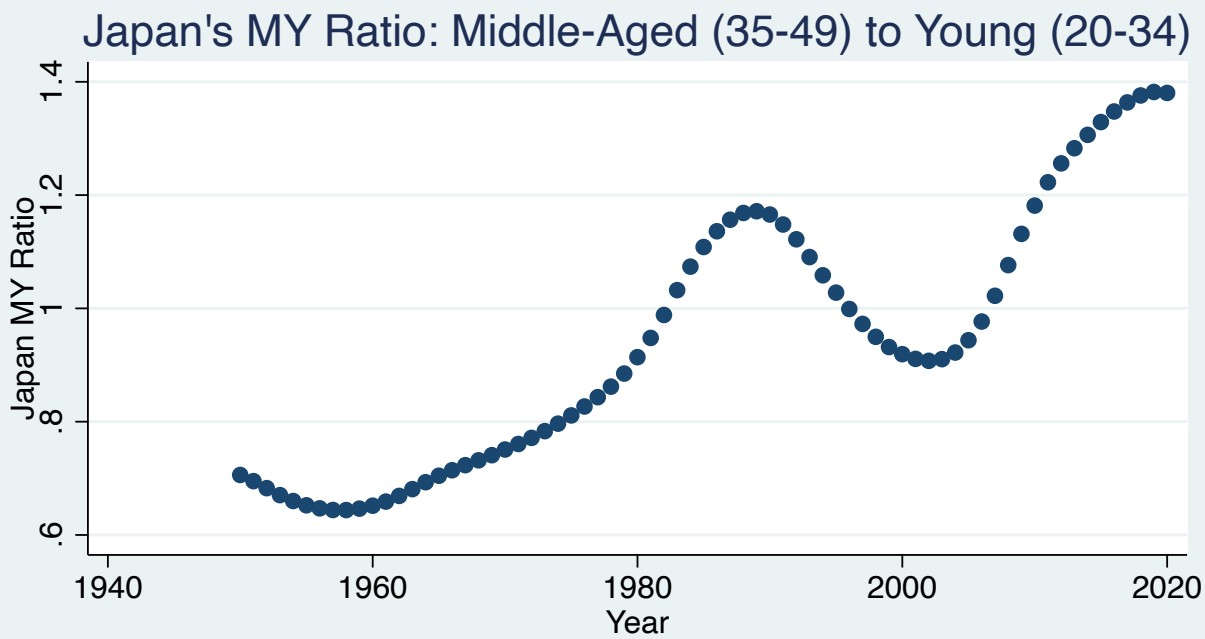
Figure 2. 16-Year Change in MY Ratio



I also examine Japan's population data collected from the United Nations. Japan is notable for its advanced aging population. The US also appears to be experiencing similar aging shifts to Japan; however, the US is about 20 years lagging behind Japan in this demographic trend. I utilize Japan to discover whether the MY ratio's movements are unique to the US and how these movements may affect a nation's stock market trends. The summary statistics for Japan's population data are displayed in Appendix Table I. Figure 3 illustrates Japan's less cyclical MY ratio than the US. One theory for Japan's cyclical behavior beginning in the 1980s is their rapid globalization and industrialization that occurred in this era. The largest peak in Japan's MY ratio is 1.38, occurring in 2019, meaning around 138 middle-aged Japanese citizens per 100 young. This is a lot higher than the US's MY ratio peak of 1.12 in 2000. For nearly two

decades, the MY ratio in Japan has been over 1, meaning there are nearly always more middle-aged citizens than young. I present the 16-year change in the Japanese MY ratio in Appendix Figure I and summary statistics for 1966 to 2020 in Appendix Table II.

Figure 3. Japan's MY Ratio, 1950-2020



Source: United Nations

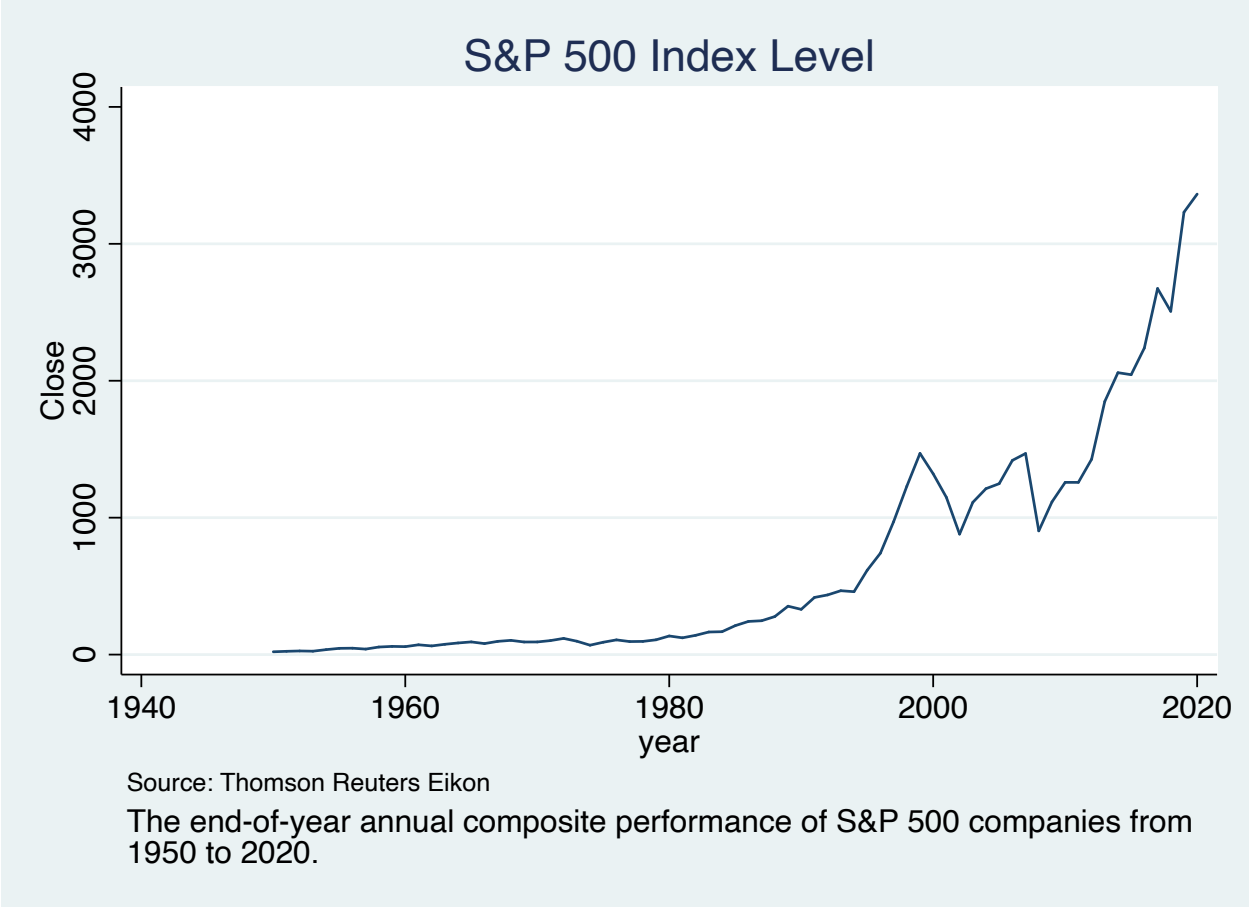
The MY ratio is the ratio of middle-aged (35-49 years old) to young (20-34 years old), in terms of the working-age population. A higher MY ratio means more middle-aged workers relative to young workers, and a lower MY ratio means more young workers relative to middle-aged workers. Each dot represents one year.

b. Stock Market Data

I collected data on the annual composite performance of Standard & Poor's 500 largest companies (S&P 500). This data comes from Thomson Reuters Eikon. The variable *SPX* contains the closing day price from the last day of the year from 1928 to 2020. Figure 4 displays the yearly index levels from 1950 to 2020. Figure 4 seems to show S&P 500 returns increase

consistently over time, but it looks like there could be some stochastic movements creating irregularity in the stock movements.

Figure 4. S&P 500 Index Level, 1950-2020



Since I am interested in seeing the 16-year change in equity prices to compare it to the 16-year change in the MY ratio, I create a variable *ann16* defined as the 16-year compounded annual growth rate of the S&P 500 index level. Because the data for the 16-year change in the MY ratio only begins in 1966, I limit my observations for the annualized S&P 500 index from 1966 to 2020. Figure 5 displays the distribution of the 55 S&P 500 index level-year observations. The figure suggests that S&P 500 returns annualized over a 16-year basis displays similar trends to the 16-year change in the MY ratio, shown in Figure 2. The mean of the 16-year annualized S&P 500 index is 6.9%, meaning that S&P index levels tend to rise 6.9% over

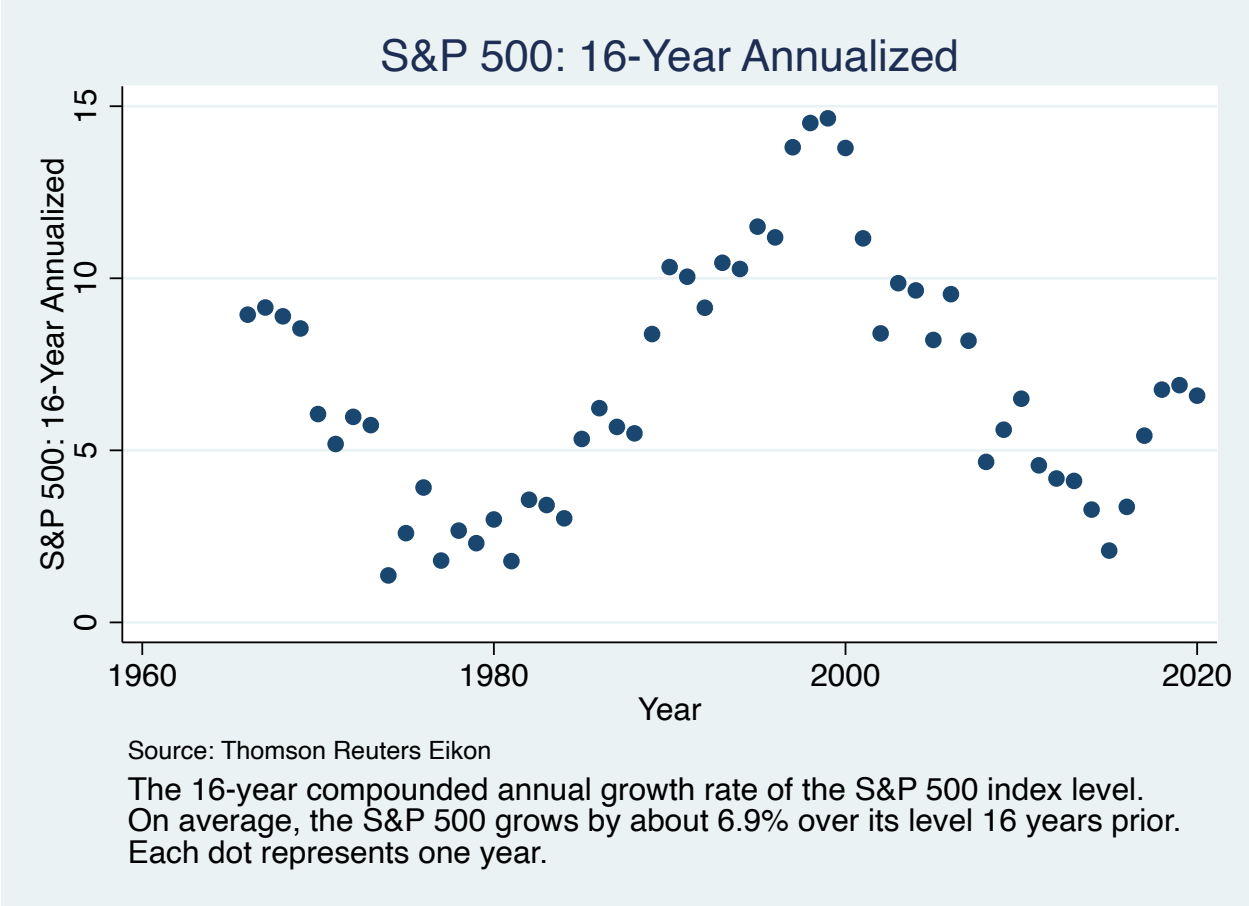
their levels 16 years prior. Table 3 and Figure 5 display returns reaching a low of around 1-2% around 1980 and 2018. The peak in S&P 500 returns of 14.7% growth from 16 years prior occurs around 2000, when the peak in the 16-year change in the MY ratio also occurs. In a later figure, I will display both Figure 2 and Figure 5 together to show how closely the two compare.

Table 3. Summary Statistics, S&P 500

Variable	N	Mean	Std. Dev.	Min	Max
S&P 500 Index Level	55	841.3824	856.9982	68.56	3363
S&P 500 16-Year Annualized Index	55	6.865568	3.502094	1.362734	14.64688

Source: Thomson Reuters Eikon

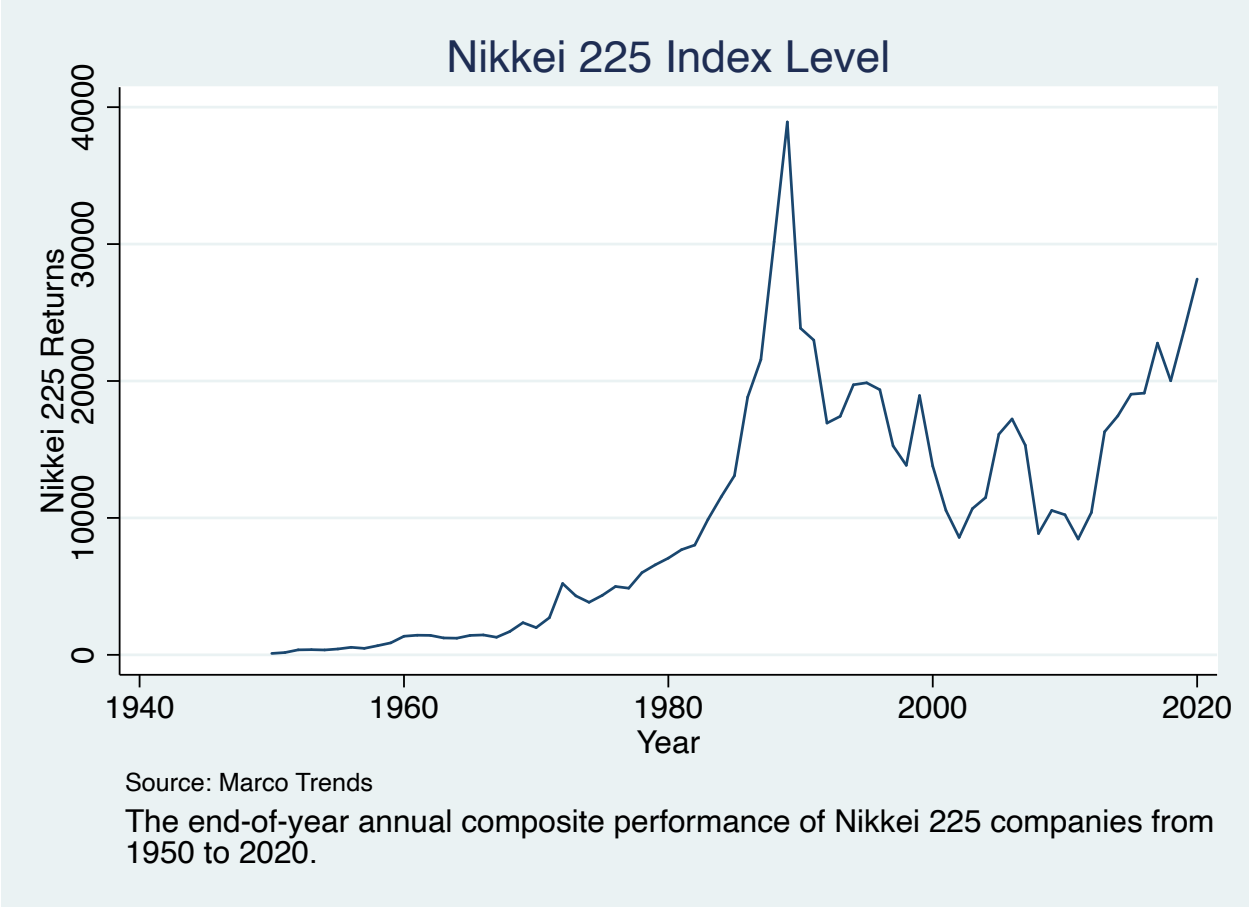
Figure 5. 16-Year Annualized S&P 500 Index



I collected data on Japan's national stock market, the Nikkei 225, from Macro Trends. Unlike the S&P 500, a free-float weighted index, the Nikkei 225 is a price-weighted index. I do not believe that this distinction should have implications on the difference between

demographics and the stock market in Japan and the US, but it is worth noting. The closing day price of the last market day from 1950 to 2020 is displayed in Figure 6. Unlike the S&P 500, which tends to consistently increase, the Nikkei 225 peaked in 1989 during an asset price bubble and has experienced depressed returns since. Thus, there is no long-run consistent upward trend in the Japanese stock market as there is in the US. The depressed returns in the Nikkei 225 can be partially explained by the nation's shrinking labor market and poor output growth (Goodhart and Pradhan, 2020, pp. 131-134). Summary statistics for the Nikkei 225 index level from 1950 to 2020 are presented in Appendix Table III. Additionally, the 16-year compounded annual growth rate of the Nikkei 225 is available in Appendix Figure II and statistics in Appendix Table IV.

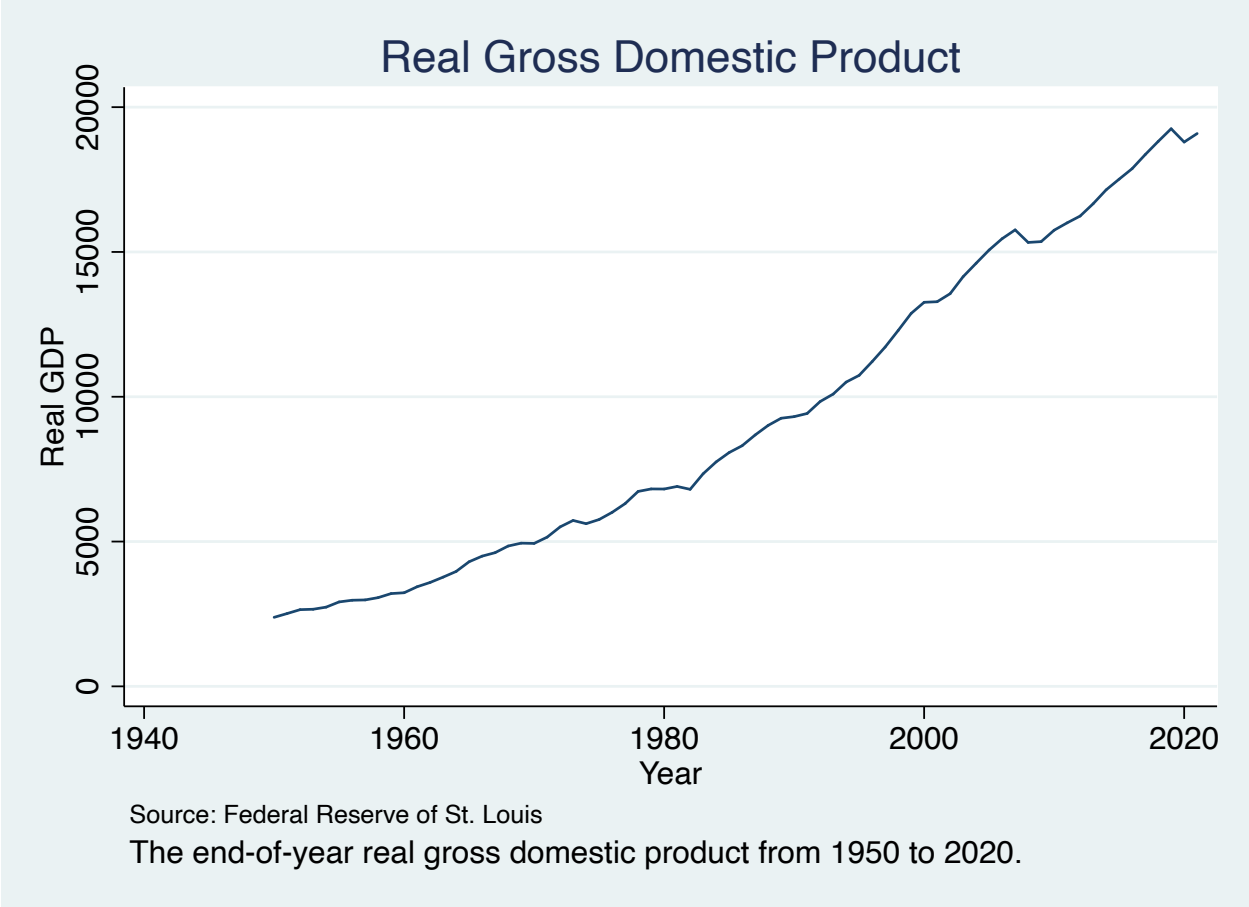
Figure 6. Nikkei 225 Index Level, 1950-2020



c. Additional Variables

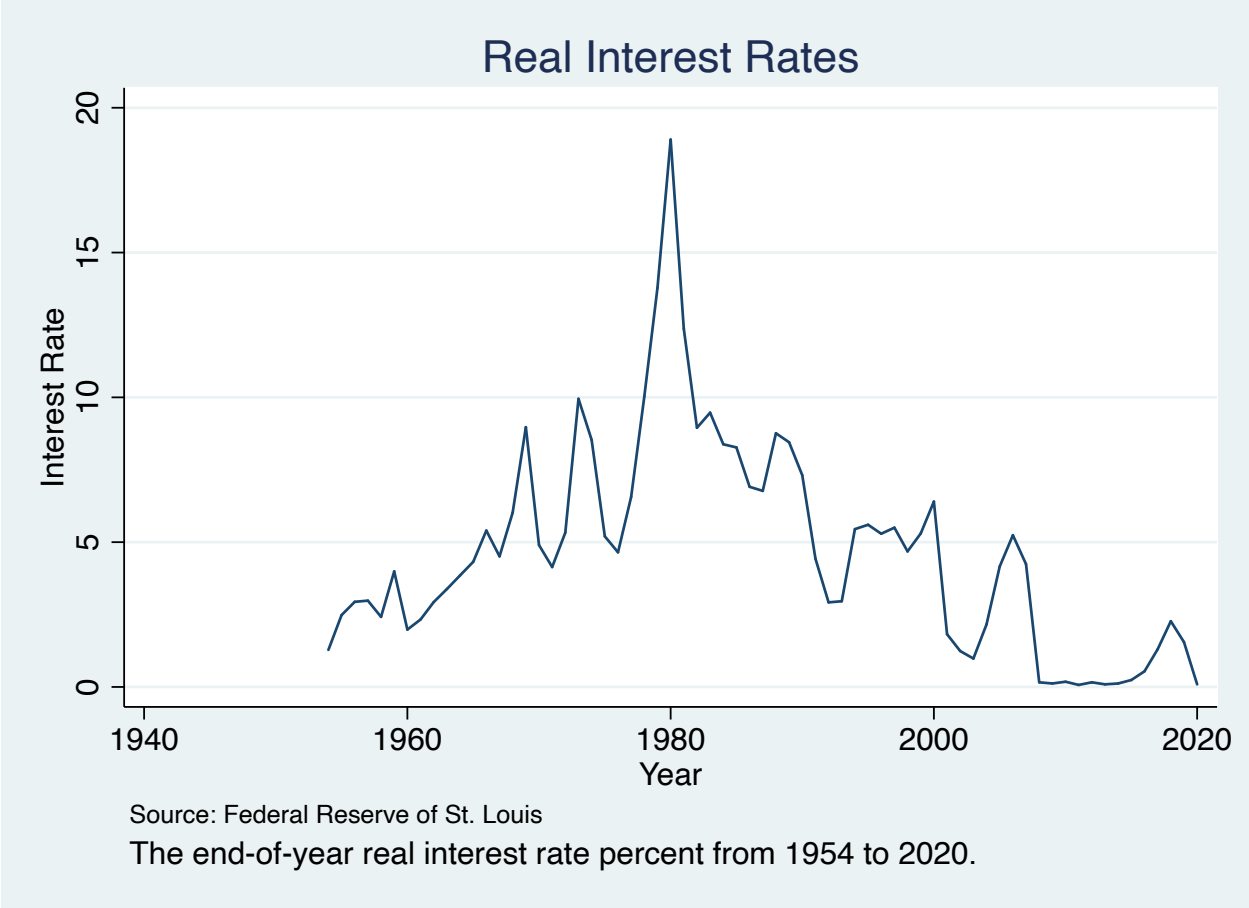
The full model for the US includes real gross domestic product (GDP), real interest rates, and foreign direct investments (FDI) to the model. These economic variables help explain equity prices as a result of other exogenous variables other than demographics. All three variables are obtained using data from the Federal Reserve Bank of St. Louis. To keep these variables in line with the MY ratio and S&P 500 variables, I take their end-of-year values to use annual levels or rates. Quayes and Jamal identify real GDP as "a proxy for income" and a helpful mechanism in understanding the "demand for equity shares" and prices (Quayes and Jamal, 2016, p. 174). Like the S&P 500, US GDP, as shown in Figure 7, tends to increase continuously. However, the rate of this growth has changed according to economic, political, and demographic factors.

Figure 7. Real GDP, 1950-2020



Real interest rates are a significant determinant of savings and investment in the economy. Additionally, an increase in real interest rates tends to correspond with higher inflation rates, such as the 1980s. When the number of young workers overcrowds the number of skilled workers, interest rates increase as there is less saving in the economy and more borrowing. Thus, real interest rates tend to move inversely to the MY ratio, with US interest rates hitting a high in 1980 when the MY ratio hits an all-time low. Currently, interest rates are at a near-historic low while the elderly population is at a near high. Interest rates more closely follow the old-age dependency ratio, which measures the amount of 65+ compared to those in the working-age population. In Japan, where the elderly make up a significant portion of the populace, interest rates have hit a zero-lower bound. Nonetheless, the short-term interest rate provides similar movements to the change in the MY ratio since both follow cyclical movements that tend to move around birth cycles. This is somewhat apparent in Figure 8, which displays the movements of the end-of-year real interest rates.

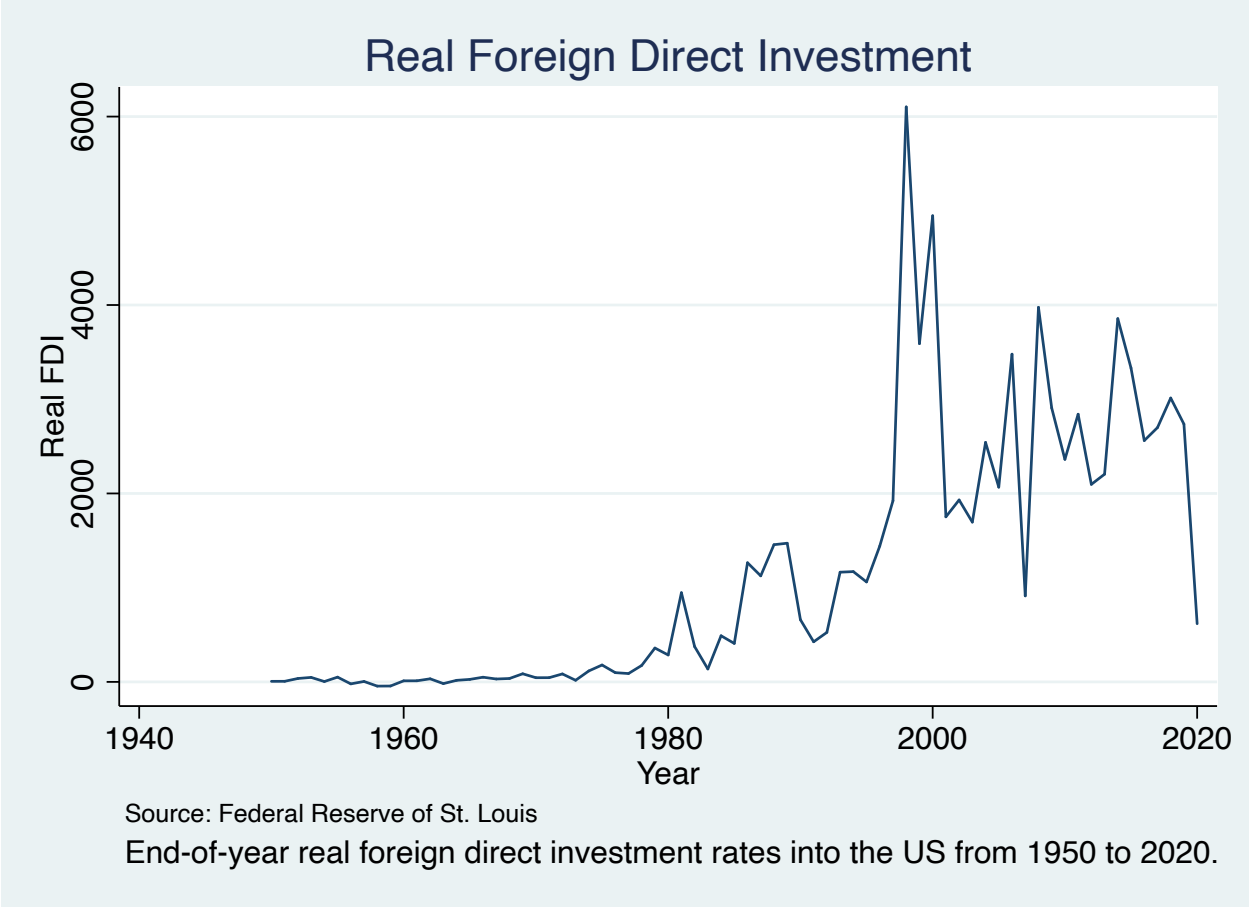
Figure 8. Real Interest Rates, 1954-2020



Lastly, I also examine real foreign direct investment (FDI) rates coming into the US. Analyzing FDI rates helps me formulate a global picture of how the US economy interacts with the global economy. FDI captures some of the inflows of capital coming outside of the US into US firms. Though FDI excludes investments going directly into the stock markets, I assume that as more foreign investment flows into the US through other expenditures, there is likely more international capital coming into the nation's equity markets. I additionally use FDI in lieu of a marker for globalization in the corporations contained in the S&P 500, as it is crucial to consider the effects on asset prices as large corporations extend their global outreach. To move FDI from nominal to real values, I divide the end-of-year annual rates by the GDP deflator. Figure 9 displays real FDI from 1950 to 2020. There appears to be a sharp increase in FDI at the end of

the 1990s that continues into the 2000s. However, this increase in foreign investment suddenly drops off due to the efforts to de-globalize during the recent pandemic in 2020.

Figure 9. Real Foreign Direct Investment, 1950-2020



IV. Methodology

Before I present my model for projecting equity market growth rates, I hope to solidify my hypothesis that the MY ratio's long-run trends follow that of the nation's stock market. I present this idea by graphing the 16-year changes in the MY ratio with the 16-year changes in the stock market index in order to demonstrate the similarities in the two variables' movements. Figure 10 displays the time series data of the 16-year change in the MY ratio and the 16-year change in S&P index level returns from 1966 to 2020. This figure is a combination of Figure 2

and Figure 5. The summary statistics are listed below in Table 4. The variables appear to move in similar cycles from peak to trough. Each variable has two peaks and two troughs occurring around the same years. A full cycle appears to be around 35 to 38 years long, with one expansionary period from 1980 to 1998-1999, and two contractionary periods lasting around 16-18 years. Peaks occur around the years 1964-1965 and 1999-2000. The most significant peak in the S&P index is in 1999, with a 14.7% 16-year annual growth rate. This means that relative to 1983, the S&P 500 index is reporting a 14.7% increase in returns. Similarly, the largest peak in the 16-year change for the MY ratio occurs one year before 1999 in 1998. In 1998, the 16-year change in the MY ratio was .41, meaning there were relatively .41 more middle-aged cohort workers relative to young workers in 1998 relative to 1982. A slightly lower peak occurs around 1966 for the MY ratio and 1967 for the S&P index.

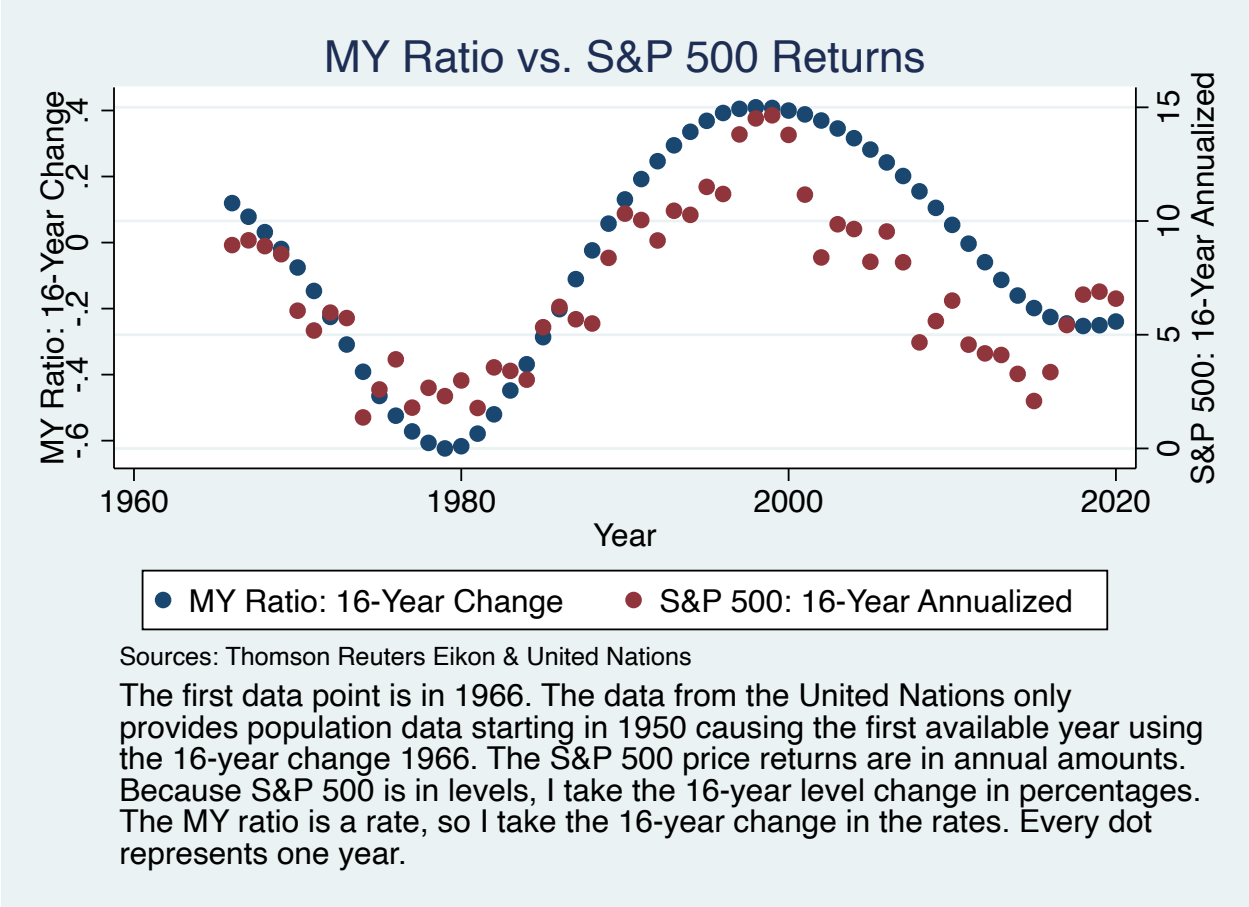
The largest trough for the change in the S&P index occurs in 1974 with a value of 1.4%, meaning S&P 500 level prices had only increased by 1.4% relative to 16 years before. This is a much lower percentage increase than most other years and the 16-year average of 6.9%. The trough for the 16-year change in the MY ratio occurs a few years later, in 1979. The 1979 MY ratio 16-year change value is -.62, meaning that relative to 16 years prior, the number of middle-aged to young workers decreased by about .62 middle-aged to 1 young worker. The trough being at the beginning of the 1980s supports the theory that baby boomers had a considerable effect on changing the makeup of the labor market. This also supports the idea that middle-aged workers, who are known to be more efficient and bring more flows into the capital markets, may be a powerful headwind to financial markets since the MY ratio is high in years when stock returns are at a higher level.

Table 4. Summary Statistics, MY Ratio and S&P 500

Variable	N	Mean	Std. Dev.	Min	Max
MY Ratio (Middle-Aged to Young)	55	0.8838919	0.1606632	0.6238878	1.11987
16-Year Changes in MY ratio	55	-0.0461477	0.322861	-0.6235682	0.4096163
S&P 500 Index Level	55	841.3824	856.9982	68.56	3363
S&P 500 16-Year Annualized Index	55	6.865568	3.502094	1.362734	14.64688

Sources: Thomson Reuters Eikon & United Nations

Figure 10. 16-Year Change in MY Ratio vs. 16-Year Annualized S&P 500 Index Returns



For the sake of comparing the US to another country, I conduct the same methods for Japan. As displayed in Figure 11, Japan appears to have smaller 16-year changes in the MY ratio than the US. In comparison with Table 4, in which the 16-year change in the US MY ratio fluctuates between -.6 to .4, Table 5 shows Japan only fluctuating between -.3 and .3. This indicates that Japan experiences milder adjustments in the 16-year change in the MY ratio. This may mean more mild results for Japan's estimated growth rate utilizing the VECM.

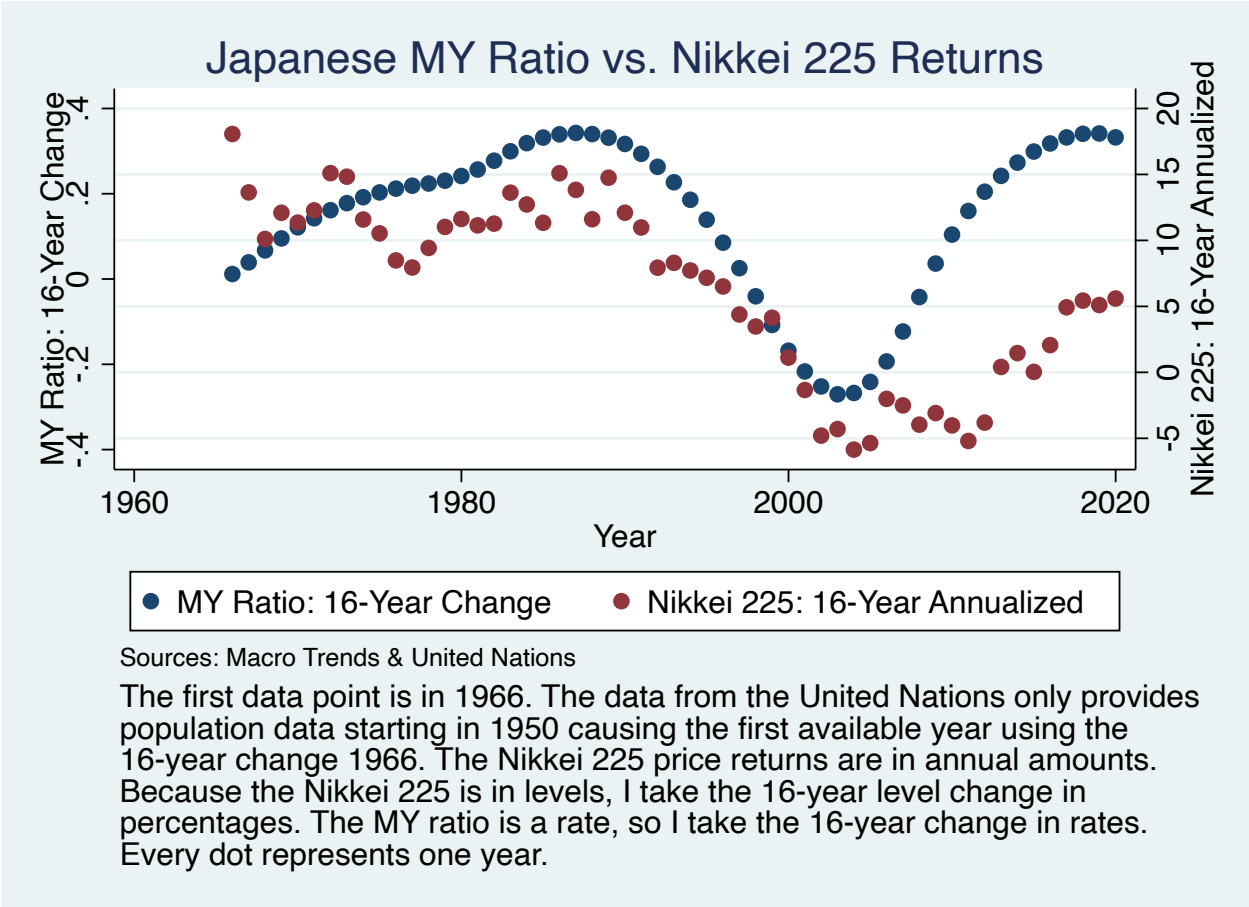
Additionally, the Nikkei 225 experienced negative 16-year annual growth rates from the 2000s into the 2010s, whereas the US experienced only positive fluctuations from peak to trough.

Table 5. Summary Statistics, Japan's MY Ratio and Nikkei 225

Variable	N	Mean	Std. Dev.	Min	Max
Japan's MY Ratio (Middle-Aged to Young)	55	1.023764	0.1944687	0.7141249	1.381922
16-Year Changes in Japan's MY ratio	55	0.1412273	0.1865175	-0.27038	0.3424208
Nikkei 225 Index Level	55	13172.4	8106.826	1283.47	38915.87
Nikkei 225 16-Year Annualized Index	55	6.290085	6.740255	-5.853644	18.0623

Sources: Macro Trends & United Nations

Figure 11. 16-Year Change in Japan's MY Ratio vs. 16-Year Annualized in Nikkei 225 Index Returns



To make assumptions about the relationship between demographics, as displayed through the MY ratio and stock market prices, I utilize a cointegration model called the vector error correction model (VECM). I include the additional variables of GDP, real interest rates, and FDI into a full version of this model to present the broader picture of the macro-economy. Applying

the VECM allows me to project how a shock or increase of the MY ratio and a shock or increase to all four independent variables would affect the S&P 500. I present both the results for the simplified VECM, which includes only the MY ratio and the S&P 500, and the results of the full VECM, including all five variables. Ultimately, I use the VECM coefficients from the simplified model and the out-of-sample population projections from the United Nations Population Division to present future forecasts of S&P 500 growth rates. Since the full VECM contains a more extensive procedure, I outline the steps I followed for it below.

Before running the cointegration model, there are several steps to be conducted. First of which is differencing or detrending the time series variables in order to view the model's stationarity (Greene, 1951, p. 637). Differencing breaks the model's series into secular and cyclical components. The secular component is associated with "long-run or permanent movement," also known as non-stationarity. The cyclical component is believed to be stationary in nature and given to dissipate over time due to movements in the business cycle (Nelson and Plosser, 1982, pp. 139-141). In the process of differencing time series variables, disruptive stochastic trends may result by way of a unit root. To test for a unit root, or rather, to test for non-stationarity in the times series, I run a Dickey-Fuller test. It is important to learn whether there is a unit root present in the model, meaning whether there is non-stationarity in the time series. If there were to be stationarity in the model, then that would mean that each variable only contains a cyclical component that dissipates over time.

I place each of the five variables (the MY ratio, S&P 500, real interest rates, GDP, and FDI) into log levels and run the Dickey-Fuller test to view which of the variables contain a unit root at the log level. After running the test, shown in Appendix Table V, it is clear that there is a unit root in the log MY process (*lnMY*). The test indicates that the test statistic for *lnMY* is -2.7,

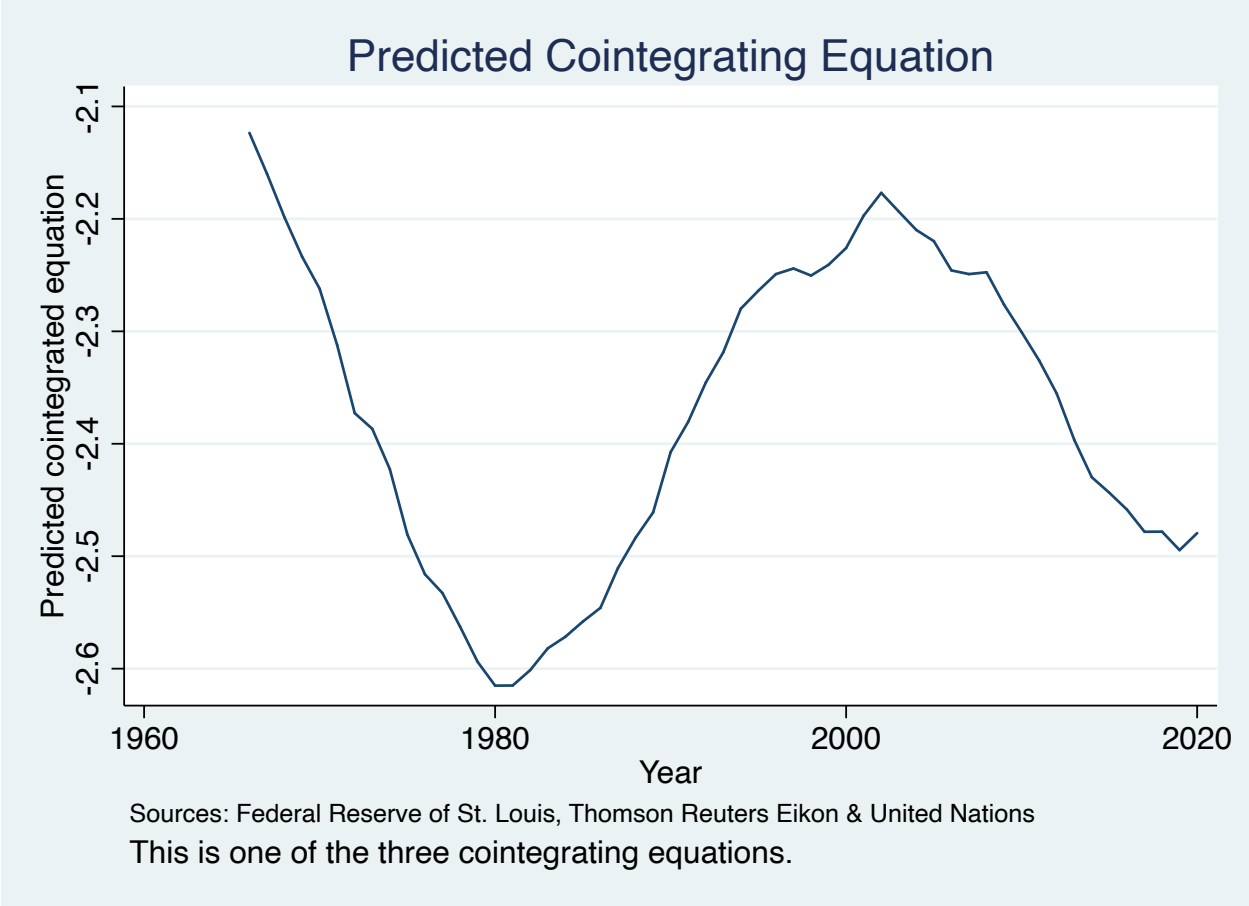
which is greater than the 10% critical value of -2.6. Since the test statistic is larger than the 10% critical value in absolute terms, I fail to reject the null hypothesis, leading me to believe there is a unit root in the log level series for MY ratio. On the other hand, the results for the log levels of the other variables, as shown in Appendix Table V, display test statistics smaller than the 5% critical value at the absolute level. Thus, I fail to conclude that there is a unit root for four of the variables. However, given the underpowered nature of the Dickey-Fuller test to correctly reject the null hypothesis of a unit root, I feel comfortable continuing my cointegration methods under the assumption that there may or may not be a unit root in the MY ratio, historic equity prices, GDP, foreign direct investment rates, and real interest rates.

Next, I need to determine the number of lags (*p*). Best practices suggest that I measure down for lag lengths (Greene, 1951, p. 644). According to Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC), two lags are optimal for my model. I then run a Johansen cointegration test with two lags. The null hypothesis of the Johansen test is that there are no cointegrating relationships. This Johansen trace test accepts that there is a maximum rank of 3 and thus rejects the null hypothesis in which there are no cointegrating relationships. Finding the trace statistic of 8.6 at the 5% critical value of 15.4, I believe that there are at most three cointegrating relationships or ranks. Since there can only be as many cointegrating ranks as one less than the number of variables in the system, finding that there are three ranks seems plausible in a five-variable model (Greene, 1951, p. 652).

The results of the full model VECM are in Appendix Table VI. The VECM displays and preserves the cointegrating relationships in which the variables experience their unique long-run relationships through a linear estimation. The VECM allows me to obtain coefficients for the

three cointegrating equations. The VECM coefficients shed light on the short- and long-term effects of a percentage change on an independent variable on the percentage change in the S&P 500. This ability to look at both short- and long-term impacts is because the VECM adds an extra restriction by way of an additional variable index so as to increase the efficiency of the cointegrated autoregression model. The cointegrating equation is a combination of the variables that are stationary in level terms. A graphical model of one of the three cointegrating equations for the VECM is shown below in Figure 12.

Figure 12. One Cointegrating Equation



After running the VECM, I run three diagnostic tests to check conditions of autocorrelation, normality, and stability of the error terms. The first diagnostic test, displayed in Appendix Table VII Figure A, checks for autocorrelation in the model's residuals using the

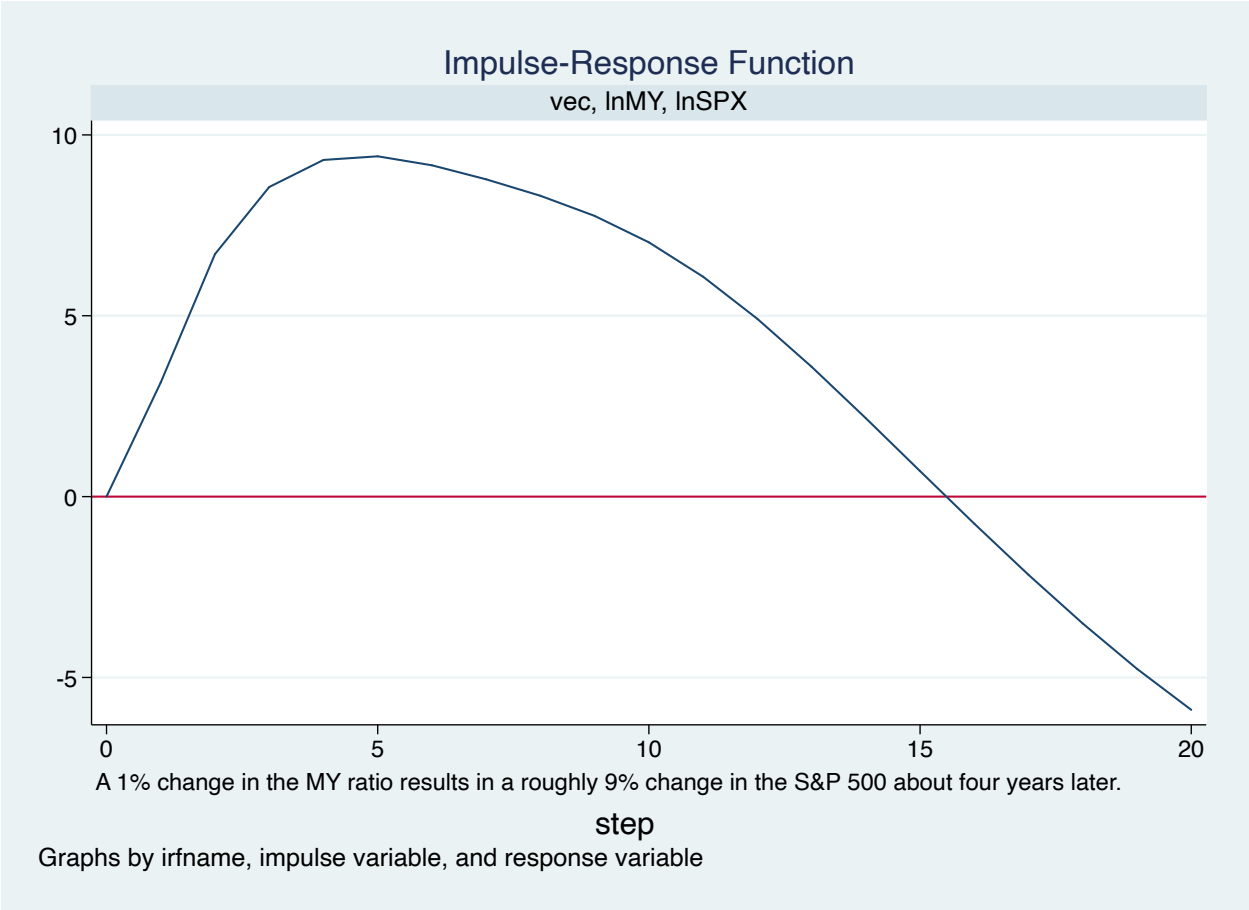
Lagrange-multiplier test. In neither of the two lags does the p-values display significant levels, indicating that the VECM does not experience issues of autocorrelation. Thus, this test suggests that there is no autocorrelation at the lag order. The second diagnostic test checks whether the errors are normally distributed, normally skewed, and experience normal kurtosis. The results of these tests are in Appendix Table VII Figure B. The Jarque-Bera test for normal distribution of the VECM's residuals displays that there may be an issue of normality for the VECM. With the exception of the *DlnMY*, all other variables experience insignificant p-values, suggesting the VECM carries an issue of normality. Additionally, the same issues can be seen in the test for skewness and kurtosis, indicating the error terms experience non-normal, skewed, and or kurtotic distributions. This becomes somewhat of an issue for me when reporting my results.

My third diagnostic test checks for the stability of the model by looking at a matrix of eigenvalues to determine whether the model is correctly specified and if variables are covariance stationary. A proper VECM has a correctly specified amount of cointegrating equations, which means for this stability test that the number of eigenvalues greater or equal to a value of 1 should be equal to the number of cointegrating equations. Eigenvalues help make future predictions of the model since they offer an explosive equation that goes far out into the future at values larger than one. Therefore, a model may be unstable if there are more eigenvalues with a value greater than or equal to 1 than the number of cointegrating equations. The eigenvalue stability test, displayed in Appendix Table VII Figure C, shows that there are only two eigenvalues with a value of 1—which is less than the number of cointegrating equations the model gives—so the VECM appears to be stable and covariance stationary under these conditions.

The impulse-response function (irf) for VECMs displays the results to one or more dependent variables after shocking one of the endogenous variables. I chose to make the MY

ratio the impulse variable in order to view the responses of the log of S&P returns to a change in the log of the MY ratio. Figure 13 displays the irf for the VECM where the change to the log of the MY ratio creates a positive response to the log of S&P 500 returns for approximately 15 years, followed by five years of negative returns. This figure suggests a 1% change in the MY ratio generates a 9% change at the peak of the S&P 500 about five years later.

Figure 13. Impulse-Response Functions



V. Results

a. Simplified VECM

To visualize the effects of the MY ratio directly onto the annual growth rate of the S&P 500, I run a simplified VECM with only the two variables *lnMY* and *lnSPX*. The coefficients are

displayed in Appendix Table VIII. Utilizing these coefficients, I create an estimate for the growth rate in the S&P 500. This growth rate is an estimated log difference, $DlnSPX_e$. The realized S&P 500 growth rate, $DlnSPX_r$, is obtained by taking the difference of a certain year's end of year level and the year prior's level and placing this difference into log levels. Since this VECM only contains two variables, there is at most one cointegrating equation meaning only one set of yearly cointegrating error terms. The error terms for this cointegrating equation are presented in Appendix Table IX. In a correctly identified econometric model, error terms are normally distributed around 0. However, the error terms of the VECM appear to be non-randomly distributed below the horizontal axis, as shown in Figure 14. I attempt to normalize these error terms by subtracting each annual error term by the average of the error terms from 1966 to 2020 (-0.25). The adjusted distribution of the error terms is available in Appendix Table X and graphed in Appendix Figure III.

Figure 14. Simplified Model's Unadjusted Error Terms

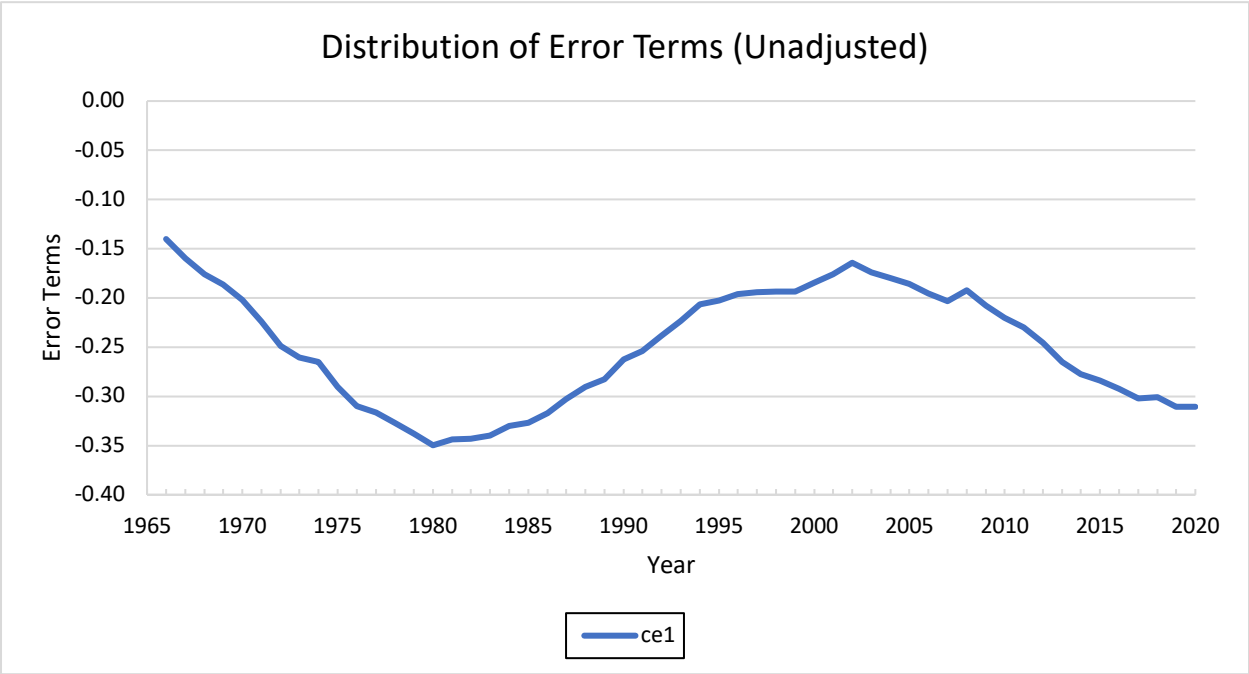
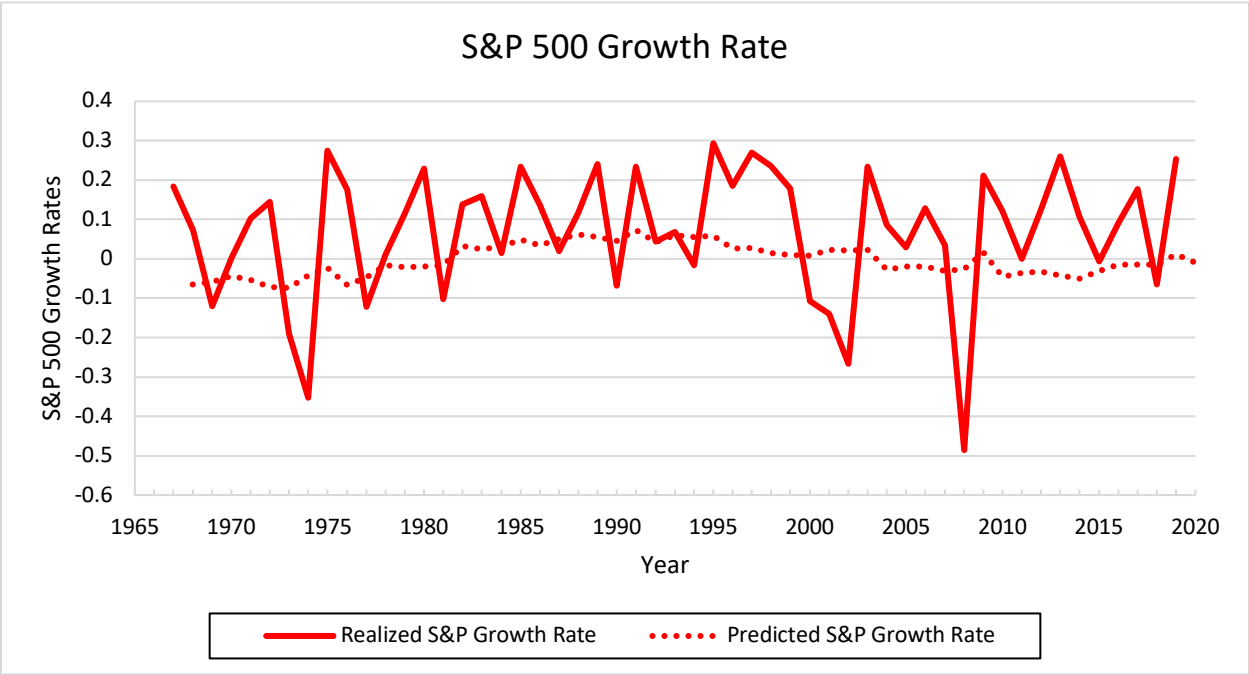


Figure 15 presents a comparison of the realized S&P 500 growth rate, $DlnSPX_r$, and the predicted S&P 500 growth rate, $DlnSPX_e$, obtained through a simplified VECM. These results use the adjusted error terms. The simplified model utilizing the unadjusted error terms is presented in Appendix Figure IV. Figure 15 exhibits how the MY ratio alone only predicts the long-run up and down trends of the S&P 500. However, it is not a good predictor of the depths of a recession nor the highs of an inflationary period. This is best exemplified by the predicted growth rate's failure to capture the lows of the 2008-2009 recession. Overall, Figure 15 suggests the long, secular moves in the MY ratio is comparable to the long, secular moves in the S&P 500.

Figure 15. Simplified Model's Realized and Predicted S&P 500 Growth Rates

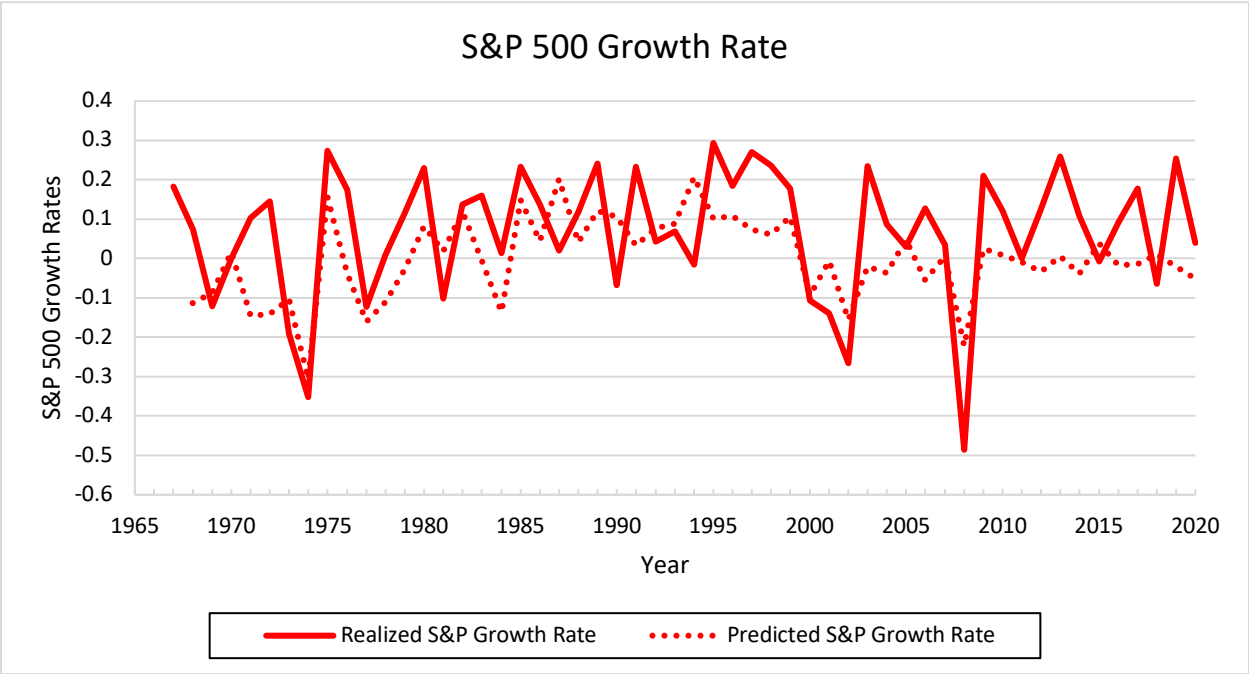


b. Full Sample VECM with Additional Variables

Next, I look at the full VECM containing the additional variables of GDP, interest rates, and foreign direct investment rates. As discussed earlier, the VECM's three cointegrating

equation's error terms have issues passing normality tests. This is again made evident in Appendix Figure V and Table XI, which displays the constants of the error terms as abnormally high and negative. As I did for the simplified model, I adjust for the issue of non-normal error terms by subtracting the average error terms of the three cointegrating equations (-2.02, -3.25, and -7.86) from their respective equations. Appendix Figure VI and Table XII displays the annual adjusted error terms. Consequently, the estimated log differences, or growth rates, are a lot closer to the realized values of the annual S&P 500 growth rate, as displayed in Figure 16. The unadjusted estimates for the full model's S&P growth rates are displayed in Appendix Figure VII. Figure 16 exemplifies that the MY ratio, along with economic variables, does a suitable job of tracking S&P 500 growth from 1966 to 2020. However, it seems that in the past decade and a half, the estimations have been milder than what actually occurs. I later discuss my thoughts on why the full sample model may fail to predict the recent trends in the S&P.

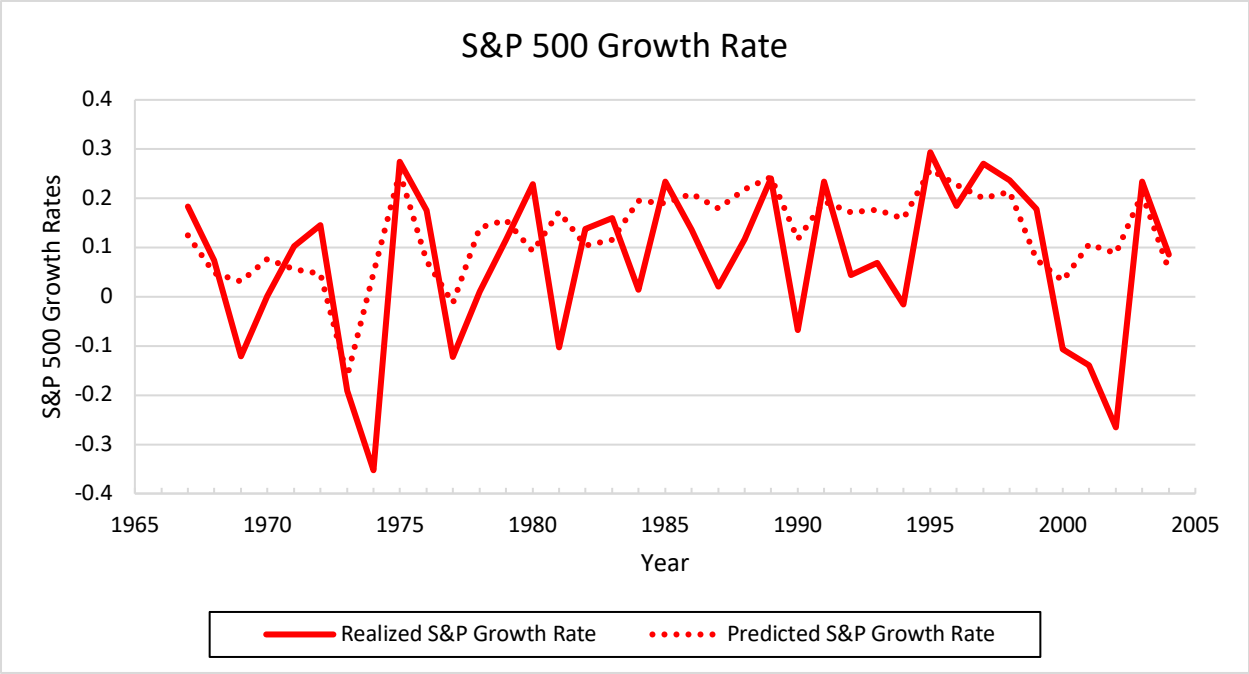
Figure 16. Realized and Predicted S&P 500 Growth Rates



c. Subsample VECM with Additional Variables

Additionally, I rerun the VECM for a subsample of the time series from 1966 to 2005. Checking the model on a subsample allows me to check for the validity of the entire model. 2005 is also the point at which the full model's predicted growth rate starts to differ from the realized growth rate. The subsample's VECM coefficients are in Appendix Table XIII. Like the full sample model, the errors of the cointegrating equations are large and not normally distributed around 0 (averaging 1.07, -4.40, and -2.24). I conduct a similar adjustment that allows the predicted growth rate to reflect the realized growth rate more accurately without non-normal error terms. These error terms, adjusted and unadjusted, can be viewed in Appendix Figure VIII, Figure IX, Table XIV, and Table XV. Figure 17 displays the subsample of the VECM after correcting for the error term adjustments. The subsample's predicted growth rate appears to overpredict the highs of an upturn and underpredict the lows. This is likely because the subsample ends before the 2008-2009 recession. The unadjusted predictions of the subsample's S&P growth rates are displayed in Appendix Figure X.

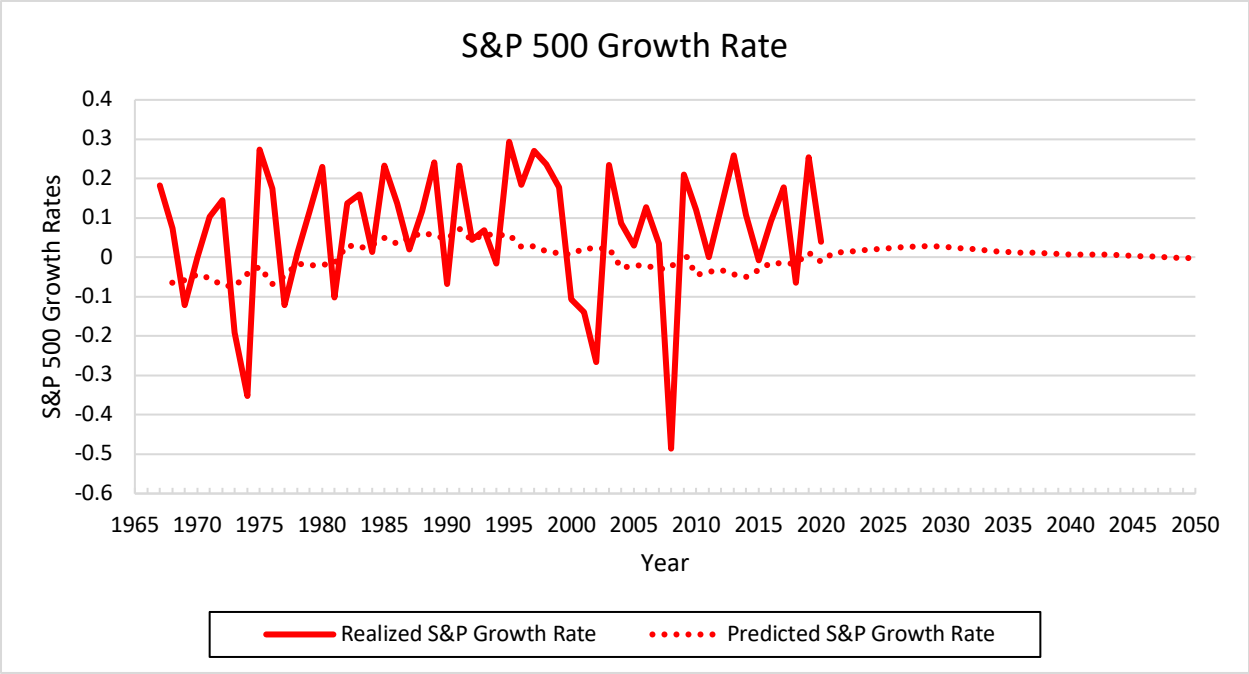
Figure 17. Subsample Realized and Predicted S&P 500 Growth Rates



d. Forecasted Growth Rates Utilizing the Simplified VECM

Since I have MY ratio projections from 2021 to 2100, I am able to forecast future S&P 500 growth rates using only the United Nations' population projections. I only forecast until 2050, since the accuracy of the population projections past a couple of decades is questionable as birth rates are moderately dependent on current economic and political circumstances. The result of this predicted forecast is displayed in Figure 18. These predictions suggest the secular bull market that started in 2016 to continue into the early 2030s. There is a break in the secular bull assumed in 2020, which is purely coincidental to the Covid-19 pandemic's effect on the global market. Though the MY ratio could have in no way been able to predict such a global crisis, it is interesting that a short-term downturn was implicitly predicted during 2020. The predictions for the S&P 500 growth rates are relatively mild in comparison to past realized rates. However, this is likely due to the weakness of the MY ratio alone to predict stock market trends without the use of other determinants.

Figure 18. Projected S&P 500 Growth Rates

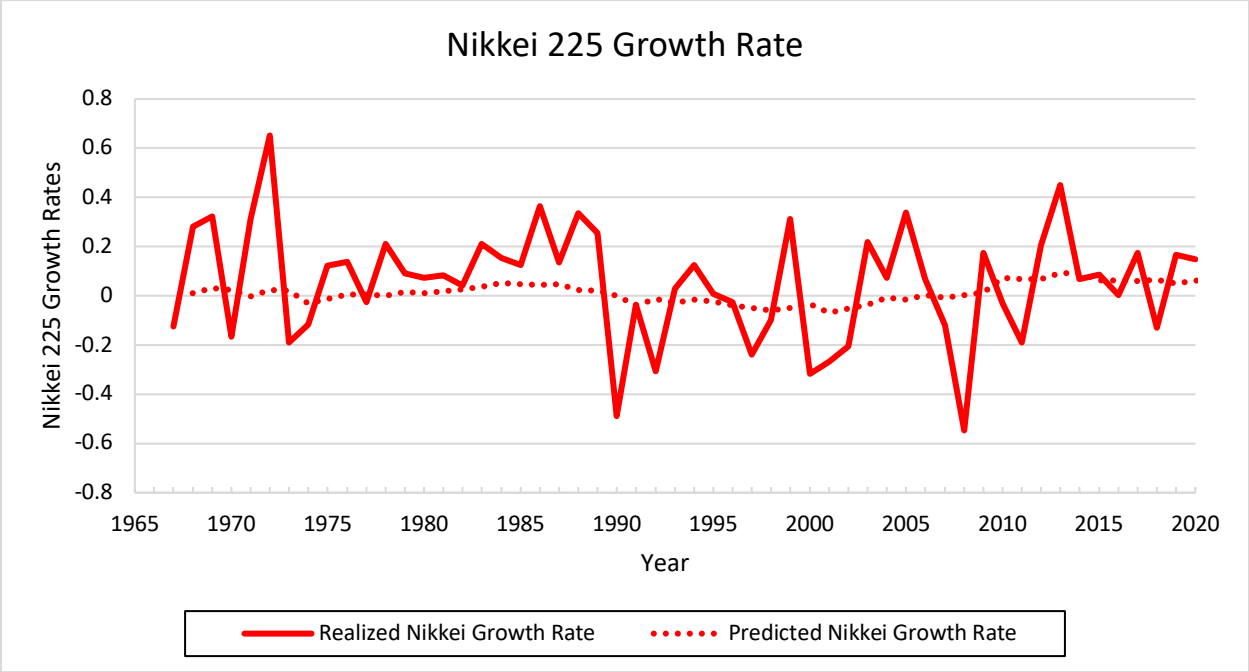


e. Japan VECM

To test the validity of my hypothesis outside of the United States, I run a VECM for Japan utilizing their MY ratio and stock market returns. Utilizing population data from the United Nations and equity pricing from Japan's largest stock market index, the Nikkei 225, I view whether a developed foreign country's economy also sees similar fluctuations at the same time as demographic changes. The results of Japan's VECM are in Appendix Table XVI. Similar to the US model, the error terms of the cointegrating model do not average around 0. Appendix Figure XI and Table XVII displays the unadjusted error terms of the cointegrating equation. I attempt to normalize the error terms by subtracting each year by the average of the errors (1.01) and display the results in Appendix Figure XII and Table XVIII. Figure 19 displays the realized and predicted Nikkei 225 growth rates utilizing only an adjusted VECM including the Japanese MY ratio and historical equity prices to form coefficients. Appendix Figure XIII displays the realized and predicted Nikkei 225 growth rates utilizing the unadjusted error terms.

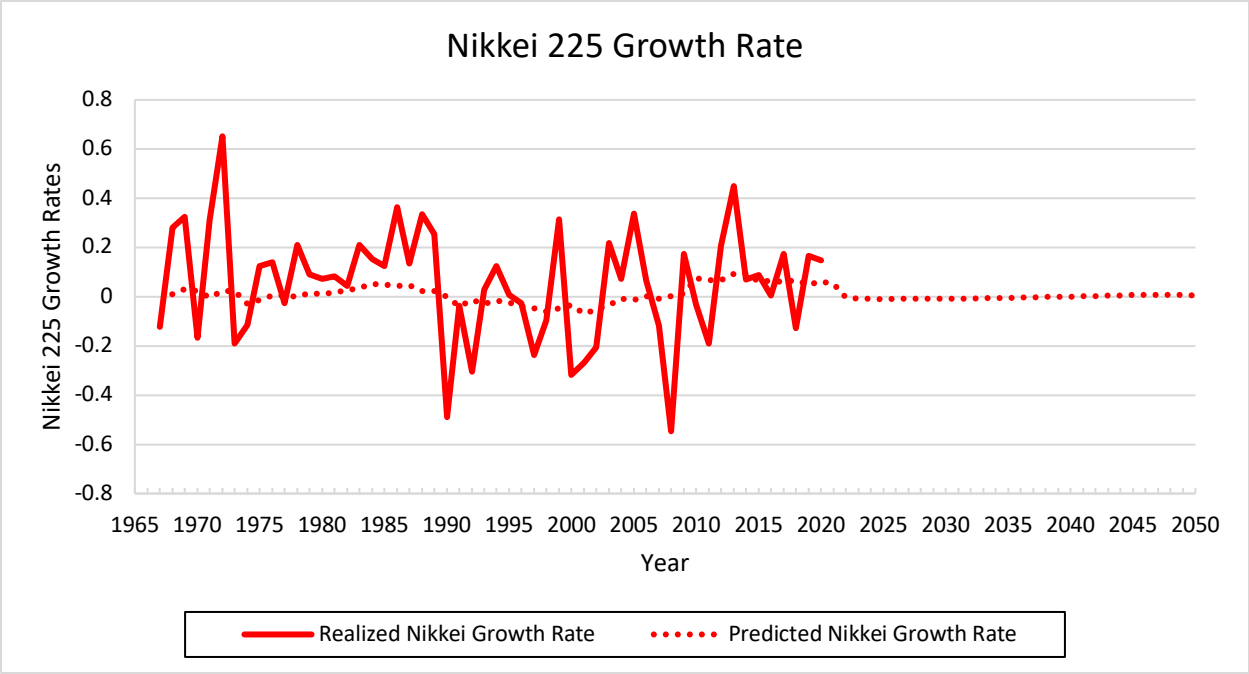
Similar to the findings for the US model in Figure 15, Figure 19 displays how Japan's MY ratio data acts as a good predictor of the long-run secular movements of the Nikkei 225.

Figure 19. Realized and Predicted Nikkei 225 Growth Rates



Using the United Nation's population data, including medium-variant predictions for Japan until 2100, I predict the next three decades of Nikkei 225 growth rates. Since the 1980s, the Japanese MY ratio has experienced less variance than the US. Due to this lack of movement, the projection of the Nikkei 225 growth rate dependent on the MY ratio flattens out after 2021. Figure 20 predicts relatively little movement or growth in Japan's equity markets. Nonetheless, Figure 20 greatly understates the likely growth rate of the Nikkei 225.

Figure 20. Projected Nikkei 225 Growth Rates



f. Further Thoughts

My conjecture for why the MY ratio has been a less accurate predictor of equity prices as of recent is all very speculative. One of the most compelling arguments is that of the aging population in most advanced economies. Japan has more dramatically experienced the effects of an aging population than the US and has for longer seen less connected long-run secular movements of the MY ratio to the Nikkei 225. In the past century, however, most developed economies have displayed similar demographic trends to Japan. Fertility rates have decreased while life expectancy has increased, causing overall population growth to decline. For this reason, I hypothesize that the US will start to follow Japan's demographic trends relatively soon. Furthermore, as citizens live longer they need to divest more of their spending into their health and move their investment cycle later in life. However, this is not necessarily true, as the average retirement age of 66 in the US has not at all increased as age expectancy has increased.

Another theory for the MY ratio's recent disconnection from stock market movements relates to the globalization and technological advancement of equity markets. Figure 9 shows that foreign direct investment has been sustained since the 2000s at levels significantly larger than in the 1980s. As markets become more accessible to global investors, domestic investors' importance may diminish over time. On the other hand, as the world globalizes, American investors have access to international markets. The S&P 500 only measures US stocks, but that does not mean US investors are only investing in US equity markets. Additionally, as technology advances and makes market trading easier and more accessible, not only do wealthy middle-aged and older investors have access to trading. Robinhood and other commission-free trading programs allow younger and less affluent tech-savvy citizens to trade nearly any stock at any time and from any market, not just American ones.

VI. Conclusion

This paper finds the MY ratio to provide a compelling case for demography's importance on equity markets. It is clear that the long-run secular moves in the MY ratio line up well with the long-run, secular moves of the S&P 500. Through examining the predictions for the MY ratio from 2020 to 2050, I believe there will likely be continued secular bull market growth in the US into the early 2030s. According to the MY ratio predictions and the average length of secular bull and bear markets, I can also surmise that a secular bear market will likely follow for about 10 to 16 years after the bull market. Thus, I believe the decades of 2030 to 2040 will likely be marked by sluggish market returns. Nevertheless, these beliefs are strictly based on the demographic predictions from the United Nations and historical performances of the S&P 500. In contrast, actual long-run market movements can dramatically alter due to long-run significant economic and political changes.

Demographics alone is not enough to forecast short-run movements in the stock market, but it is a helpful indicator to keep in mind when considering the long-run moves. Future research making use of historical data to predict long-run market returns should consider demographics as a critical component. Demographics play a role in consumer's consumption and saving behaviors. Thus, knowing the number of citizens in different age ranges can provide meaningful assumptions about individual sector performance and capital markets' index performance.

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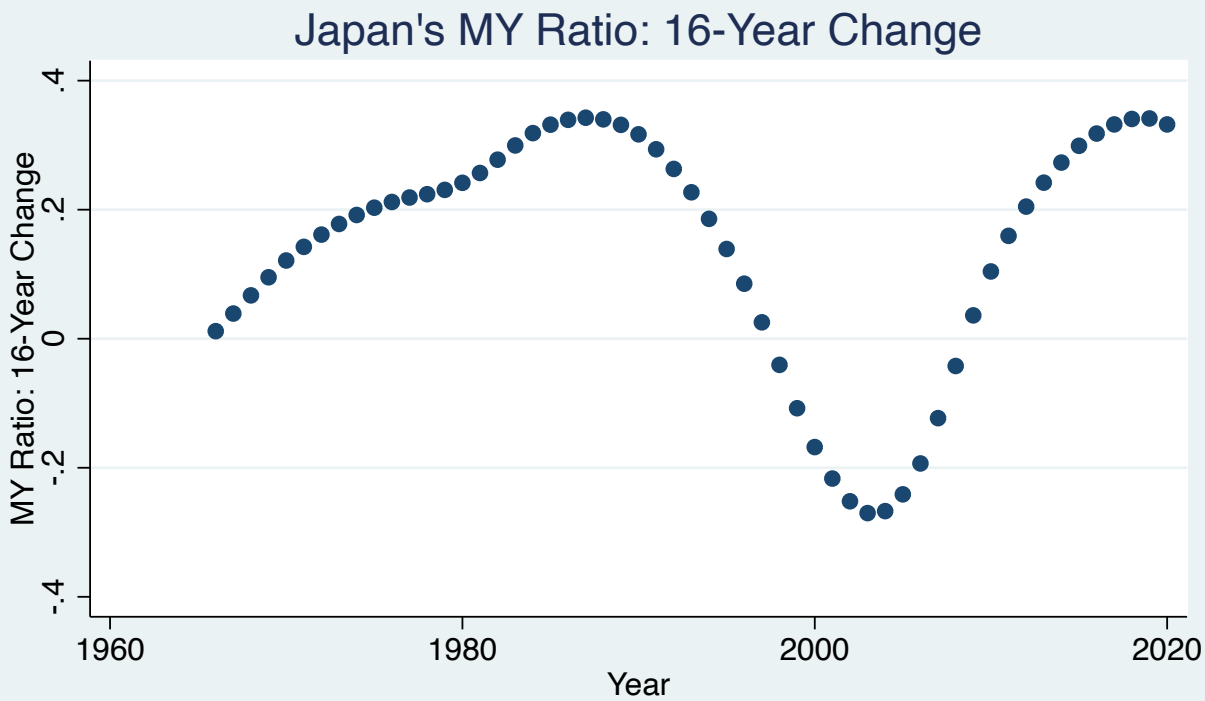
Appendix

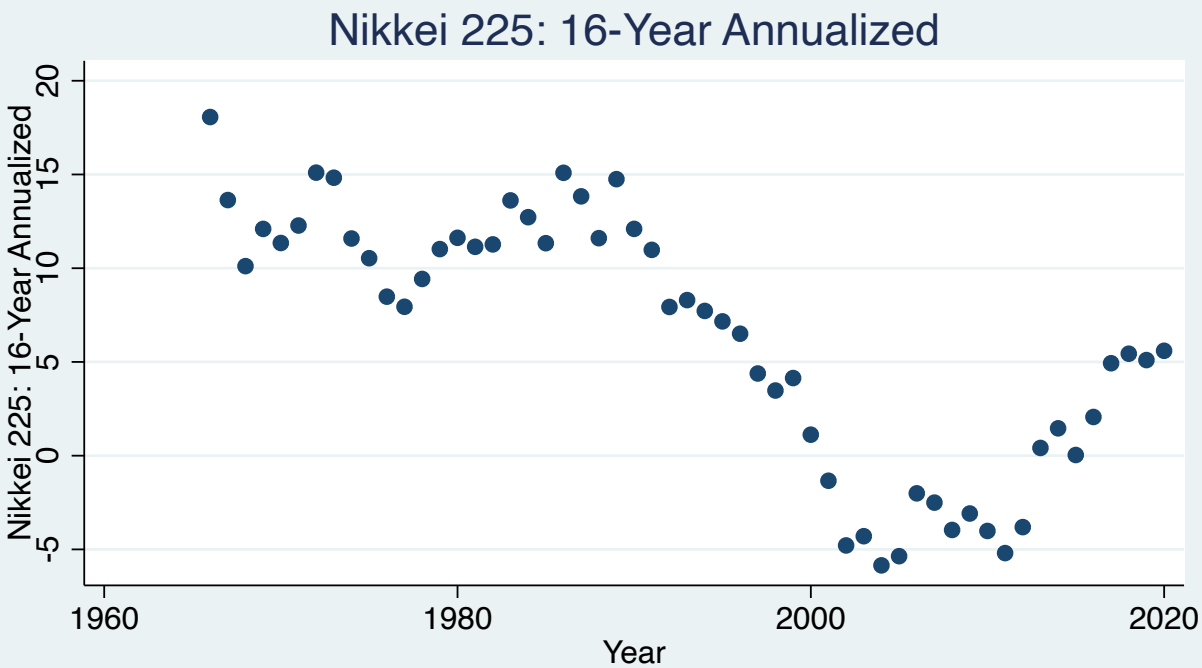
Figure I: 16-Year Change in Japan's MY Ratio



Source: United Nations

The 16-year change in the MY ratio captures the length of the average generation. The vertical axis captures the percentage change in the MY ratio year over year. Each dot represents one year.

Figure II: 16-Year Annualized Nikkei 225 Index



Source: Marco Trends

The Nikkei 225 had its greatest 16-year growth from the 1970s to the late 1980s. However, very low to negative growth occured in the 2000s. Japanese stock market growth has more recently seen an increase from these returns a decade and a half prior. Each dot represents one year.

Figure III: Simplified Model's Adjusted Error Terms

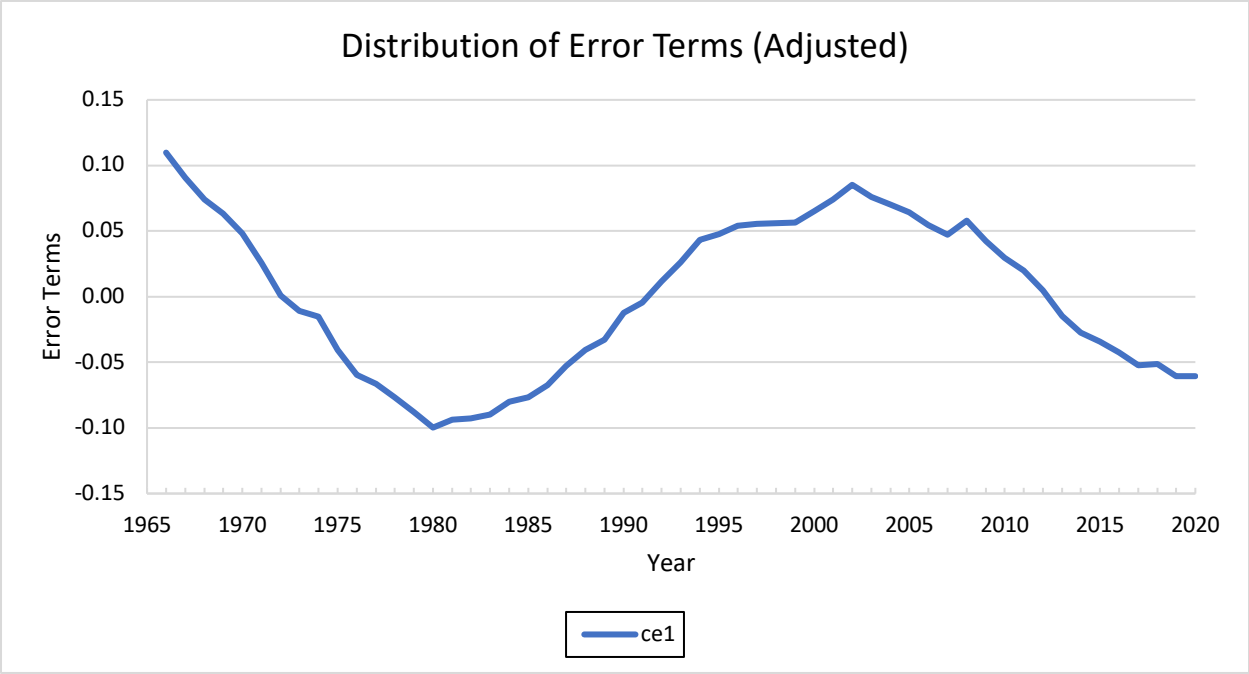


Figure IV: Simplified Model's S&P 500 Growth Rate (Unadjusted Error Terms)

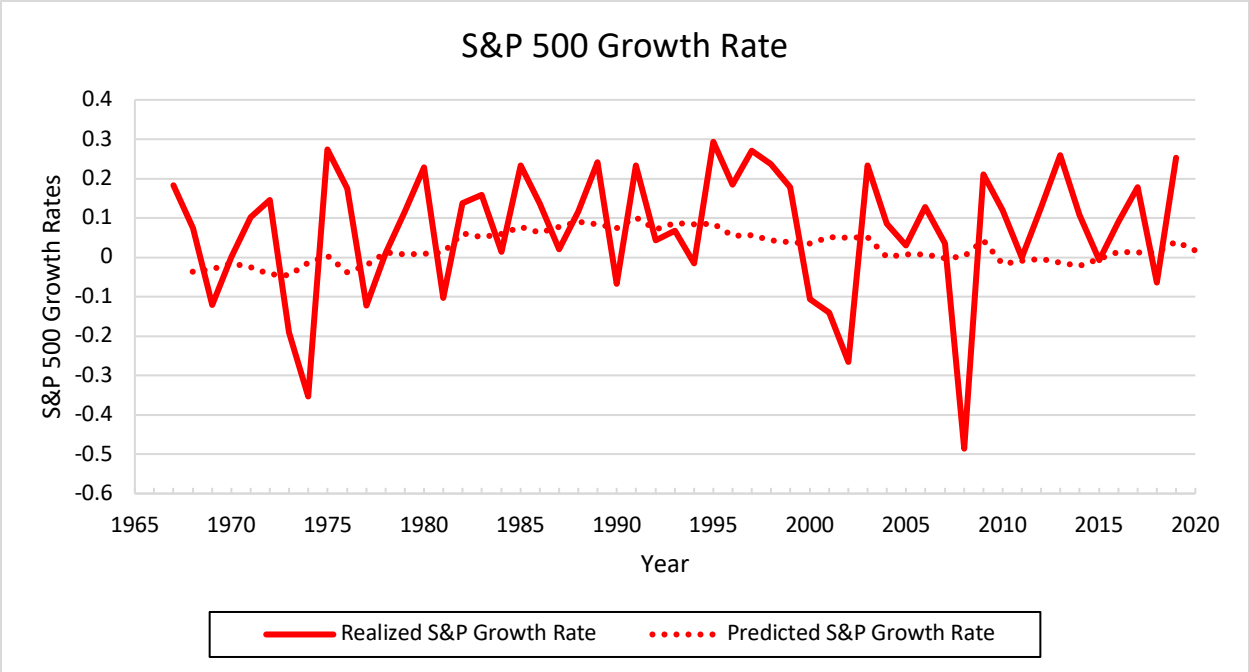


Figure V: Full Sample Model's Unadjusted Error Terms

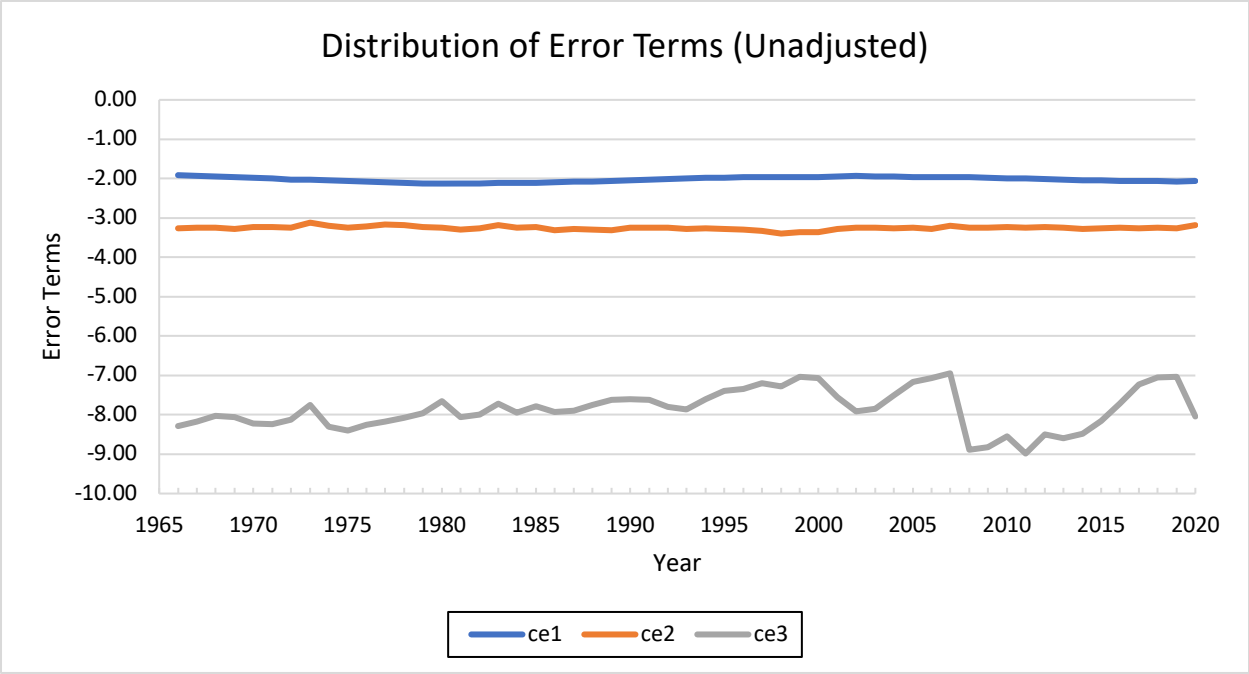


Figure VI: Full Sample Model's Adjusted Error Terms

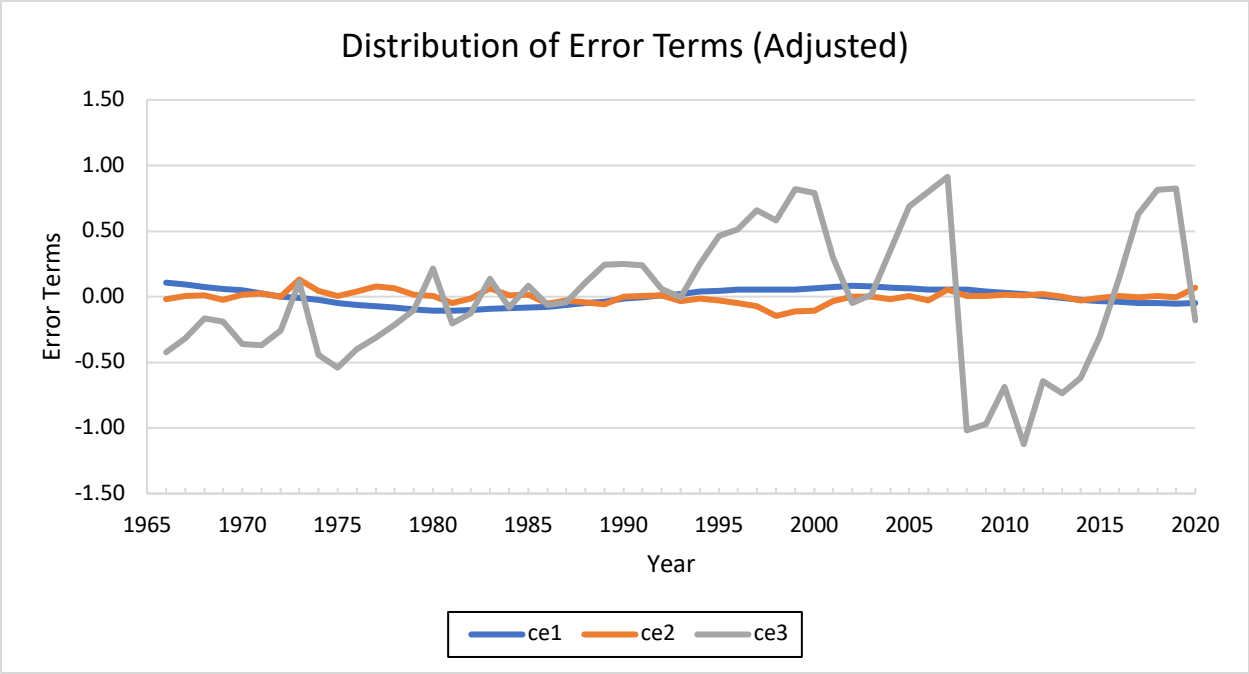


Figure VII: Full Sample Model's S&P 500 Growth Rate (Unadjusted Error Terms)

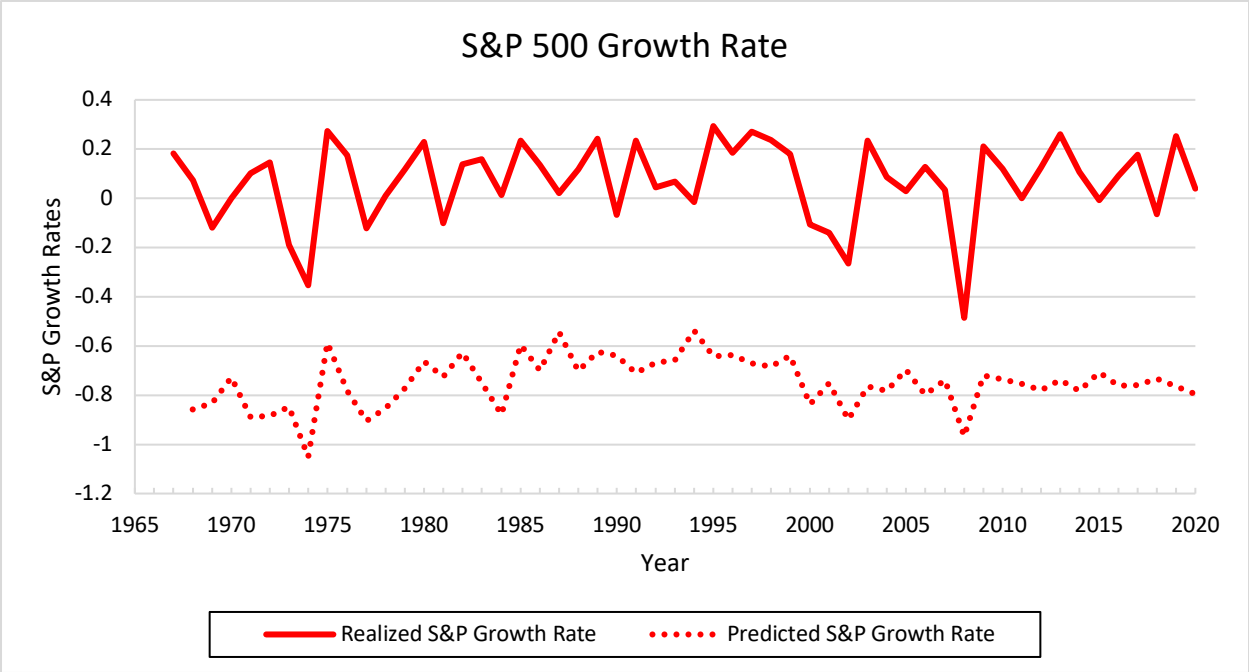


Figure VIII: Subsample Model's Unadjusted Error Terms

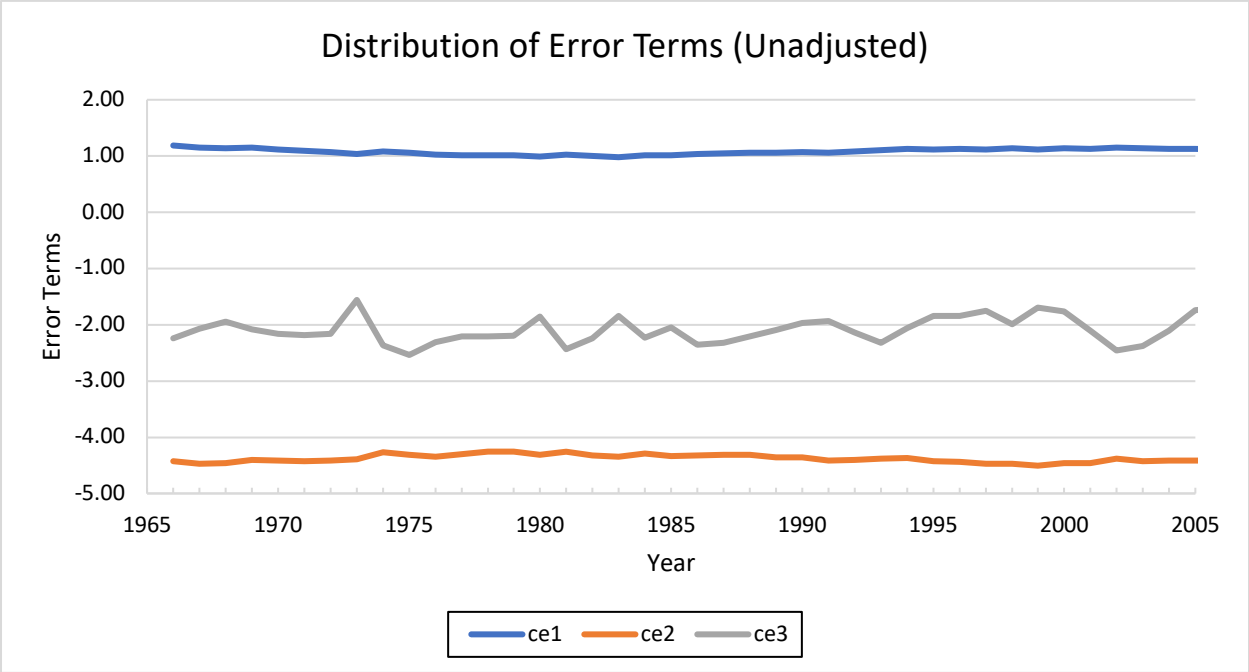


Figure IX: Subsample Model's Adjusted Error Terms

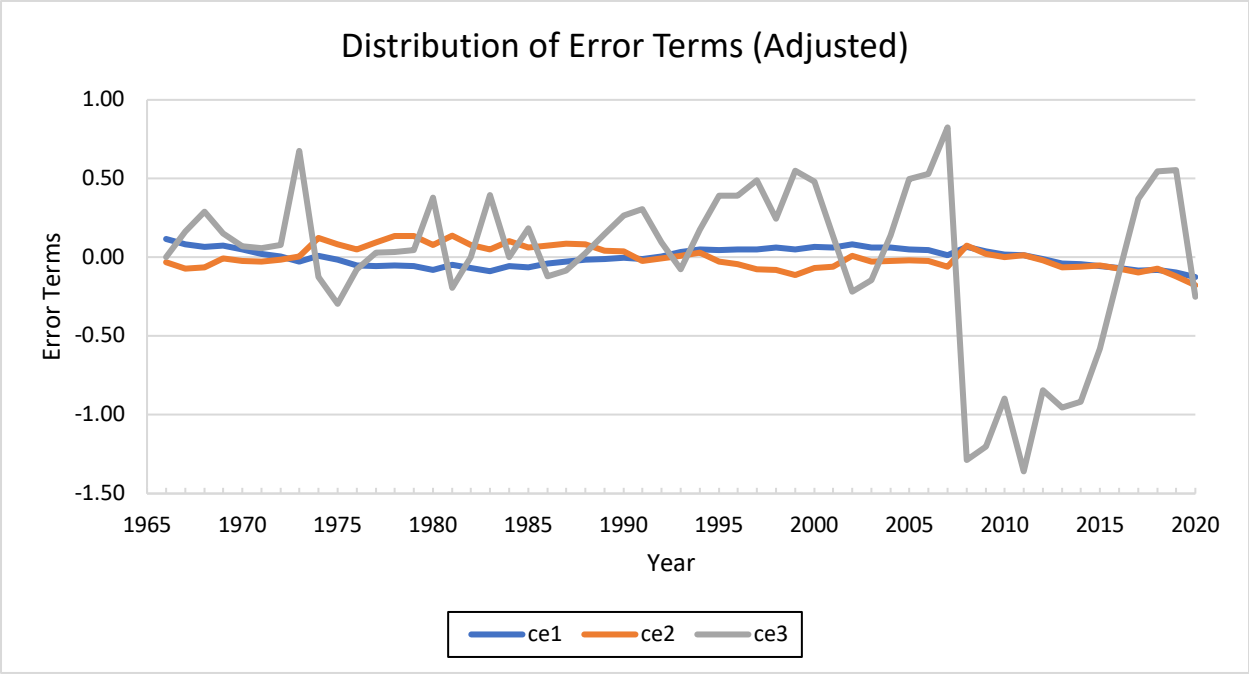


Figure X: Subsample Model's S&P 500 Growth Rate (Unadjusted Error Terms)

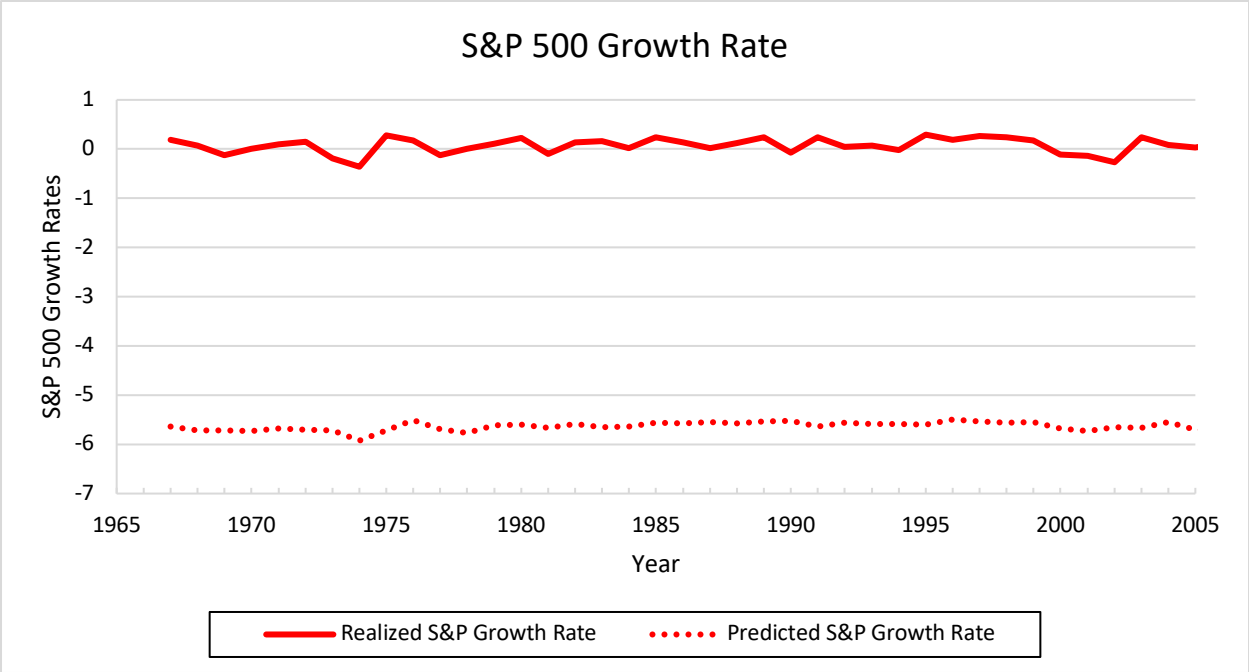


Figure XI: Japan Model's Unadjusted Error Terms

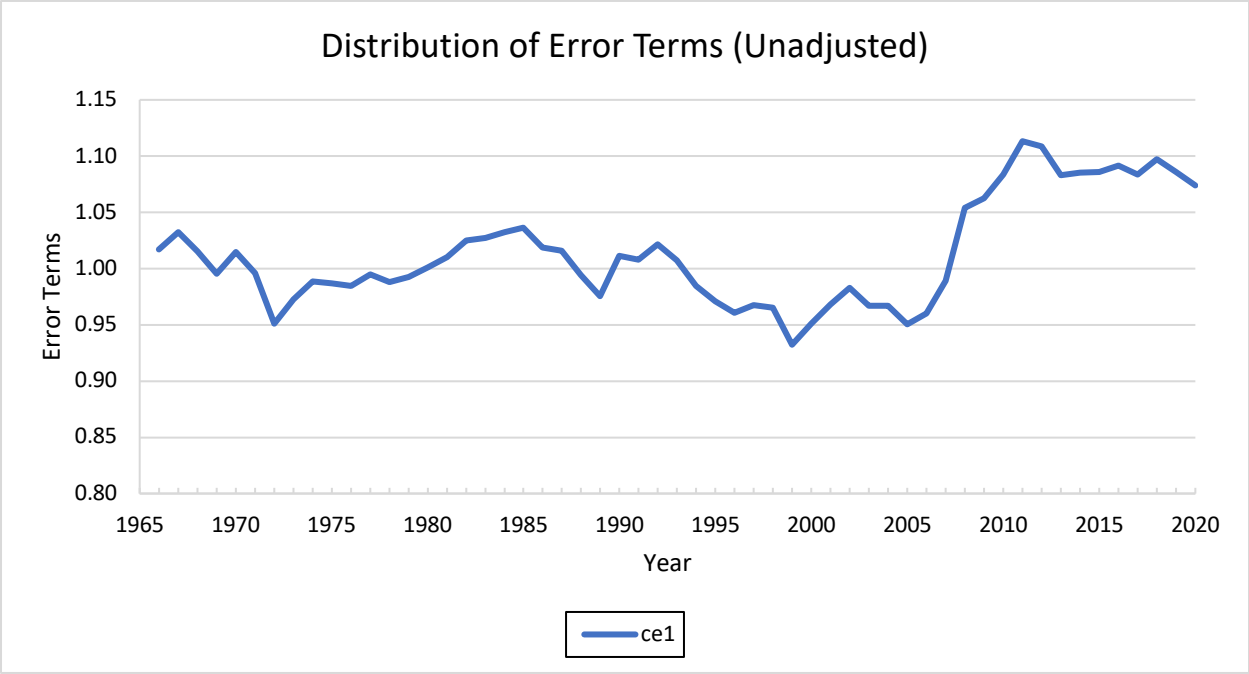


Figure XII: Japan Model's Adjusted Error Terms

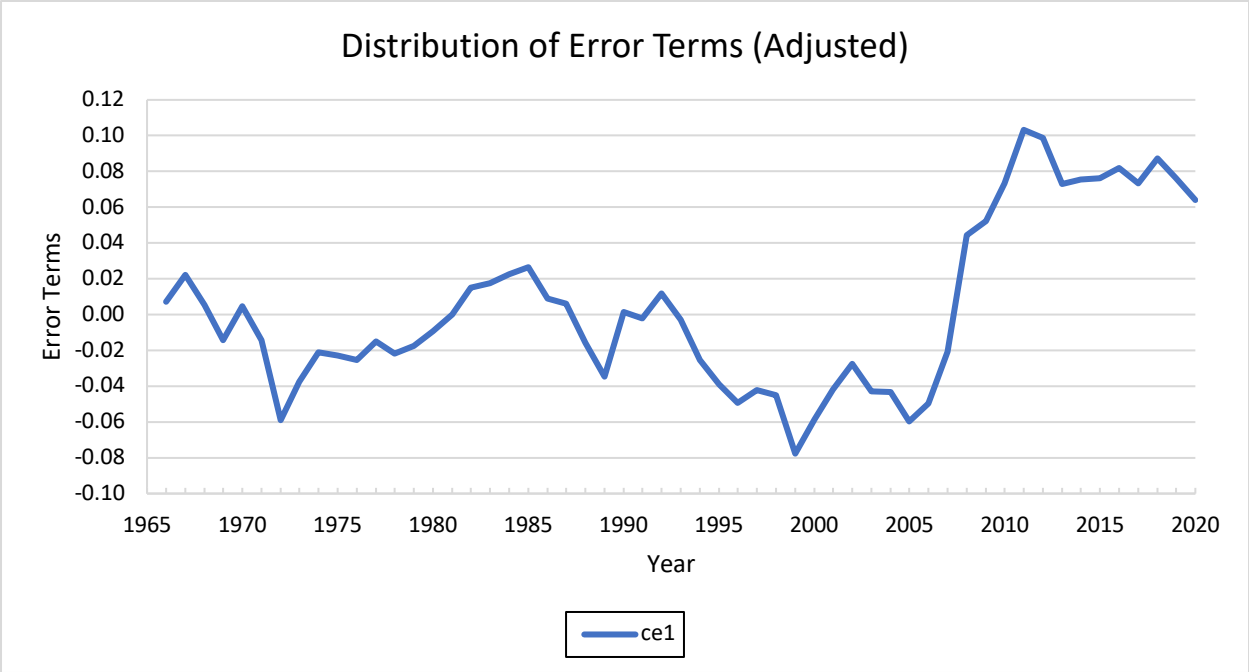


Figure XIII: Nikkei 225 Growth Rate (Unadjusted Error Terms)

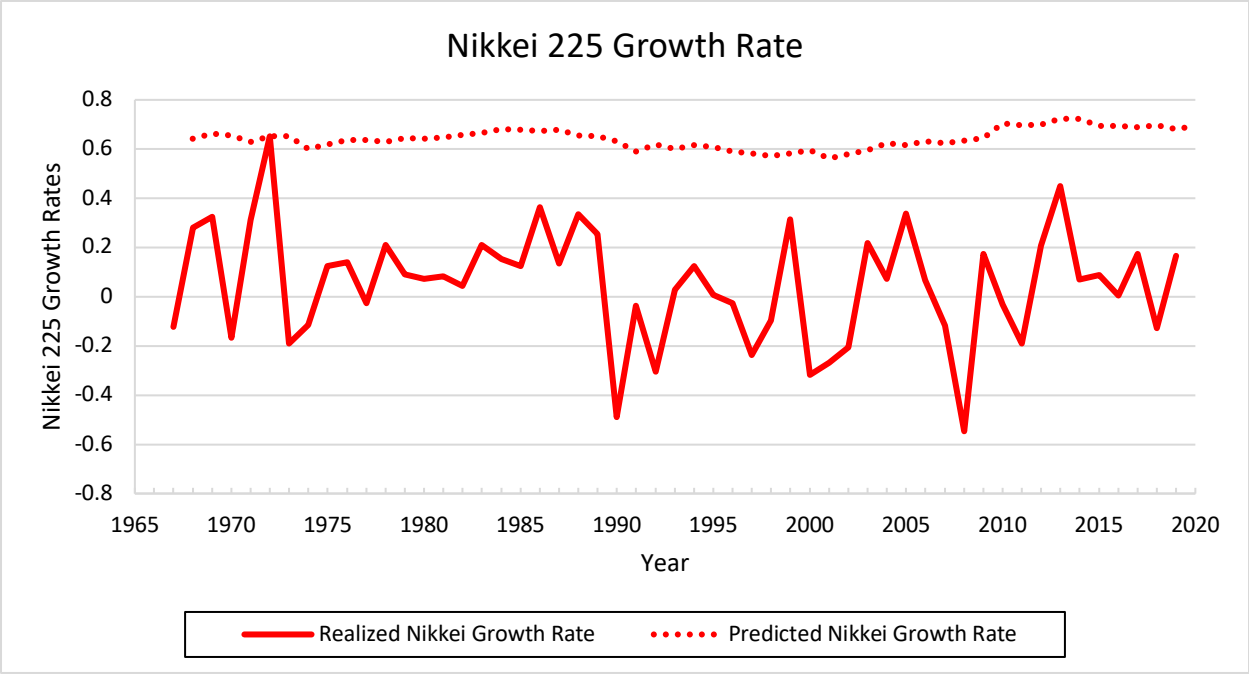


Table I: Summary Statistics, Japan's MY Ratio

Variable	N	Mean	Std. Dev.	Min	Max
Japan's MY Ratio (Middle-Aged to Young)	71	0.943815	0.2270743	0.643815	1.381922

Source: United Nations

Table II: Summary Statistics, Japan's MY Ratio

Variable	N	Mean	Std. Dev.	Min	Max
Japan's MY Ratio (Middle-Aged to Young)	55	1.023764	0.1944687	0.7141249	1.381922
16-Year Changes in Japan's MY ratio	55	0.1412273	0.1865175	-0.27038	0.3424208

Source: United Nations

Table III: Summary Statistics, Nikkei 225

Variable	N	Mean	Std. Dev.	Min	Max
Nikkei 225	71	10379.04	8829.275	101.91	38915.87

Source: Macro Trends

Table IV: Summary Statistics, Nikkei 225

Variable	N	Mean	Std. Dev.	Min	Max
Nikkei 225	55	13172.4	8106.826	1283.47	38915.87
Nikkei 225 16-Year Annualized Index	55	6.290085	6.740255	-5.853644	18.0623

Sources: Macro Trends

Table V: The Dickey-Fuller Test at Log Levels

```
. dfuller lnMY, lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =        52

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -2.741            -3.577            -2.928            -2.599
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0673

. dfuller lnSPX, lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =        52

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)              0.215            -3.577            -2.928            -2.599
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9731

. dfuller lnInt, lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =        52

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -1.178            -3.577            -2.928            -2.599
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.6828
```

```
. dfuller lnGDP, lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =        52

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -1.724            -3.577            -2.928            -2.599
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.4187

. dfuller lnReal, lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =        52

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -2.098            -3.577            -2.928            -2.599
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.2454
```

Table VI: Full Sample VECM

		Coef.	Std. Err.	z	P>|z|	[95% Confidence Interval]	
D_lnMY							
	_ce1						
	L1.	-0.0274751	0.0021719	-12.65	0	-0.0317319	-0.0232183
	_ce2						
	L1.	0.0038716	0.0037583	1.03	0.303	-0.0034944	0.0112377
	_ce3						
	L1.	0.0002588	0.0002881	0.9	0.369	-0.000306	0.0008235
	lnMY						
	LD.	0.9673606	0.0127686	75.76	0	0.9423346	0.9923866
	lnGDP						
	LD.	-0.0334715	0.0145171	-2.31	0.021	-0.0619245	-0.0050185
	lnInt						
	LD.	0.0004752	0.0004918	0.97	0.334	-0.0004888	0.0014392
	lnReal						
	LD.	0.0007907	0.0004594	1.72	0.085	-0.0001096	0.001691
	lnSPX						
	LD.	0.0015007	0.0019304	0.78	0.437	-0.0022828	0.0052842
	_cons	-0.0655175	0.004447	-14.73	0	-0.0742335	-0.0568015
D_lnGDP							
	_ce1						
	L1.	0.0119774	0.0256773	0.47	0.641	-0.0383491	0.062304
	_ce2						
	L1.	-0.0142369	0.0444332	-0.32	0.749	-0.1013243	0.0728505
	_ce3						
	L1.	-0.0073356	0.0034067	-2.15	0.031	-0.0140125	-0.0006586
	lnMY						
	LD.	0.1710349	0.15096	1.13	0.257	-0.1248411	0.466911
	lnGDP						
	LD.	0.2350629	0.1716324	1.37	0.171	-0.1013304	0.5714562
	lnInt						
	LD.	0.0003849	0.0058148	0.07	0.947	-0.011012	0.0117817
	lnReal						
	LD.	-0.0012935	0.0054308	-0.24	0.812	-0.0119378	0.0093508
	lnSPX						
	LD.	0.029384	0.0228227	1.29	0.198	-0.0153476	0.0741156
	_cons	0.0307084	0.0525762	0.58	0.559	-0.0723391	0.1337559

D_lnInt							
	_ce1						
	L1.	0.356345	0.7959148	0.45	0.654	-1.203619	1.916309
	_ce2						
	L1.	-1.53339	1.377288	-1.11	0.266	-4.232825	1.166044
	_ce3						
	L1.	-0.4431065	0.1055958	-4.2	0	-0.6500705	-0.2361425
	lnMY						
	LD.	3.896739	4.679282	0.83	0.405	-5.274485	13.06796
	lnGDP						
	LD.	8.882945	5.320061	1.67	0.095	-1.544184	19.31007
	lnInt						
	LD.	0.3872718	0.180241	2.15	0.032	0.0340059	0.7405377
	lnReal						
	LD.	0.0441248	0.1683391	0.26	0.793	-0.2858138	0.3740635
	lnSPX						
	LD.	-0.1132228	0.7074303	-0.16	0.873	-1.499761	1.273315
	_cons	-0.0052421	1.629696	0	0.997	-3.199388	3.188904
D_lnReal							
	_ce1						
	L1.	1.171617	0.762613	1.54	0.124	-0.3230766	2.666311
	_ce2						
	L1.	4.427052	1.319661	3.35	0.001	1.840564	7.013539
	_ce3						
	L1.	0.0198194	0.1011776	0.2	0.845	-0.178485	0.2181239
	lnMY						
	LD.	7.621246	4.483496	1.7	0.089	-1.166246	16.40874
	lnGDP						
	LD.	6.118854	5.097465	1.2	0.23	-3.871994	16.1097
	lnInt						
	LD.	0.0247069	0.1726996	0.14	0.886	-0.313778	0.3631918
	lnReal						
	LD.	-0.1292082	0.1612957	-0.8	0.423	-0.4453419	0.1869254
	lnSPX						
	LD.	0.1568181	0.6778307	0.23	0.817	-1.171706	1.485342
	_cons	-0.0042816	1.561508	0	0.998	-3.064781	3.056218

D_lnSPX							
	_ce1						
	L1.	0.1112713	0.1717199	0.65	0.517	-0.2252935	0.4478361
	_ce2						
	L1.	0.2738496	0.297152	0.92	0.357	-0.3085576	0.8562568
	_ce3						
	L1.	-0.0470825	0.0227825	-2.07	0.039	-0.0917353	-0.0024297
	lnMY						
	LD.	3.043637	1.009562	3.01	0.003	1.064931	5.022343
	lnGDP						
	LD.	-1.926801	1.147812	-1.68	0.093	-4.17647	0.3228686
	lnInt						
	LD.	0.0569215	0.0388873	1.46	0.143	-0.0192962	0.1331392
	lnReal						
	LD.	0.1140004	0.0363194	3.14	0.002	0.0428156	0.1851852
	lnSPX						
	LD.	0.1210411	0.1526292	0.79	0.428	-0.1781066	0.4201889
	_cons	0.0423873	0.3516095	0.12	0.904	-0.6467547	0.7315293
_ce1							
	lnMY	1	.	.	.	.	.
	lnGDP	-1.39E-17	.	.	.	.	.
	lnInt	-2.37E-18	.	.	.	.	.
	lnReal	-0.010199	0.0174413	-0.58	0.559	-0.0443832	0.0239853
	lnSPX	-0.0681183	0.0199716	-3.41	0.001	-0.1072619	-0.0289747
	_cons	-1.751107	.	.	.	.	.
_ce2							
	lnMY	0	(omitted)				
	lnGDP	1.00E+00	.	.	.	.	.
	lnInt	-6.64E-19	.	.	.	.	.
	lnReal	-0.1344742	0.0374221	-3.59	0	-0.2078202	-0.0611283
	lnSPX	-0.2407733	0.0428511	-5.62	0	-0.3247599	-0.1567867
	_cons	-6.232826	.	.	.	.	.
_ce3							
	lnMY	0	(omitted)				
	lnGDP	-4.44E-16	.	.	.	.	.
	lnInt	1	.	.	.	.	.
	lnReal	-0.3182368	0.4461817	-0.71	0.476	-1.192737	0.5562632
	lnSPX	1.460953	0.5109113	2.86	0.004	0.4595852	2.462321
	_cons	-11.25799	.	.	.	.	.

Table VII: Diagnostic Tests

Figure A: Lagrange-Multiplier Test for Serial Correlation of Errors

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	**31.9300**	**25**	**0.16005**
2	**26.8719**	**25**	**0.36231**

H0: no autocorrelation at lag order

Figure B. Tests for Normal Distribution of Errors

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_lnMY	45.300	2	0.00000
D_lnGDP	0.648	2	0.72333
D_lnInt	1.451	2	0.48419
D_lnReal	1.660	2	0.43610
D_lnSPX	2.647	2	0.26624
ALL	51.705	10	0.00000

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_lnMY	-.97145	8.336	1	0.00389
D_lnGDP	.06795	0.041	1	0.83996
D_lnInt	-.40297	1.434	1	0.23105
D_lnReal	-.33034	0.964	1	0.32620
D_lnSPX	-.5227	2.413	1	0.12030
ALL		13.189	5	0.02167

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_lnMY	7.0913	36.964	1	0.00000
D_lnGDP	3.5243	0.607	1	0.43593
D_lnInt	2.9144	0.016	1	0.89877
D_lnReal	3.5613	0.696	1	0.40418
D_lnSPX	2.675	0.233	1	0.62908
ALL		38.516	5	0.00000

Figure C. Test of Stability of Errors Using Eigenvalues

Eigenvalue stability condition

Eigenvalue	Modulus
1	1
1	1
.9733539 + .1568135*i*	.985905
.9733539 − .1568135*i*	.985905
.5331883 + .5167934*i*	.74254
.5331883 − .5167934*i*	.74254
.08524417 + .2844711*i*	.296969
.08524417 − .2844711*i*	.296969
.181523	.181523
−.02426779	.024268

The VECM specification imposes 2 unit moduli.

Table VIII: Simplified VECM

		Coef.	Std. Err.	z	P>|z|	[95% Confidence Interval]	
D_lnMY							
	_ce1						
	L1.	-0.0296109	0.0019154	-15.46	0	-0.033365	-0.0258568
	lnMY						
	LD.	0.9661475	0.0096777	99.83	0	0.9471795	0.9851154
	lnSPX						
	LD.	-0.0008502	0.0015972	-0.53	0.595	-0.0039807	0.0022803
	_cons	-0.0178859	0.0012148	-14.72	0	-0.020267	-0.0155049
D_lnSPX							
	_ce1						
	L1.	-0.1130217	0.1702005	-0.66	0.507	-0.4466086	0.2205651
	lnMY						
	LD.	1.496797	0.859956	1.74	0.082	-0.1886862	3.182279
	lnSPX						
	LD.	-0.0865391	0.1419286	-0.61	0.542	-0.3647141	0.1916358
	_cons	0.004686	0.1079502	0.04	0.965	-0.2068926	0.2162645
_ce1							
	lnMY	1	.	.	.	.	.
	lnSPX	-8.49E-02	0.0073206	-11.59	0	-0.099229	-0.0705327
	_cons	3.62E-02	.	.	.	.	.

Table IX: Simplified VECM Unadjusted Error Terms

	ce1
1966	-0.14
1967	-0.16
1968	-0.18
1969	-0.19
1970	-0.20
1971	-0.22
1972	-0.25
1973	-0.26
1974	-0.27
1975	-0.29
1976	-0.31
1977	-0.32
1978	-0.33
1979	-0.34
1980	-0.35
1981	-0.34
1982	-0.34
1983	-0.34
1984	-0.33
1985	-0.33
1986	-0.32
1987	-0.30
1988	-0.29
1989	-0.28
1990	-0.26
1991	-0.25
1992	-0.24
1993	-0.22
1994	-0.21
1995	-0.20
1996	-0.20
1997	-0.19
1998	-0.19
1999	-0.19
2000	-0.18
2001	-0.18
2002	-0.16
2003	-0.17
2004	-0.18
2005	-0.19
2006	-0.20
2007	-0.20
2008	-0.19
2009	-0.21
2010	-0.22
2011	-0.23
2012	-0.25
2013	-0.26
2014	-0.28
2015	-0.28
2016	-0.29
2017	-0.30
2018	-0.30
2019	-0.31
2020	-0.31

Table X: Simplified Model's Adjusted Error Terms

	ce1
1966	0.11
1967	0.09
1968	0.07
1969	0.06
1970	0.05
1971	0.03
1972	0.00
1973	-0.01
1974	-0.02
1975	-0.04
1976	-0.06
1977	-0.07
1978	-0.08
1979	-0.09
1980	-0.10
1981	-0.09
1982	-0.09
1983	-0.09
1984	-0.08
1985	-0.08
1986	-0.07
1987	-0.05
1988	-0.04
1989	-0.03
1990	-0.01
1991	0.00
1992	0.01
1993	0.03
1994	0.04
1995	0.05
1996	0.05
1997	0.06
1998	0.06
1999	0.06
2000	0.07
2001	0.07
2002	0.09
2003	0.08
2004	0.07
2005	0.06
2006	0.05
2007	0.05
2008	0.06
2009	0.04
2010	0.03
2011	0.02
2012	0.00
2013	-0.01
2014	-0.03
2015	-0.03
2016	-0.04
2017	-0.05
2018	-0.05
2019	-0.06
2020	-0.06

Table XI: Full Sample VECM Unadjusted Error Terms

	ce1	ce2	ce3
1966	-1.91	-3.27	-8.28
1967	-1.93	-3.25	-8.18
1968	-1.95	-3.24	-8.03
1969	-1.96	-3.27	-8.05
1970	-1.97	-3.23	-8.22
1971	-1.99	-3.23	-8.23
1972	-2.02	-3.25	-8.12
1973	-2.03	-3.12	-7.74
1974	-2.04	-3.20	-8.30
1975	-2.07	-3.25	-8.40
1976	-2.08	-3.21	-8.26
1977	-2.09	-3.17	-8.17
1978	-2.10	-3.18	-8.07
1979	-2.12	-3.23	-7.96
1980	-2.13	-3.24	-7.65
1981	-2.13	-3.30	-8.06
1982	-2.12	-3.26	-7.99
1983	-2.11	-3.19	-7.72
1984	-2.11	-3.24	-7.94
1985	-2.10	-3.24	-7.77
1986	-2.10	-3.30	-7.92
1987	-2.08	-3.28	-7.90
1988	-2.07	-3.29	-7.75
1989	-2.06	-3.31	-7.62
1990	-2.04	-3.25	-7.61
1991	-2.02	-3.24	-7.62
1992	-2.01	-3.24	-7.80
1993	-2.00	-3.28	-7.86
1994	-1.98	-3.26	-7.61
1995	-1.97	-3.28	-7.40
1996	-1.97	-3.30	-7.35
1997	-1.97	-3.32	-7.20
1998	-1.97	-3.40	-7.28
1999	-1.96	-3.36	-7.04
2000	-1.96	-3.36	-7.07
2001	-1.94	-3.28	-7.56
2002	-1.94	-3.25	-7.91
2003	-1.94	-3.25	-7.84
2004	-1.95	-3.27	-7.50
2005	-1.95	-3.25	-7.17
2006	-1.97	-3.28	-7.06
2007	-1.97	-3.20	-6.95
2008	-1.97	-3.24	-8.88
2009	-1.98	-3.25	-8.83
2010	-1.99	-3.24	-8.55
2011	-2.00	-3.24	-8.98
2012	-2.01	-3.23	-8.50
2013	-2.03	-3.25	-8.60
2014	-2.05	-3.28	-8.48
2015	-2.05	-3.26	-8.16
2016	-2.06	-3.25	-7.72
2017	-2.07	-3.26	-7.23
2018	-2.07	-3.24	-7.04
2019	-2.07	-3.26	-7.03
2020	-2.07	-3.18	-8.04

Table XII: Full Sample VECM Adjusted Error Terms

	ce1	ce2	ce3
1966	0.11	-0.02	-0.42
1967	0.09	0.00	-0.32
1968	0.07	0.01	-0.17
1969	0.06	-0.02	-0.19
1970	0.05	0.02	-0.36
1971	0.03	0.02	-0.37
1972	0.00	0.00	-0.26
1973	-0.01	0.13	0.12
1974	-0.02	0.05	-0.44
1975	-0.05	0.00	-0.54
1976	-0.06	0.04	-0.40
1977	-0.07	0.08	-0.31
1978	-0.08	0.07	-0.21
1979	-0.10	0.02	-0.10
1980	-0.11	0.01	0.21
1981	-0.11	-0.05	-0.20
1982	-0.10	-0.01	-0.13
1983	-0.09	0.06	0.14
1984	-0.09	0.01	-0.08
1985	-0.08	0.01	0.09
1986	-0.08	-0.05	-0.06
1987	-0.06	-0.03	-0.04
1988	-0.05	-0.04	0.11
1989	-0.04	-0.06	0.24
1990	-0.02	0.00	0.25
1991	0.00	0.01	0.24
1992	0.01	0.01	0.06
1993	0.02	-0.03	0.00
1994	0.04	-0.01	0.25
1995	0.05	-0.03	0.46
1996	0.05	-0.05	0.51
1997	0.05	-0.07	0.66
1998	0.05	-0.15	0.58
1999	0.06	-0.11	0.82
2000	0.06	-0.11	0.79
2001	0.08	-0.03	0.30
2002	0.08	0.00	-0.05
2003	0.08	0.00	0.02
2004	0.07	-0.02	0.36
2005	0.07	0.00	0.69
2006	0.05	-0.03	0.80
2007	0.05	0.05	0.91
2008	0.05	0.01	-1.02
2009	0.04	0.00	-0.97
2010	0.03	0.01	-0.69
2011	0.02	0.01	-1.12
2012	0.01	0.02	-0.64
2013	-0.01	0.00	-0.74
2014	-0.03	-0.03	-0.62
2015	-0.03	-0.01	-0.30
2016	-0.04	0.00	0.14
2017	-0.05	-0.01	0.63
2018	-0.05	0.01	0.82
2019	-0.05	-0.01	0.83
2020	-0.05	0.07	-0.18

Table XIII: Subsample VECM

		Coef.	Std. Err.	z	P>|z|	[95% Confidence Interval]	
D_lnMY							
	_ce1						
	L1.	-0.0298022	0.0076709	-3.89	0	-0.0448368	-0.0147675
	_ce2						
	L1.	0.0060371	0.0074842	0.81	0.42	-0.0086317	0.0207059
	_ce3						
	L1.	0.0008737	0.0012383	0.71	0.48	-0.0015533	0.0033006
	lnMY						
	LD.	0.9678486	0.0114622	84.44	0	0.9453832	0.9903141
	lnGDP						
	LD.	-0.0438983	0.0187823	-2.34	0.019	-0.080711	-0.0070857
	lnInt						
	LD.	0.0011148	0.0012785	0.87	0.383	-0.0013911	0.0036207
	lnReal						
	LD.	0.0012276	0.0005344	2.3	0.022	0.0001801	0.002275
	lnSPX						
	LD.	0.0026233	0.0025388	1.03	0.301	-0.0023526	0.0075992
	_cons	0.0233421	0.0017999	12.97	0	0.0198145	0.0268698
D_lnGDP							
	_ce1						
	L1.	-0.1246672	0.0802435	-1.55	0.12	-0.2819415	0.0326071
	_ce2						
	L1.	-0.1468646	0.078291	-1.88	0.061	-0.3003122	0.006583
	_ce3						
	L1.	-0.0324247	0.0129532	-2.5	0.012	-0.0578125	-0.0070368
	lnMY						
	LD.	0.0448303	0.1199035	0.37	0.708	-0.1901762	0.2798368
	lnGDP						
	LD.	0.0171504	0.1964781	0.09	0.93	-0.3679396	0.4022403
	lnInt						
	LD.	0.0037821	0.0133746	0.28	0.777	-0.0224317	0.0299958
	lnReal						
	LD.	-0.0017682	0.0055904	-0.32	0.752	-0.0127251	0.0091888
	lnSPX						
	LD.	0.0206161	0.0265576	0.78	0.438	-0.0314358	0.0726679
	_cons	0.036818	0.018828	1.96	0.051	-0.0000841	0.0737201

D_lnInt							
	_ce1						
	L1.	-0.9213157	1.194995	-0.77	0.441	-3.263463	1.420832
	_ce2						
	L1.	-1.693983	1.165919	-1.45	0.146	-3.979143	0.5911765
	_ce3						
	L1.	-0.7496877	0.1929006	-3.89	0	-1.127766	-0.3716095
	lnMY						
	LD.	-0.9208915	1.785617	-0.52	0.606	-4.420636	2.578853
	lnGDP						
	LD.	4.331769	2.925975	1.48	0.139	-1.403036	10.06657
	lnInt						
	LD.	0.5638704	0.1991763	2.83	0.005	0.1734921	0.9542487
	lnReal						
	LD.	-0.1174848	0.0832525	-1.41	0.158	-0.2806567	0.0456871
	lnSPX						
	LD.	0.6597927	0.3954984	1.67	0.095	-0.1153699	1.434955
	_cons	-0.0030615	0.2803881	-0.01	0.991	-0.5526121	0.5464891
D_lnReal							
	_ce1						
	L1.	1.643654	2.904635	0.57	0.571	-4.049327	7.336635
	_ce2						
	L1.	3.072368	2.833961	1.08	0.278	-2.482093	8.626829
	_ce3						
	L1.	0.9072949	0.4688771	1.94	0.053	-0.0116872	1.826277
	lnMY						
	LD.	-3.644677	4.340239	-0.84	0.401	-12.15139	4.862036
	lnGDP						
	LD.	11.04047	7.112069	1.55	0.121	-2.898933	24.97987
	lnInt						
	LD.	-0.4097975	0.4841311	-0.85	0.397	-1.358677	0.539082
	lnReal						
	LD.	-0.2632202	0.2023591	-1.3	0.193	-0.6598368	0.1333964
	lnSPX						
	LD.	0.0416955	0.9613248	0.04	0.965	-1.842466	1.925857
	_cons	-0.0016203	0.6815301	0	0.998	-1.337395	1.334154

D_lnSPX							
	_ce1						
	L1.	1.685415	0.5201274	3.24	0.001	0.6659843	2.704846
	_ce2						
	L1.	1.662294	0.5074719	3.28	0.001	0.6676671	2.65692
	_ce3						
	L1.	0.1143614	0.0839609	1.36	0.173	-0.0501989	0.2789218
	lnMY						
	LD.	1.143919	0.7771982	1.47	0.141	-0.3793616	2.6672
	lnGDP						
	LD.	0.8666457	1.273545	0.68	0.496	-1.629456	3.362747
	lnInt						
	LD.	-0.1219472	0.0866924	-1.41	0.16	-0.2918612	0.0479668
	lnReal						
	LD.	0.0161501	0.0362361	0.45	0.656	-0.0548713	0.0871715
	lnSPX						
	LD.	0.4322515	0.1721426	2.51	0.012	0.0948583	0.7696447
	_cons	0.0030422	0.1220403	0.02	0.98	-0.2361523	0.2422368
_ce1							
	lnMY	1	.	.	.	.	.
	lnGDP	0.00E+00	(omitted)				
	lnInt	6.94E-18	.	.	.	.	.
	lnReal	0.0403058	0.016827	2.4	0.017	0.0073254	0.0732861
	lnSPX	-0.155935	0.021208	-7.35	0	-0.1975019	-0.1143681
	_cons	1.430023	.	.	.	.	.
_ce2							
	lnMY	1.11E-16	.	.	.	.	.
	lnGDP	1.00E+00	.	.	.	.	.
	lnInt	-1.04E-17	.	.	.	.	.
	lnReal	0.0593426	0.0229353	2.59	0.01	0.0143902	0.104295
	lnSPX	-0.5136754	0.0289066	-17.77	0	-0.5703314	-0.4570195
	_cons	-7.200476	.	.	.	.	.
_ce3							
	lnMY	0	(omitted)				
	lnGDP	4.44E-16	.	.	.	.	.
	lnInt	1	.	.	.	.	.
	lnReal	-0.6291105	0.1284057	-4.9	0	-0.8807811	-0.37744
	lnSPX	1.365266	0.1618367	8.44	0	1.048072	1.68246
	_cons	-4.501804	.	.	.	.	.

Table XIV: Subsample VECM Unadjusted Error Terms

	ce1	ce2	ce3
1966	1.19	-4.43	-2.24
1967	1.15	-4.47	-2.07
1968	1.14	-4.46	-1.95
1969	1.15	-4.40	-2.09
1970	1.12	-4.42	-2.17
1971	1.09	-4.42	-2.18
1972	1.08	-4.41	-2.16
1973	1.04	-4.39	-1.56
1974	1.08	-4.27	-2.36
1975	1.06	-4.31	-2.53
1976	1.02	-4.35	-2.31
1977	1.02	-4.30	-2.21
1978	1.02	-4.26	-2.20
1979	1.01	-4.26	-2.19
1980	0.99	-4.32	-1.86
1981	1.02	-4.26	-2.43
1982	1.00	-4.32	-2.24
1983	0.98	-4.35	-1.84
1984	1.01	-4.29	-2.24
1985	1.01	-4.33	-2.05
1986	1.03	-4.32	-2.36
1987	1.04	-4.31	-2.32
1988	1.06	-4.31	-2.21
1989	1.06	-4.35	-2.09
1990	1.07	-4.36	-1.97
1991	1.06	-4.42	-1.93
1992	1.08	-4.40	-2.14
1993	1.10	-4.39	-2.32
1994	1.12	-4.36	-2.06
1995	1.12	-4.42	-1.85
1996	1.12	-4.44	-1.85
1997	1.12	-4.47	-1.75
1998	1.13	-4.47	-1.99
1999	1.12	-4.51	-1.69
2000	1.14	-4.46	-1.76
2001	1.13	-4.46	-2.10
2002	1.15	-4.39	-2.46
2003	1.13	-4.42	-2.38
2004	1.13	-4.42	-2.10
2005	1.12	-4.42	-1.74

Table XV: Subsample VECM Adjusted Error Terms

	ce1	ce2	ce3
1966	0.12	-0.03	0.00
1967	0.08	-0.07	0.17
1968	0.07	-0.06	0.29
1969	0.08	-0.01	0.15
1970	0.05	-0.02	0.07
1971	0.02	-0.03	0.06
1972	0.01	-0.01	0.08
1973	-0.03	0.00	0.68
1974	0.01	0.12	-0.13
1975	-0.01	0.08	-0.30
1976	-0.05	0.05	-0.08
1977	-0.05	0.09	0.03
1978	-0.05	0.14	0.03
1979	-0.06	0.14	0.04
1980	-0.08	0.08	0.38
1981	-0.05	0.14	-0.19
1982	-0.07	0.08	0.00
1983	-0.09	0.05	0.40
1984	-0.06	0.10	0.00
1985	-0.06	0.06	0.19
1986	-0.04	0.07	-0.12
1987	-0.03	0.09	-0.09
1988	-0.01	0.08	0.03
1989	-0.01	0.04	0.15
1990	0.00	0.04	0.27
1991	-0.01	-0.02	0.31
1992	0.01	-0.01	0.09
1993	0.03	0.01	-0.08
1994	0.05	0.03	0.18
1995	0.05	-0.03	0.39
1996	0.05	-0.04	0.39
1997	0.05	-0.08	0.49
1998	0.06	-0.08	0.24
1999	0.05	-0.11	0.55
2000	0.07	-0.07	0.48
2001	0.06	-0.06	0.13
2002	0.08	0.01	-0.22
2003	0.06	-0.03	-0.15
2004	0.06	-0.02	0.14
2005	0.05	-0.02	0.50

Table XVI: Japan VECM

D_lnJPMY							
	_ce1						
	L1.	-0.0368045	0.0061309	-6	0	-0.0488208	-0.0247882
	lnJPMY						
	LD.	1.048895	0.0303055	34.61	0	0.9894971	1.108292
	lnNIK						
	LD.	-0.0012628	0.0026518	-0.48	0.634	-0.0064603	0.0039347
	_cons	0.0019555	0.0007553	2.59	0.01	0.0004751	0.0034359
D_lnNIK							
	_ce1						
	L1.	0.6244651	0.3183488	1.96	0.05	0.0005129	1.248417
	lnJPMY						
	LD.	0.5474728	1.573627	0.35	0.728	-2.536779	3.631725
	lnNIK						
	LD.	0.0780181	0.137698	0.57	0.571	-0.191865	0.3479012
	_cons	0.0001152	0.0392197	0	0.998	-0.076754	0.0769845
_ce1							
	lnJPMY	1	.	.	.	.	.
	lnNIK	-1.80E-01	0.0199621	-9.01	0	-0.2188973	-0.1406475
	_cons	1.73E+00	.	.	.	.	.

Table XVII: Japan VECM Unadjusted Error Terms

	ce1
1966	1.02
1967	1.03
1968	1.02
1969	1.00
1970	1.01
1971	1.00
1972	0.95
1973	0.97
1974	0.99
1975	0.99
1976	0.98
1977	1.00
1978	0.99
1979	0.99
1980	1.00
1981	1.01
1982	1.03
1983	1.03
1984	1.03
1985	1.04
1986	1.02
1987	1.02
1988	0.99
1989	0.98
1990	1.01
1991	1.01
1992	1.02
1993	1.01
1994	0.98
1995	0.97
1996	0.96
1997	0.97
1998	0.97
1999	0.93
2000	0.95
2001	0.97
2002	0.98
2003	0.97
2004	0.97
2005	0.95
2006	0.96
2007	0.99
2008	1.05
2009	1.06
2010	1.08
2011	1.11
2012	1.11
2013	1.08
2014	1.09
2015	1.09
2016	1.09
2017	1.08
2018	1.10
2019	1.09
2020	1.07

Table XVIII: Japan VECM Adjusted Error Terms

	ce1
1966	0.01
1967	0.02
1968	0.01
1969	-0.01
1970	0.00
1971	-0.01
1972	-0.06
1973	-0.04
1974	-0.02
1975	-0.02
1976	-0.03
1977	-0.01
1978	-0.02
1979	-0.02
1980	-0.01
1981	0.00
1982	0.02
1983	0.02
1984	0.02
1985	0.03
1986	0.01
1987	0.01
1988	-0.02
1989	-0.03
1990	0.00
1991	0.00
1992	0.01
1993	0.00
1994	-0.03
1995	-0.04
1996	-0.05
1997	-0.04
1998	-0.04
1999	-0.08
2000	-0.06
2001	-0.04
2002	-0.03
2003	-0.04
2004	-0.04
2005	-0.06
2006	-0.05
2007	-0.02
2008	0.04
2009	0.05
2010	0.07
2011	0.10
2012	0.10
2013	0.07
2014	0.08
2015	0.08
2016	0.08
2017	0.07
2018	0.09
2019	0.08
2020	0.06