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ABSTRACT

A central challenge in asset pricing is the weak connection between stock returns and observable economic fundamentals. We provide evidence that this connection is stronger than previously thought. We use a modified version of the Bry-Boschan algorithm to identify long-run swings in the stock market. We call these swings long-run bull and bear episodes. We find that there is a high correlation between stock returns and fundamentals across bull and bear episodes. This correlation is much higher than the analogous time-series correlations. We show that several asset pricing models cannot simultaneously account for the low time-series and high episode correlations.

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1. Introduction

Consumption-based asset pricing models in the tradition of Lucas (1978) and Breedan (1979) emphasize the theoretical link between asset returns and economic fundamentals, such as consumption growth. Much of the empirical literature has tested these theories using annual, quarterly, and higher frequency data. Classic examples include Shiller (1981), Hansen and Singleton (1982), and Mehra and Prescott (1985). A central challenge that has emerged from this work is the apparent weak relation between stock returns and observable economic fundamentals.

In this paper, we re-examine this relation using an empirical strategy inspired by Burns and Mitchell's (1946) work on business cycles which uses expansions and recessions as the basic unit of analysis.[1] In this spirit, we investigate whether the elusive relation between economic fundamentals and asset prices emerges more clearly across long-run bull and bear episodes.

We begin by reproducing the standard finding that consumption and output growth are weakly correlated with stock returns. We then use a modified version of the algorithm developed by Bry and Boschan (1971) to identify peaks and troughs in long-run stock market trends. We call "bulls" the episodes that occur between a trough and a peak and "bears" the episodes that occur between a peak and a trough. These bull and bear episodes are identified using *only* stock market data. We find that the correlation between stock returns and fundamentals across bull and bear episodes is much higher (about twice as high) than the time-series correlations. This finding holds for the U.S., G7, and OECD countries.

As a check on our procedure, we also date episodes using only consumption data or only output data rather than stock returns. Once again, we find that for the U.S., G7, and OECD countries, the correlation between stock returns and fundamentals across bull and bear episodes is much higher than the time-series correlations.

Our results are consistent with the idea that fundamentals do not drive stock prices at short and even relatively long periods of time. from period to period. But over the course of episodes sparked by major technological, military or political events, stock prices do reflect fundamentals.

We investigate whether this new fact–episode correlations between stock returns and fundamentals are much stronger than time-series correlations–is consistent with three asset-

[1] Stock (1987) pursues a modern version of this approach.

pricing models. The first is the external-habit model proposed by Campbell and Cochrane (1999). The second is the long-run risk model proposed by Bansal, Kiku and Yaron (2012). The third is the valuation-risk model proposed by Albuquerque, Eichenbaum, Luo, and Rebelo (2014). We find that none of these models can explain our basic fact.

Both the external-habit model and the long-run risk model do well at accounting for the high episode correlations. However, they imply time-series correlations between stock returns and consumption growth which are too high relative to the data, even taking sampling uncertainty into account. This result holds at the one-, five-, ten- and 15-year horizons. As stressed in Albuquerque, Eichenbaum, Luo, and Rebelo (2014), this shortcoming reflects the fact that the only source of uncertainty in those models comes from the production side of the economy. The valuation-risk model of Albuquerque, Eichenbaum, Luo, and Rebelo (2014) accounts for the time-series correlations at all horizons when sampling uncertainty is taken into consideration. However, the model fails to account for the high episode correlations.

We investigate whether the difference between the time-series and episode correlations might be an artifact of the historical sample that we have at our disposal. At least for the U.S., this possibility seems very unlikely. The evidence is somewhat more mixed for the G7 and OECD countries.

We redo our analysis using dividends and earnings as alternative measures of fundamentals. Our results for earnings growth are similar to those that we obtain with consumption and output growth. The results with dividend growth are more nuanced. Dividend growth is uncorrelated with stock returns at a yearly frequency. However, these series are correlated at the 5- 10- and 15-year horizon, with a point estimate of roughly 0.5. There is a great deal of sampling uncertainty associated with the episode correlation so that one can't reject the hypothesis that the episode and the long-horizon correlations are the same. A similar pattern emerges for the G7 countries.[2]

Considering the evidence as a whole, we are left with a puzzle: why is the correlation between stock returns and fundamentals much stronger across bull and bear episodes than the time-series correlations?

Our paper is organized as follows. In section 2 we describe our modified version of the Bry-Boschan filter, the data we use, and our empirical results. Section 3 describes the three asset-pricing models we consider and their implications for time-series and episode

[2] We cannot do this analysis for OECD countries because of data availability.

correlations between stock returns and fundamentals. Section 4 concludes.

2. Measuring long-run booms and busts

There is a long tradition of characterizing turning points in economic time series that goes back at least to the work of Burns and Mitchell (1946) on dating business cycles. This tradition gave rise to a large literature that uses time-series methods to estimate turning points (see Stock and Watson (2010) and the references therein). An early, important contribution to this literature is Bry and Boschan (1971) who develop an algorithm for dating the beginnings and ends of recessions. This algorithm has recently been used to characterize high-frequency bull and bear stock markets (see e.g. Pagan and Sossounov (2002) and Gonzalez, Powel, Shi and Wilson (2005)).

This paper focuses on low-frequency swings in the stock market which we refer to as long-run bulls and bears. The solid line in Figure 1 displays an annual index of U.S. stock prices for the time period 1869 to 2013. It is evident that there are periods of irregular length in which stock prices are dominated by either upward or downward movements. To determine the turning points that mark the beginning and end of long-run bulls and bears, we develop a modified version of the Bry and Boschan (1971) algorithm.

The remainder of this section is organized as follows. In subsection 2.1, we describe the modified Bry-Boschan (1971) algorithm. In subsection 2.2 we describe the data we use. In subsection 2.3 we apply the algorithm to U.S. data and discuss historical events around the identified turning points. In subsection 2.4 we revisit a classic question in asset pricing: what is the correlation between fundamentals (consumption and output growth) and realized returns to the stock market? We also extend our basic analysis to G7 and OECD countries. In subsection 2.5 we pursue an alternative strategy for dating long-run bulls and bears, which relies on consumption and output data. In subsection 2.6 we conduct tests to assess whether our results are spurious in the sense of being an artifact of the filter that we use to date bull and bear episodes. We also discuss the possibility that our results might reflect small-sample bias.

2.1. A modified Bry-Boschan algorithm

The Bry and Boschan (1971) algorithm is a series of ad-hoc filters designed to determine turning points in times-series data.[3] As emphasized by Watson (2004), the algorithm identifies local maxima and minima subject to constraints on the length and amplitude of expansions and contractions.

To focus on long-run movements in stock prices, we adopt the following modified version of the Bry-Boschan algorithm. In the first step, we take logarithms of the data and eliminate high frequencies and business-cycle frequencies (those lower than 8 years) using the bandpass filter proposed by Christiano and Fitzgerald (1999).[4] We refer to the resulting series as the long-run stock price index, which we denote by $\bar{P}(t)$. In step two, we identify peaks by finding dates, t, for which $\bar{P}(t)$ is higher than $\bar{P}(t+j)$ for $j \in J$, where $J = \{-3, -2, -1, 1, 2, 3\}$. Similarly, we identify troughs by finding dates, t, for which $\bar{P}(t)$ is lower than $\bar{P}(t+j)$ for $j \in J$. In step three, we check whether there are two subsequent peaks or two subsequent troughs. If we find two subsequent peaks (troughs), we retain only the most extreme peak (trough). If the values of the peaks (troughs) are equal, we select the last peak (trough). Finally, we refine the peaks and troughs using the original series instead of the long-run stock price index. For every peak (trough) date identified using the long-run stock price index, we search three years before or after the peak (trough) for higher (lower) values of the actual stock price index.[5] We identify the final peak (trough) as the highest (lowest) value of the actual stock price index within that window. Unlike Bry and Boschan (1971), we do not require a minimum duration for a bull or bear episode. An important aspect of our algorithm is that it dates bull and bear episodes using *only* stock market data.

[3] See King and Plosser (1994) for a detailed description of the Bry-Boschan algorithm.

[4] Our algorithm to compute turning points uses a two-sided bandpass filter. The two-sided nature of this filter does not pose a problem for our analysis because we are characterizing ex-post features of the data, as opposed to forecasting or testing trading strategies. Obtaining accurate estimates of the long-run trend requires the use of a long two-sided moving average. In fact, an ideal bandpass filter requires an infinite two-sided moving average (see Baxter and King (1999) and Christiano and Fitzgerald (2003)). It is difficult to estimate bandpass trends in the beginning and end of the sample, because long lags of the series are not available. For this reason, one-sided versions of the bandpass filter generally produce very noisy trend estimates (see Watson (2007) for a detailed discussion). Consistent with Watson (2007), we find that the one-sided version of the bandpass filter produces a trend that is volatile and takes on values that are actually closer to the original series than to the two-sided bandpass trend.

[5] To assess the robustness of our results, we redid our analysis using the Bry-Boschan procedure without this last refinement. We find that refining the Bry-Boschan procedure eliminates some of the episodes but the basic facts about the correlations between realized stock returns and various measures of fundamentals are very robust.

2.2. Data

Our data sets come from two sources. First, we obtain annual real stock returns for the G7 and the OECD countries from Global Financial Data. The countries (sample periods) included in our data set are: Australia (1901-2013), Austria (1947-2013), Belgium (1947-2013), Canada (1900-2013), Chile (1900-2013), Denmark (1900-2013), Finland (1923-2013), France (1942-2013), Germany (1851-2013), Greece (1953-2013), Italy (1900-2013), Japan (1894-2013), Korea (1963-2013), Mexico (1902-2013), Netherlands (1947-2013), New Zealand (1947-2013), Norway (1915-2013), Spain (1941-2013), Sweden (1900-2013), Switzerland (1900-2013), United Kingdom (1830-2013), and United States (1869-2013).

Second, we use the data set on real per capita personal consumer expenditures and real per capita Gross Domestic Product (GDP) originally constructed by Barro and Ursúa (2008) and updated by these authors until 2009.

Third, we obtain data for dividends and earnings for the G7 from Global Financial Data.

2.3. Long-run bulls and bears

The solid line in Figure 1 corresponds to the logarithm of the U.S. real stock price index. The dotted line is the bandpass-filtered version of the solid line in which high frequencies and business-cycle frequencies have been removed. Circles and stars denote the peaks and troughs identified by our algorithm.

Table 1 provides summary statistics for bull and bear episodes. Consider the results for the U.S. First, bull markets are on average much longer than bear markets, 14.8 years versus 3.2 years. On net, the economy spends 80 percent of the time in bull markets and only 20 percent in bear markets. The annual realized excess return to equity is, on average, 7.5 percent in our sample. However, this excess return is very different across bull and bear markets: 13.0 percent in bull markets versus -14.3 percent in bear markets. This sharp difference primarily reflects the fact that equity returns are on average 14.2 percent in bull markets but -15.5 percent in bear markets. The last two lines of Table 1 report the growth rate of two measures of fundamentals that are at the core of standard asset pricing theory: consumption and output. The average growth rate of consumption is higher in bull markets (2.3 percent) than in bear markets (0.7 percent). While the average growth rate of output is also higher in bull than in bear episodes (2.4 versus 2 percent), the difference is not as dramatic as in the case of consumption. The results for consumption for the G7 and OECD are quite similar to the results for the U.S. There is a sizable difference between the growth rate of output in bull and bear episodes for the G7 and OECD.

Table 2 lists the dates of U.S. bull and bear episodes along with a summary of major technological, military or political events associated with these episodes. While it is easy to rationalize dates ex-post, many of the 20th century turning points are instantly recognizable. The bear market of 1915-20 is associated with World War I and its aftermath. The bull market of 1920 to 1928 is associated with a well-know period of fast technological progress. The bear market of 1928-31 is associated with the Great Depression, while the bull market of 1931-36 is associated with the recovery from the Great Depression. This episode also falls squarely in the period that Fields (2011) calls "the most technologically progressive decade of the century." The bear market of 1936-41 coincides with the uncertainties associated with the run up to World War II. The great bull market from 1941 to 1972 is associated with the period of "pax Americana" as well as major developments like the emergence of the commercial aviation industry and the construction of the interstate highway system. The 1972-74 bear market reflects adverse shocks to the price of oil. The bull market of 1974-1999 coincides with the information technology revolution that included the personal computer and the internet. The bear market of 1999-2002 is associated with the Nasdaq crash and the 9/11 terrorist attacks. The bull market of 2002-07 coincides with the credit and housing boom, while the bear market of 2007-08 is associated with the Great Recession.

Figures 2 and 3 display, for the G7 and the OECD, the logarithm of the stock price index, the bandpass trend and the peaks and troughs associated with booms and busts episodes. Figure 2 suggests that the boom and bust episodes are correlated across G7 countries. Recall that we interpret long-run bull and bear episodes as being driven by major technological, political, and military events. From this perspective, it is reasonable to expect that the episodes would be correlated across countries.

We use the concordance index proposed by Harding and Pagan (2002, 2006) to measure the extent to which bull and bear episodes are synchronized across countries. To compute this index, we define the indicator S_t^j for country j which takes on the value one if the country is in a long-run bull at time t and zero otherwise. We use country index one to denote the U.S. The concordance index between the U.S. and country j, I_j, is computed as:

$$I_j = \frac{1}{T}\left\{\sum_{t=1}^{T} S_t^1 S_t^j + \sum_{t=1}^{T}\left(1 - S_t^1\right)\left(1 - S_t^j\right)\right\}.$$

This index measures the fraction of time that two countries spend in the same stock-market phase. Table 3 presents our results, ordering countries by their concordance with the U.S. The degree of concordance between the U.S. and the other countries in our sample is higher than 0.7 for most developed countries. Presumably, this statistic reflects the presence of a common factor inducing long-run bulls and bears in stock returns across different countries and the fact that the long-term trend for stock prices is positive most of the time.

2.4. Correlations between fundamentals and stock returns

Table 4 reports the correlation between stock returns and the growth rate of consumption and output for the U.S., the G7, and the OECD. We report correlations at the one-, five-, ten- and 15-year horizons. Correlations at horizons longer than one year are computed using overlapping observations. We report Newey-West (1987) heteroskedasticity-consistent standard errors.[6] We compute correlations for the G7 and the OECD countries pooling data across all countries. This procedure implies that countries with longer time series receive more weight in the calculations. Below we assess the sensitivity of our results to this assumption.

Consistent with results in Cochrane and Hansen (1992), Campbell and Cochrane (1999), and Albuquerque, Eichenbaum, Luo and Rebelo (2014), we find that there is a relatively weak correlation between consumption and output growth and stock returns at all the horizons we consider. This result obtains for horizons as long as 15 years. One exception is the five-year correlation between U.S. consumption growth and U.S. stock returns which is relatively high. This result only holds in U.S. data: the analogue five-year correlation is not high for the G7 and OECD countries.

A key question is: what is the correlation between stock returns and fundamentals like consumption and output growth across episodes. Recall that bull and bear episodes are identified using *only* stock market data.

Table 4 reports two versions of the correlation between the average growth rate of fundamentals and the average annual stock returns across episodes. The first is a simple correlation. The second is a correlation that gives more weight to longer episodes. The weighted correlation between variable x and y is computed as:

[6] To compute standard errors for the 1, 5, 10, and 15 year correlatio,n we use 6, 11, 16 and 21 lags, respectively.

$$\frac{\sum_i w_i(x_i - \bar{x})(y_i - \bar{y})}{\left[\sum_i w_i(x_i - \bar{x})^2\right]^{1/2}\left[\sum_i w_i(y_i - \bar{y})^2\right]^{1/2}},$$

where i indexes episodes, a bar over a variable denotes the mean value of that variable over the whole sample, and w_i denotes the number of years in episode i. The variables x_i and y_i denote the average annual growth rate of x and y, respectively, measured from the beginning to the end of episode i. The variables $\bar{x}$ and $\bar{y}$ represent weighted sample averages.

From Table 4 we see that there is a very high correlation between consumption growth rates and stock returns across U.S. episodes. The simple correlation is 0.635 and the weighted correlation is 0.626. In both cases, the correlation is significantly different from zero and insignificantly different from one.[7] Similar results emerge for the G7 and OECD countries. For the G7, the simple and weighted correlations between consumption growth and stock returns are 0.757 and 0.794, respectively. The corresponding correlations for OECD countries are 0.579 and 0.604, respectively.

The correlations between output growth and stock returns follow a similar pattern. For the U.S., the highest time-series correlation (0.253) occurs at a five-year horizon. The lowest correlation (-0.034) occurs at a 15-year horizon. Correlations across episodes are much higher: 0.462 and 0.328 for simple and weighted correlations, respectively. For the G7, the correlation between output growth and stock returns across episodes is about twice as high as the time-series correlation. For the OECD, the episode correlations are about 2.5 times the time-series correlations.

Table 5 reports the time-series correlations between stock returns and fundamentals within bull and bear episodes for the U.S., G7, and the OECD. As above, we compute correlations for the G7 and the OECD countries by pooling data across all countries. In sharp contrast with the positive correlations across episodes, correlations within bulls and bear episodes are essentially zero.

Next, we assess the robustness of our key results to different ways of combining observations for the G7 and OECD countries. The rows in Table 6 that are labeled "pooled" report correlations obtained by pooling observations from the G7 and OECD countries. These statistics are the same as those reported in Table 4. The rows labeled "average" report the average of country-specific statistics. While the magnitude of the correlations varies, the

[7] Our results are robust to omitting the longest U.S. episode (1941-72). In this case the simple and weighted correlation between stock returns and consumption growth are 0.61 (0.25) and 0.58 (0.19), where numbers in parenthesis denote standard errors.

episode correlations are roughly twice as high as the time-series correlations.

2.5. Dating the episodes with consumption and output data

Up to this point, we dated episodes using data on stock prices and argued that there is a high correlation between stock returns and fundamentals across episodes. A natural question is: does a similar correlation obtain if we date episodes using data on consumption or output? Presumably, if stock returns are reacting to those fundamentals, there should be a similar correlation to the one obtained dating episodes with the stock market.

Consider first the results obtained dating episodes with consumption data. According to Table 7, the correlations between stock returns and consumption growth are similar to those obtained dating the episodes with stock price data.[8] This pattern also holds for the correlation between stock returns and output growth.

Table 7 also displays the results obtained dating episodes with data on output. For the U.S., taking sampling uncertainty into account, the correlations across episodes for both consumption and output are very similar to those obtained when we date episodes with stock-price data. For the G7 and OECD we find, once again, very high correlations between stock returns and both consumption growth and output growth.

We conclude that, regardless of how episodes are dated, there is a strong episode correlation between stock returns and our measures of fundamentals.

2.6. Alternative measures of fundamentals

In this subsection, we assess whether our results are robust to using dividend growth and earnings growth as measures of fundamentals. We report our results in Table 4.

The pattern that emerges with earnings growth is quantitatively very similar to the one that emerges with consumption or output growth. The result with dividend growth are more complicated. Like with our other measures of fundamentals the correlation between stock returns and dividend growth is very low at the one-year horizon. However, the correlation rises to roughly 0.5 at the 5-, 10-, and 15-year horizon. So there is less of a puzzle with respect to dividend growth at long horizons than there is with consumption growth or output.

The point estimate for the episode and weighted-episode correlation between stock return and dividend growth is somewhat lower than the long-horizon time-series correlations. How-

[8] Given the smooth behavior of consumption there are fewer consumption-based episodes than stock-price-based episodes. This fact explains the relatively high standard errors associated with the U.S. correlations.

ever, there is a great deal of sampling uncertainty, so we do not reject the hypothesis that the long-horizon and episode correlation are high and roughly the same. A similar picture emerges when we look at the G7 countries.

2.7. Robustness checks

It is well known that Bry-Boschan-type filters applied to data generated by an univariate random walk identify bull- and bear-like episodes. In fact, if we simulate a random walk for stock prices and apply our version of the Bry-Boschan filter to the artificial data, the filter identifies bull and bear episodes. From this perspective, one might be concerned that the bull (bear) episodes identified by the Bry-Boschan filter simply result from a random sequence of good (bad) shocks. In this case, there would be no reason to expect a correlation across episodes between stock returns and consumption or output growth. Indeed, if we simulate two independent random walks we find that both the time series and the episode correlations are zero in population.

In this subsection, we conduct two additional experiments designed to shed light on the possibility that the correlation across episodes between fundamentals and stock returns emerges is simply an artifact of the properties of our version of the Bry-Boschan filter.

In the first experiment, we estimate a trivariate VAR(2) using annual U.S. data for the growth rate of consumption, the growth rate of output, and stock returns. We obtain the following representation:

$$\begin{aligned}\begin{bmatrix} 100\times\ln(C_{t+1}/C_t) \\ 100\times\ln(Y_{t+1}/Y_t) \\ 100\times\ln(R_{t+1}) \end{bmatrix} &= \begin{bmatrix} 0.7842 \\ 0.8273 \\ 7.1982 \end{bmatrix} + \begin{bmatrix} 0.0381 & -0.0134 & 0.1072 \\ -0.0446 & 0.3181 & 0.1135 \\ -0.2431 & 0.0888 & 0.0029 \end{bmatrix} \begin{bmatrix} 100\times\ln(C_t/C_{t-1}) \\ 100\times\ln(Y_t/Y_{t-1}) \\ 100\times\ln(R_t) \end{bmatrix} \\ & \begin{bmatrix} 0.1487 & 0.0131 & -0.0048 \\ 0.2106 & -0.0184 & -0.0697 \\ 0.0244 & 0.0632 & -0.1958 \end{bmatrix} \begin{bmatrix} 100\times\ln(C_{t-1}/C_{t-2}) \\ 100\times\ln(Y_{t-1}/Y_{t-2}) \\ 100\times\ln(R_{t-1}) \end{bmatrix} + \begin{bmatrix} \xi^1_{t+1} \\ \xi^2_{t+1} \\ \xi^3_{t+1} \end{bmatrix}.\end{aligned}$$

The estimated covariance matrix for the vector error term is given by:

$$\hat{V} = \begin{bmatrix} 8.0567 & 6.0687 & 7.2453 \\ 6.0687 & 17.3227 & 10.2668 \\ 7.2453 & 10.2668 & 350.2595 \end{bmatrix}.$$

We construct a synthetic time series of length $10,000$ using the estimated VAR(2). We simulate the VAR by sampling the disturbances with replacement from the vector of actual VAR residuals. We then calculate the time-series and episode correlations using the synthetic data. The results are reported in Table 8. We find that the time-series correlations are quite similar to those estimated from actual data. However, the synthetic data implies that the episode correlations are similar to the time-series correlations. This property contrasts sharply with the results obtained from actual data. One possible interpretation of this result is that the episode correlations reflect either non-linearities or non-stationarity not captured by the VAR.

As an additional robustness check, we scramble the bull and bear episodes as follows.[9] Define the sequence of stock returns for bull episode i by the vector U_i and the sequence of stock returns for bear episode j by the vector D_j. We place the six booms in our data in urn $\bar{U}$ and the six busts in urn $\bar{D}$:

$$\begin{aligned} \bar{U} &= \{U_1, U_2, U_3, U_4, U_5, U_6\}, \\ \bar{D} &= \{D_1, D_2, D_3, D_4, D_5, D_6\}. \end{aligned}$$

We choose the first episode to be a bull or bear with probability $1/2$. We then sample without replacement alternating between the two urns. We match the resulting time series for stock returns with the original time series for consumption returns. The last row of Table 8 shows that both the time-series and episode correlations are close to zero. We infer that the actual timing of the bull and bear episodes reveals important information about the comovement between fundamentals and stock returns.

2.8. Small-sample properties

In this subsection, we investigate the possibility that the difference between the episode correlations and the time-series correlations simply reflects small-sample bias. Suppose that the true data-generating process is a linear VAR. Then, consistent with Table 8, there should be no difference in population between episode and time-series correlations at five-, ten-, and 15-year horizons. But, it is possible that in a small sample we would find seemingly significant differences between time-series and episode correlations. To investigate this possibility, we proceed as follows. For every country in the OECD, we estimate a trivariate VAR(2) for the growth rate of consumption, the growth rate of output, and stock returns. This VAR specification is the same as in Section 2.6. We sample from the VAR residuals to construct $10,000$ synthetic time series for each of the variables in the VAR. For each country, each

[9] We thank Òscar Jordà for suggesting this calculation.

time series has the length equal to the corresponding number of observations in our actual data set. For example, in the U.S. case the length is equal to 144 observations. Using the synthetic time series we calculate the frequency of various events of interest.

For each synthetic time series we compute the time-series and episode correlations. Define k_i^c to be the ratio of the episode correlation and the time-series correlation between consumption growth and stock returns at horizon i. Define k_i^y to be the ratio of the episode correlation and the time-series correlation between output growth and stock returns at horizon i. Both k_i^c and k_i^y are computed with our empirical estimates of the correlations.

We define event 1 to be: the episode correlation between consumption growth and stock returns is positive and greater than the product of k_i^c and the analogue time-series correlation at horizon i for either $i = 1, 5, 10$, and 15. In addition, the episode correlation between output growth and stock returns is positive and greater than the product of k_i^y and the analogue time-series correlation at horizon i for either $i = 1, 5, 10$. Event 2 differs from event 1 in only one dimension: the contemporaneous correlation ($i = 1$) is excluded from the definition of the event. The motivation for this specification is as follows. Bull and bear episodes last, on average, 15 and three years, respectively. So, it seems reasonable to assess the robustness of our results by excluding the contemporaneous correlation from the specification.

Table 9 reports results based on VARs that are estimated using ordinary least squares. For the U.S., events 1 and 2 occurs with less than one percent probability, regardless of whether we look at simple episodes or weighted episodes. The results are somewhat more mixed for the G7 and the OECD. In both cases, event 1 occurs with less than 5 percent probability. Event 2 occurs with less than 5 percent probability for simple episodes and slightly higher than 5 percent probability for weighted episodes.

Viewing the evidence as a whole, it seems unlikely that the difference between the time-series and the episode correlations are an artifact of small sample bias.

3. Three asset-pricing models

We consider three models: the external-habit model of Campbell-Cochrane (1999), the long-run risk model of Bansal, Kiku and Yaron (2012), and the valuation-risk model of Albuquerque, Eichenbaum, Luo, and Rebelo (2015). We assume that agents make decisions on a monthly basis. We aggregate the monthly data simulated from the parameterized models to produce annual data.

3.1. The external-habit model

The representative agent maximizes utility given by:

$$U = E\sum_{t=0}^{\infty}\delta^t \frac{(C_t - X_t)^{1-\gamma} - 1}{1-\gamma},$$

C_t denotes consumption at time t.

The dynamics of the habit variable, X_t, are implied by the law of motion of consumption and surplus consumption. The latter is given by:

$$S_t = \frac{C_t - X_t}{C_t}.$$

The variable $s_t = \ln(S_t)$ evolves according:

$$s_{t+1} = (1-\phi)\bar{s} + \phi s_t + \lambda(s_t)\left[\Delta c_{t+1} - E\left(\Delta c_{t+1}\right)\right],$$

where $\bar{s}$ is the unconditional mean of s_t, ϕ is a parameter that controls the persistence of s_t, and $c_t = \ln(C_t)$. The deterministic function $\lambda(s_t)$ is given by:

$$\lambda(s_t) = \begin{cases} \left(1/\bar{S}\right)\sqrt{1-2(s_t-\bar{s})} - 1, & \text{when } s_t < s_{\max}, \\ 0, & \text{when } s_t \geq s_{\max}, \end{cases}$$

where $\bar{S}$ is equal to:

$$\bar{S} = \sigma_{\upsilon}\sqrt{\frac{\gamma}{1-\phi}},$$

and

$$s_{\max} = \bar{s} + \frac{1}{2}(1-\bar{S}^2).$$

The logarithm of consumption follows a random walk with drift:

$$c_{t+1} = c_t + \mu + \upsilon_{t+1},$$

where υ_{t+1} is an i.i.d. normally distributed variable with mean zero and variance σ_{υ}^2. We solve the model using the algorithm discussed in Wachter (2005).[10] We take the parameter values from Table 1 in Wachter (2005). These values correspond to those used by Campbell and Cochrane (1999), adapted for simulating the model at a monthly frequency. We summarize these parameter values in Table 10. As in Wachter (2005), we consider a version of the model in which equities are a claim to consumption.

[10] We thank Jessica Wacher for sharing her program for solving the Campbell-Cochrane model with us.

3.2. The long-run risk model

The representative agent has the constant-elasticity version of Kreps-Porteus (1978) preferences used by Epstein and Zin (1991) and Weil (1989). The life-time utility of the representative agent is a function of current utility and the certainty equivalent of future utility:

$$U_t = \left[(1-\delta)C_t^{(1-\gamma)/\theta} + \delta\left(E_t U_{t+1}^{1-\gamma}\right)^{1/\theta}\right]^{\theta/(1-\gamma)},$$

where δ is a positive scalar. The variable θ is given by:

$$\theta = \frac{1-\gamma}{1-1/\psi}.$$

The parameters ψ and γ represent the elasticity of intertemporal substitution and the coefficient of relative risk aversion, respectively.

The process for consumption growth is given by:

$$\begin{aligned} \log(C_{t+1}/C_t) &= \mu + x_t + \sigma_t \varepsilon_{t+1}^c, \\ x_{t+1} &= \rho x_t + \phi_e \sigma_t e_{t+1}, \end{aligned}$$

When ρ is close to one, this process captures the notion that there are shocks to the long-run growth rate of consumption.

Dividends evolve according to:

$$\log(D_{t+1}/D_t) = \mu + \phi x_t + \pi \sigma_t \eta_{t+1} + \varphi \sigma_t \varepsilon_{t+1}^d.$$

The volatility of consumption growth evolves according to:

$$\sigma_{t+1}^2 = \sigma^2(1-\nu) + \nu\sigma_t^2 + \sigma_w \varepsilon_{t+1}^\sigma.$$

The variables ε_{t+1}^c, e_{t+1}, ε_{t+1}^d, and ε_{t+1}^σ are mutually uncorrelated and follow a standard-normal distribution.

We use the parameter values proposed by Bansal, Kiku and Yaron (2012), which we summarize in Table 11.

3.3. The valuation-risk model

The preferences of the representative agent are given by:

$$U_t = \max_{C_t}\left[\lambda_t C_t^{(1-\gamma)/\theta} + \delta\left(E_t U_{t+1}^{1-\gamma}\right)^{1/\theta}\right]^{\theta/(1-\gamma)}. \tag{3.1}$$

The variable $\Lambda_{t+1} = \log(\lambda_{t+1}/\lambda_t)$ determines how agents trade off current versus future utility. This ratio is known at time t. We refer to Λ_{t+1} as the time-preference shock.

The growth rate of the time-preference shock evolves according to:

$$\begin{aligned} \Lambda_{t+1} &= x_t + \sigma_\eta \eta_{t+1}, \\ x_{t+1} &= \rho x_t + \sigma_\Lambda \varepsilon^{\Lambda}_{t+1}. \end{aligned} \tag{3.2}$$

Here $\varepsilon^{\Lambda}_{t+1}$ and η_{t+1} are uncorrelated, i.i.d. standard normal shocks. We think of x_t as capturing low-frequency changes in the growth rate of the discount rate. In contrast, η_{t+1} can be thought of as high-frequency changes in investor sentiment that affect the demand for assets as in the model proposed by Dumas, Kurshev, and Uppal (2009).

The consumption process is given by:

$$\log(C_{t+1}/C_t) = \mu + \rho_c \log(C_t/C_{t-1}) + \alpha_c \left(\sigma^2_{t+1} - \sigma^2\right) + \pi_{c\lambda}\varepsilon^{\Lambda}_{t+1} + \sigma_t \varepsilon^{c}_{t+1}.$$

A share of stock is a claim on dividends which evolve according to:

$$\begin{aligned} \log(D_{t+1}/D_t) &= \mu + \rho_d \log(D_{t+1}/D_t) + \alpha_d \left(\sigma^2_{t+1} - \sigma^2\right) \\ &\quad + \pi_{d\lambda}\varepsilon^{\Lambda}_{t+1} + \pi_{dc}\sigma_t \varepsilon^{c}_{t+1} + \sigma_d \sigma_t \varepsilon^{d}_{t+1}. \end{aligned}$$

Volatility follows the process:

$$\sigma^2_{t+1} = \sigma^2 + v\left(\sigma^2_t - \sigma^2\right) + \sigma_w w_{t+1},$$

Variables ε^{c}_{t+1}, ε^{d}_{t+1}, $\varepsilon^{\Lambda}_{t+1}$, and w_{t+1} are mutually uncorrelated, i.i.d. standard normal shocks.

We use the parameter values estimated in Albuquerque, Eichenbaum, Luo, and Rebelo (2015) for their extended model. We summarize these parameters in Table 12.

3.4. Evaluating the models

To evaluate the performance of the models, we compare their implications for time-series and episode correlations with estimates for the U.S. Our results are summarized in Table 13.

First, consider the external habit model of Campbell and Cochrane (1999). As discussed in Albuquerque, Eichenbaum, Luo, and Rebelo (2015), the time-series correlations between stock returns and consumption growth are uniformly too high relative to the data, even taking sampling uncertainty into account. This shortcoming reflects the fact that the only source of uncertainty in that model comes from the endowment side of the economy. Interestingly, the non-linearities in the model imply that the episode correlations are higher than the time-series correlations. So, arguably this model does well at accounting for the episode correlations but does not do well at accounting for the time-series correlations.

Next, consider the long-risk model of Bansal, Kiku and Yaron (2012). Like the Campbell-Cochrane model, this model does reasonably well at accounting for the high episode correlations. But it implies counterfactually high time-series correlations, even taking sampling uncertainty into account. As with the external-habit model, this shortcoming reflects the fact that all uncertainty stems from the production side of the economy. However, unlike the external-habit model, the long-run risk model does not generate an episode correlation that is substantially higher than the time series correlations.

Next, consider the valuation-risk model of Albuquerque, Eichenbaum, Luo, and Rebelo (2015). The time-series correlations implied by this model are uniformly lower than the corresponding point estimates from the data. Taking sampling uncertainty into account, the model accounts for the time-series correlations at all horizons. However, the model does not capture the high episode correlations.

4. Conclusion

Our main finding in this paper is that there is a high correlation between stock returns and fundamentals across bull and bear episodes. This high correlation stands in sharp contrast with the low time-series correlations between stock returns and fundamentals that have been documented in the literature. We show that several asset-pricing models cannot simultaneously account for the low time-series correlations and the high episode correlations.

There are two words for time in ancient Greek. Chronos is the word for calendar time. Kairos refers to a moment of indeterminate time in which something special happens. To account for our findings, we need a model in which the relation between stock returns and consumption growth is different in chronos and kairos time.

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Table 1

Basic statistics

	United States			G7			OECD		
	Bulls	Bears	Full sample	Bulls	Bears	Full sample	Bulls	Bears	Full sample
Length in years	14.8	3.2		12.7	4.1		11.5	4.3	
Fraction of time	0.8	0.2		0.8	0.2		0.7	0.3	
Equity returns	14.2	-15.5	8.1	14.4	-14.5	6.9	17.0	-13.3	8.3
Volatility	16.4	18.9	20.7	21.2	19.4	24.3	26.4	17	27.7
Bond returns	1.1	-1.1	0.7	2.1	-5.2	0.2	1.9	-2.5	0.7
Volatility	4.1	6.4	4.7	7.8	17.6	11.6	8.2	13	10
Equity premium	13	-14.3	7.5	12.3	-9.3	6.7	15.1	-10.9	7.6
Volatility	16	20.7	20.2	22.7	18.9	23.7	27.8	17.6	27.9
Consumption growth	2.3	0.7	2	2.4	1.3	2.1	2.4	1.9	2.2
Volatility	3.1	3.9	3.3	3.5	6.7	4.6	4.4	5.7	4.8
Output growth	2.4	2	2.3	2.8	0.9	2.3	2.8	1.7	2.4
Volatility	4.7	6.8	5.2	3.9	8.1	5.4	3.9	6	4.6

Table 2
U.S. booms and busts and historial events

Boom/bust episode	Historical events
1869-1915	Victory on Spanish American war, technical progress (telegraph, escalator, movies, Yukon goldrush, car production starts)
1915-20	World War I (1914) and its aftermath
1920-28	Period of fast technological progress, automobiles, road building, telephone electricity spreads, urbanization
1928-31	The Great Depression
1931-36	Innovations in chemical engineering, infrastructure, diffusion of electricity, machinery, and the automotive
1936-41	Uncertainty associated with World War II
1941-72	Pax Americana, commercial aviation, interstate highway system
1972-74	Oil shocks
1974-99	Computers for businesses, personal computers, robotics, the internet
1999-2002	Nasdaq crash and 9/11
2002-07	Housing boom
2007-08	Financial crisis, onset of Great Recession

Table 3

Concordance between U.S. episodes and episodes in OECD countries

Canada	0.92	France	0.74
Sweden	0.89	New Zealand	0.72
Switzerland	0.85	Spain	0.71
U.K.	0.85	Italy	0.69
Netherlands	0.85	Korea	0.67
Australia	0.83	Chile	0.66
Norway	0.82	Finland	0.65
Denmark	0.79	Mexico	0.54
Germany	0.79	Greece	0.51
Japan	0.76	Austria	0.49
Belgium	0.75		

Table 4
Correlation between stock returns and fundamentals

	1 year	5 year	10 year	15 year	Episodes	Weighted episodes
			United States			
Consumption growth	0.099	0.401	0.240	0.239	0.635	0.626
	(0.079)	(0.173)	(0.171)	(0.196)	(0.246)	(0.207)
Output growth	0.136	0.253	0.017	-0.034	0.462	0.328
	(0.085)	(0.133)	(0.106)	(0.146)	(0.223)	(0.210)
Dividend growth	0.008	0.424	0.532	0.531	0.242	0.399
	(0.084)	(0.158)	(0.173)	(0.153)	(0.203)	(0.122)
Earnings growth	0.228	0.473	0.358	0.377	0.743	0.699
	(0.096)	(0.169)	(0.110)	(0.115)	(0.413)	(0.258)
			G7			
Consumption growth	0.013	0.189	0.280	0.307	0.757	0.794
	(0.061)	(0.105)	(0.130)	(0.175)	(0.107)	(0.041)
Output growth	0.178	0.345	0.397	0.373	0.788	0.821
	(0.079)	(0.091)	(0.117)	(0.170)	(0.090)	(0.050)
Dividend growth	0.118	0.300	0.417	0.494	0.394	0.463
	(0.107)	(0.080)	(0.057)	(0.066)	(0.175)	(0.054)
Earnings growth	0.080	0.396	0.241	0.213	0.545	0.561
	(0.049)	(0.070)	(0.124)	(0.212)	(0.105)	(0.046)
			OECD			
Consumption growth	0.038	0.130	0.151	0.134	0.579	0.604
	(0.033)	(0.067)	(0.103)	(0.139)	(0.086)	(0.026)
Output growth	0.125	0.272	0.262	0.210	0.644	0.656
	(0.045)	(0.067)	(0.104)	(0.148)	(0.075)	(0.028)

Table 5

Correlation within episodes

	Consumption growth and stock returns			Output growth and stock returns	
	Bulls	Bears		Bulls	Bears
United States	0.045	0.042	United States	0.151	0.186
	(0.095)	(0.196)		(0.107)	(0.201)
G7	0.033	-0.107	G7	0.086	0.158
	(0.054)	(0.172)		(0.058)	(0.124)
OECD	0.066	-0.028	OECD	0.094	0.129
	(0.029)	(0.098)		(0.034)	(0.087)

Table 6

	1 year	5 years	10 years	15 years	Episodes	Weighted episodes
			Stock returns and consumption growth			
Pooled						
G7	0.013	0.189	0.280	0.308	0.757	0.794
OECD	0.038	0.130	0.151	0.134	0.579	0.604
Average						
G7	0.035	0.164	0.191	0.225	0.406	0.436
OECD	0.039	0.087	0.023	-0.028	0.270	0.220
			Stock returns and output growth			
Pooled						
G7	0.178	0.354	0.397	0.373	0.788	0.821
OECD	0.125	0.272	0.262	0.210	0.644	0.656
Average						
G7	0.173	0.222	0.206	0.188	0.466	0.450
OECD	0.098	0.186	0.099	0.027	0.384	0.325

Table 7

	Episodes dated using consumption			Episodes dated using output	
Correlation between stock returns and consumption growth			**Correlation between stock returns and consumption growth**		
	Simple	Weighted		Simple	Weighted
U.S.	0.83	0.73	U.S.	0.25	0.43
	(0.39)	(0.18)		(0.25)	(0.15)
G7	0.76	0.66	G7	0.81	0.78
	(0.15)	(0.02)		(0.14)	(0.03)
OECD	0.69	0.61	OECD	0.77	0.70
	(0.11)	(0.02)		(0.10)	(0.02)
Correlation between stock returns and output growth			**Correlation between stock returns and output growth**		
	Simple	Weighted		Simple	Weighted
U.S.	0.85	0.72	U.S.	0.27	0.31
	(0.49)	(0.22)		(0.24)	(0.14)
G7	0.81	0.75	G7	0.82	0.78
	(0.16)	(0.03)		(0.13)	(0.04)
OECD	0.71	0.64	OECD	0.78	0.71
	(0.12)	(0.02)		(0.11)	(0.02)

Concordance between episodes dated with stock market and consumption or output

	Consumption	Output
U.S.	0.84	0.78
G7	0.63	0.68
OECD	0.61	0.61

Table 8
Correlation between stock returns and fundamentals
Implied by VAR(2), consumption growth, output growth, and stock returns

	1 year	5 year	10 year	15 year	Episodes	Weighted episodes
	Correlation between stock returns and consumption growth					
Ordinary least squares	0.116	0.459	0.520	0.543	0.460	0.585
U.S. Data	0.099	0.401	0.240	0.239	0.635	0.626
	Correlation between stock returns and output growth					
Ordinary least squares	0.126	0.301	0.307	0.308	0.425	0.474
U.S. Data	0.099	0.401	0.240	0.239	0.635	0.626
	Correlation between consumption growth and permutations of stock returns					
	0.02	0.00	-0.01	0.00	-0.02	-0.02

Table 9
Small sample properties

VAR estimated with OLS

Event 1
Correlations at 1-, 5-, 10-, and 15-year horizons

	Episodes	Weighted episodes
U.S.	0.001	0.001
G7	0.024	0.039
OECD	0.015	0.031

Event 2
Correlations at 5-, 10-, and 15-year horizons

	Episodes	Weighted episodes
U.S.	0.002	0.002
G7	0.047	0.076
OECD	0.037	0.062

Table 10

Parameter values

Campbell and Cochrane (1999) model

Preferences	δ	γ	ϕ
	$0.90^{1/12}$	2	$0.87^{1/12}$
Consumption	μ	σ_ν	
	$1.89/12$	$1.50/\sqrt{12}$	

Table 11

Parameter values

Bansal, Kiku, and Yaron (2012) model

Preferences	δ	γ	ψ	
	0.9989	10	1.5	
Consumption	μ	ρ	ϕ_e	
	0.0015	0.975	0.038	
Dividends	μ	ϕ	π	φ
	0.0015	2.5	2.6	5.96
Volatility	σ	v	σ_w	
	0.0072	0.999	0.0000028	

Table 12

Parameter values

Albuquerque, Eichenbaum, Luo, and Rebelo (2015) model

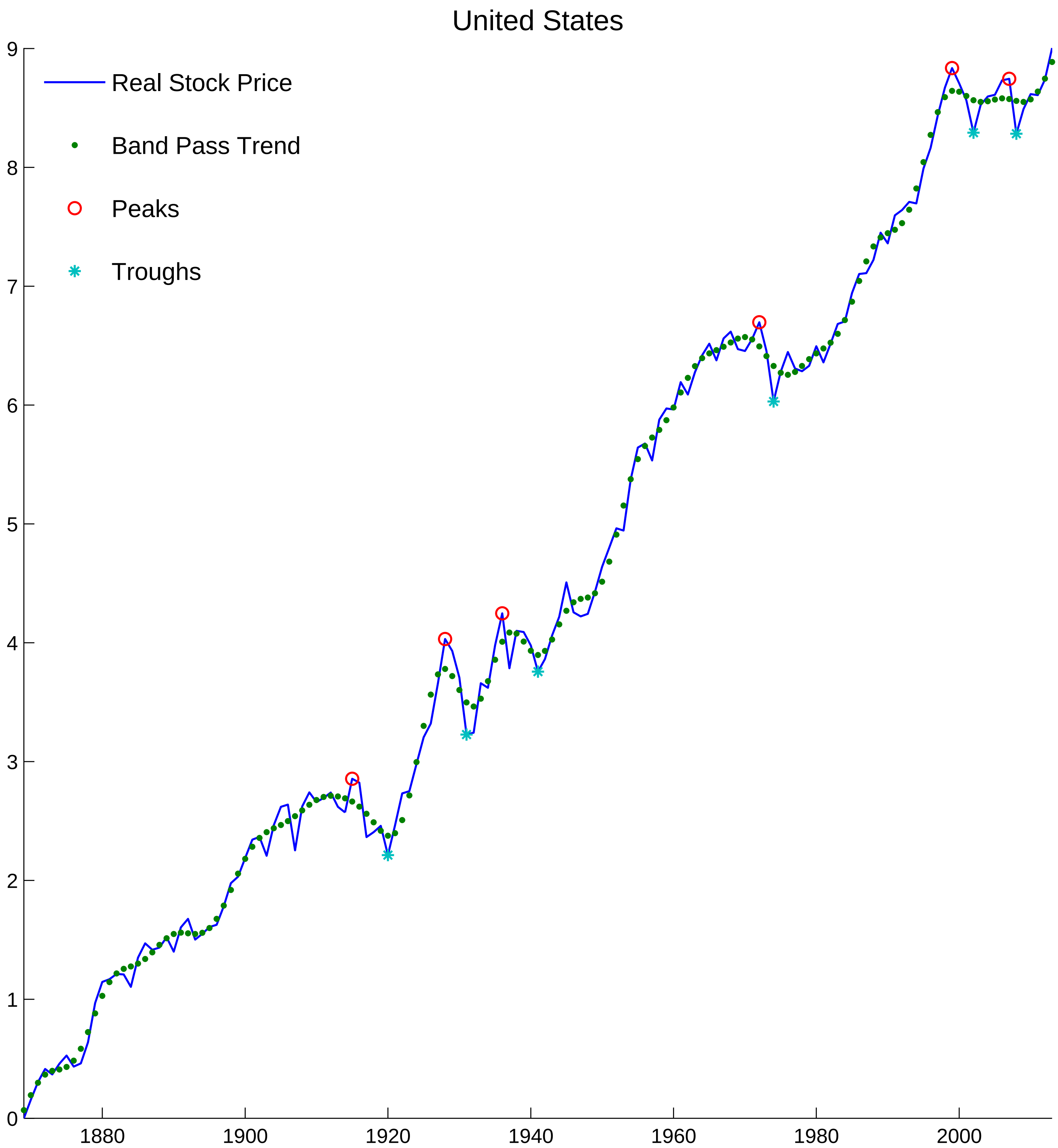
Preferences	δ	γ	ψ			
	0.9978	2.2228	2.3876			
Consumption	μ	ρ_c	α_c	$\pi_{c\Lambda}$		
	0.0009	0.0903	-119.39	-0.0019		
Dividends	μ	ρ_d	α_d	$\pi_{d\lambda}$	π_{dc}	σ_d
	0.0009	0.3344	-145.5	-0.0104	-1.3161	0.0256
Preference shocks	ρ	σ_Λ	σ_η			
	0.9911	0.0004	0.0083			
Volatility	σ	v	σ_w			
	0.0046	0.9967	1.7×10^{-6}			

Table 13

Correlation between stock returns and consumption growth

	1 year	5 year	10 year	15 year	Episodes	Weighted episodes
US data	0.099	0.401	0.240	0.239	0.635	0.626
External habit (Campbell and Cochrane (1999))	0.53	0.69	0.62	0.56	0.92	0.88
Long-run risk (Bansal, Kiku and Yaron (2012))	0.34	0.50	0.53	0.53	0.52	0.58
Valuation risk (Albuquerque, Eichenbaum, Luo, and Rebelo (2015))	-0.06	0.14	0.28	0.35	-0.12	0.09

Figure 1


United States
Real Stock Price
Band Pass Trend
Peaks
Troughs
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1
2
3
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5
6
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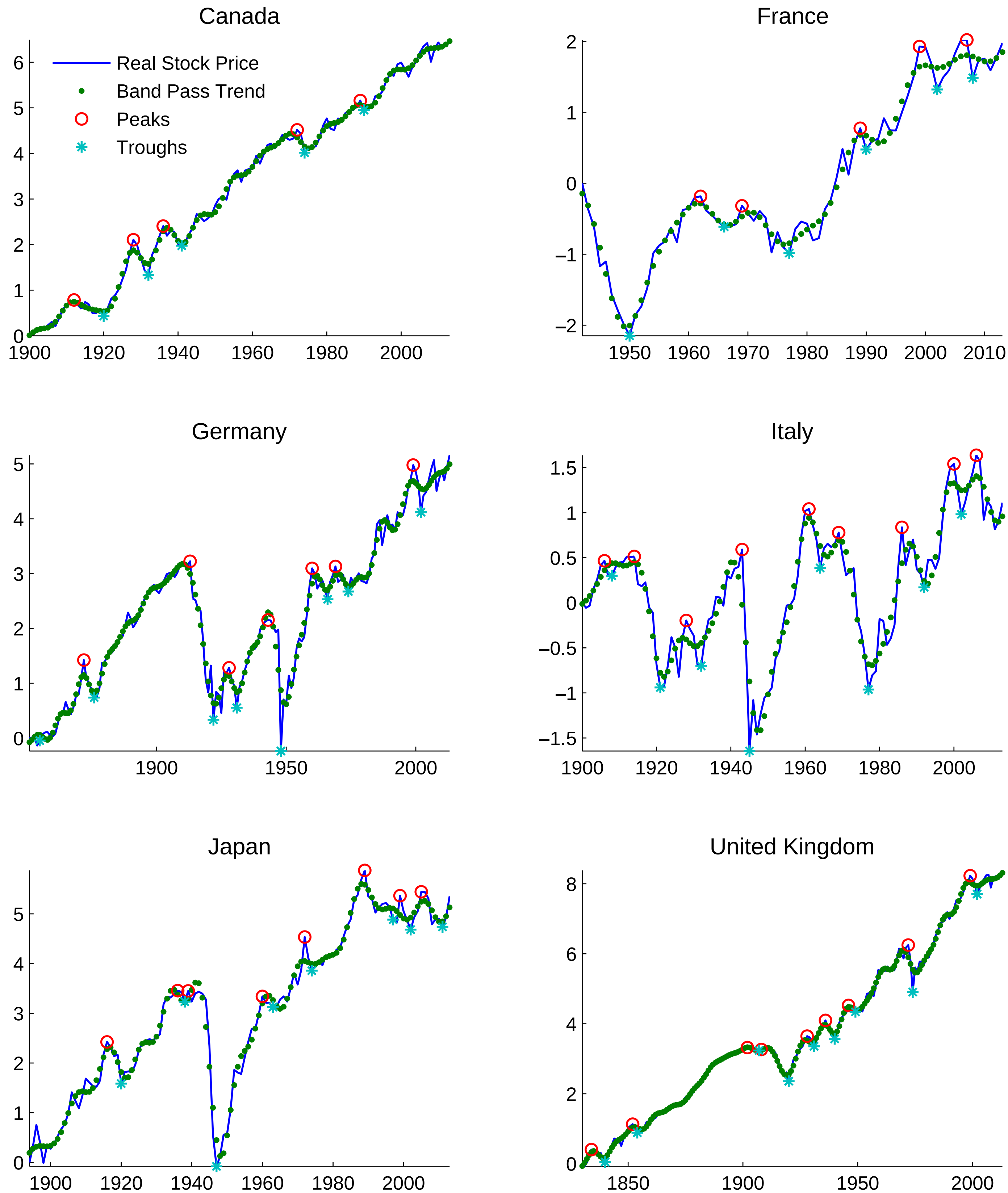
8
9
1880
1900
1920
1940
1960
1980
2000

Figure 2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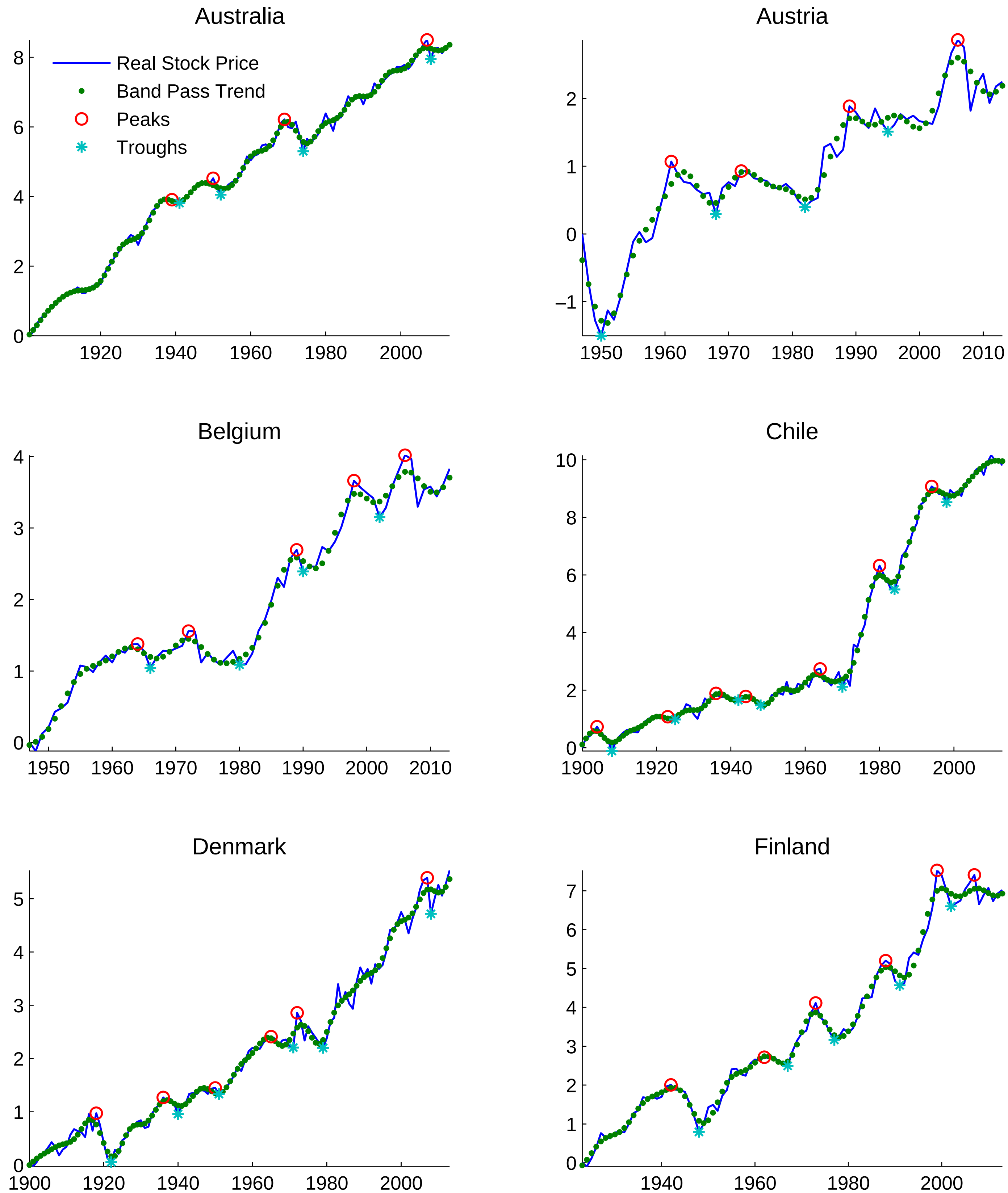
Real Stock Price
Band Pass Trend
Peaks
Troughs
France
Germany
Italy
Japan
United Kingdom

Figure 3


Australia
Real Stock Price
Band Pass Trend
Peaks
Troughs
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4
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1920
1940
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1980
2000
Austria
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Belgium
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Denmark
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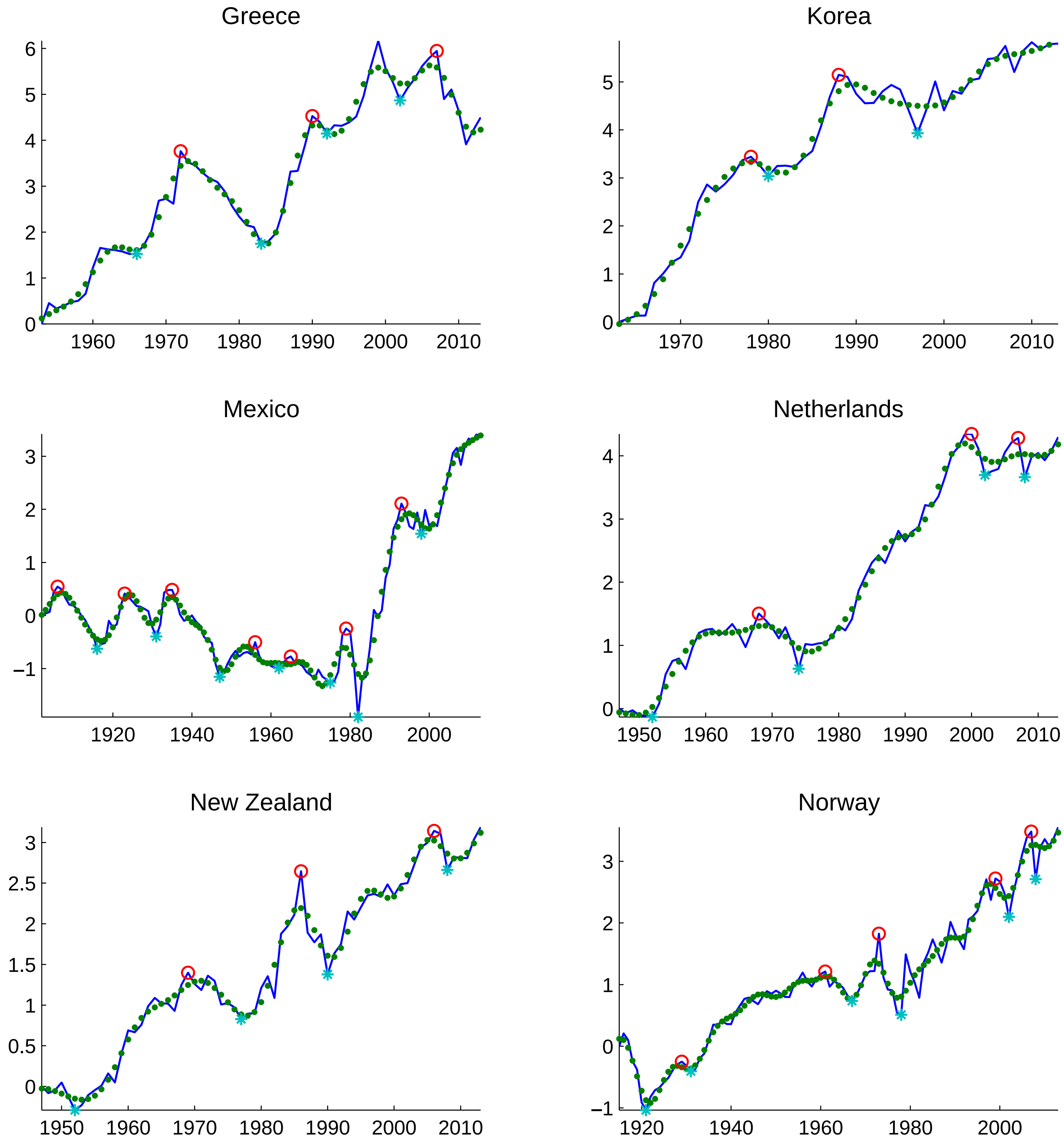
Greece
0 1 2 3 4 5 6
1960 1970 1980 1990 2000 2010
Korea
0 1 2 3 4 5
1970 1980 1990 2000 2010
Mexico
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1920 1940 1960 1980 2000
Netherlands
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New Zealand
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1950 1960 1970 1980 1990 2000 2010
Norway
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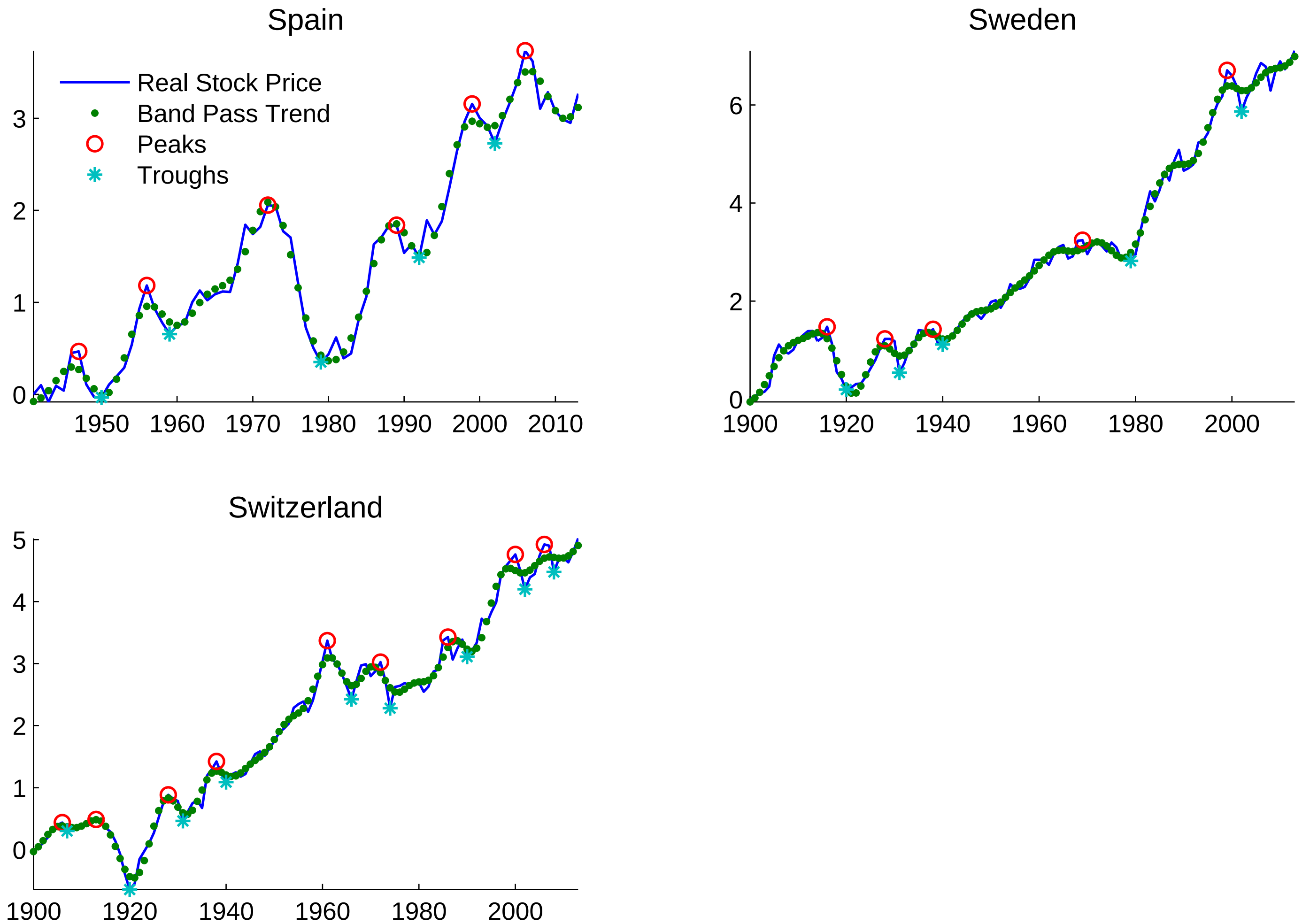
1920 1940 1960 1980 2000


Spain
Real Stock Price
Band Pass Trend
Peaks
Troughs
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1950
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1980
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Sweden
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