Have Risk Premia Vanished?

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July 28, 2021

Abstract

We apply a new methodology for identifying pervasive and discrete changes ("breaks") in cross-sectional risk premia and find empirical evidence that these are economically important for understanding returns on US stocks. Size, value, and investment risk premia have fallen off to the point where they are insignificantly different from zero at the end of the sample. The market risk premium has also declined systematically over time but remains significant and positive as do the momentum and profitability risk premia. We construct a new instability risk factor from cross-sectional differences in individual stocks' exposure to time-varying risk premia and show that this factor earns a premium comparable to that of commonly used risk factors. Using industry- and characteristics-sorted portfolios, we show that some breaks to the return premium process are broad-based, affecting all stocks regardless of industry- or firm characteristics, while others are limited to stocks with specific style characteristics. Moreover, we identify distinct lead-lag patterns in how breaks to the risk premium process impact stocks in different industries and with different style characteristics.

Keywords: Cross-sectional variation in risk premia, instability risk factor, industry and style portfolios, Bayesian analysis

JEL classifications: G10, C11, C15

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1. Introduction

Equity risk premia play a key role for investment strategies in the stock market. Empirical findings that stock characteristics such as book-to-market value, market cap, return momentum, investment, and profitability are associated with sizeable risk premia have profoundly impacted the investment industry with countless mutual funds specializing in investment styles such as small caps, growth, value, or momentum stocks.[1] The attractiveness of such investment strategies hinges critically not only on the magnitude of the associated risk premia, but also on their stability over time. For example, high allocations to value or small-cap stocks will be notably less attractive if the risk premia associated with these types of stocks have been significantly reduced over time. Shifts in risk premia also introduce an additional source of risk for investors, particularly if their impact varies across industries and firm characteristics.

Recognizing the need to formally test for shifts in risk premia, Fama and French (2021) report evidence of a substantial decline in the value risk premium but are unable to reject the null hypotheses that the value premium (i) is constant across pre- and post-1992 subsamples and (ii) is zero in the post-1992 subsample. However, their test uses just a handful of portfolios and likely has low power given the inherent noise in monthly premia. Moreover, the use of portfolios may mask the risk-return tradeoff in underlying stocks (Lewellen et al. 2010). Finally, they do not consider if their break date (1992) is the break location supported by the data or if there are more than a single break.

In this paper, we propose a novel approach to test for and model instability in risk premia which exploits information in large cross-sections of individual stock returns. Our approach is very flexible and does not assume that the dates of any breaks or even the number of breaks is known in advance. Using cross-sectional information turns out to be key to our ability to accurately estimate the location and magnitude of shifts to risk premia.[2] In turn, more accurate estimates of risk premia enhance our ability to test hypotheses such as constant risk premia, zero risk premia at the end of the sample, or even a monotonically

[1]Several studies have found that firm characteristics are priced, e.g., Fama and French (1993); Berk et al. (1999); Carlson et al. (2004); Zhang (2005); Carlson et al. (2006); Novy-Marx (2013).

[2]Data on individual stocks for improved estimation of risk premia has also recently been used to deal with the errors-in-variables bias by Jegadeesh et al. (2019).

declining pattern in risk premia, allowing us to sharpen the conclusions about risk premia in Fama and French (2021).

Using monthly returns data on a sample of more than 23,000 stocks from 1950 to 2018, we find strong evidence of four breaks in a six-factor model that allows for breaks in the intercept ("alpha"), risk premium coefficients, and idiosyncratic volatility. The break dates are located at July 1972, October 1981, June 2001, and October 2008, thus coinciding with the oil price shocks of the early seventies, the change in the Fed's monetary policy regime, the crash of the Tech bubble, and the Global Financial Crisis (GFC).

We find that the market equity, value, and size risk premia all vary significantly over time and have declined systematically over the nearly seven decades covered by our sample, with particularly large declines observed for the size and value premia. Conversely, after an initial decline in the early seventies, the momentum risk premium has recovered and is back to a level close to its value in the 1950s. Investment and profitability risk premia were notably higher during the two decades from 1981 to 2001 but have come down markedly in subsequent years. Tests conducted on the final (post-2008) regime do not reject the null hypothesis that the size, value, and investment risk premia have fallen to zero. We also cannot reject the null that the size and value risk premia have declined monotonically over the last seven decades. Conversely, we strongly reject that the market, momentum, and profitability risk premia are zero in the last regime and that they have declined uniformly over time. Our evidence suggests that all four breaks are broad-based and affect both the risk premium coefficients as well as individual stock alphas and idiosyncratic volatility parameters.[3]

We next examine the cross-sectional asset pricing implications of instability in the risk premium process. Stocks with different (style) characteristics have different exposures to variation in risk premia and so should also vary in how vulnerable they are to instability in risk premia. Stocks with greater exposure to instability risk should earn a greater instability risk premium provided that instability risk is priced in the cross-section.

To see if this prediction holds, we construct a break risk factor using the difference between forecasts of individual stock returns from models with and without breaks. We

[3] Evidence of mispricing is much stronger during the early part of our sample, declining significantly after 2001. It is also far greater for the less liquid microcaps compared to larger stocks.

use this break risk factor to explore whether stocks with the largest sensitivity to the break risk factor earn higher returns than stocks with lower break sensitivity. We find that returns on break sensitivity-sorted portfolios increase monotonically with the high-sensitivity quintile of stocks earning a statistically significant 3.4% higher annual return than the low-sensitivity quintile of stocks. Similarly, Fama-MacBeth regressions that control for other stock characteristics such as market beta, size, value, prior return performance, investment, and profitability, show that the break characteristic obtains a similar level of significance as the investment characteristic and is more significant than size, book-to-market, momentum, and profitability.

To better understand the portfolio implications of instability in risk premia, we next examine which stock characteristics – e.g., industry and investment style – are associated with high exposure to instability risk. To this end, we use industry and characteristics-sorted portfolios to dissect differences in break sensitivity. Across industries, we find that Telecommunication, Utility, Oil, Business Equipment, and Financial stocks exhibit the greatest break sensitivity. Conversely, stocks in the Wholesale, Textile, Mining, Books, and Meals industries exhibit the smallest break sensitivity. Small firms' returns are more sensitive to breaks while big firms are the least sensitive. Conditional on size, value firms are more sensitive to breaks than growth firms, firms with conservative investments and robust profitability tend to be more sensitive than aggressively investing firms with weak operating profits, and loser stocks are more sensitive than winner stocks.

Next, we explore the economic drivers of breaks by generalizing the common break framework introduced by Smith and Timmermann (2021) to allow breaks to be noncommon, possibly hitting any subset of series in the cross-section at different times. This analysis, which uses the methodology developed by Smith (2018a), allows us to (i) differentiate between market-wide and style-specific breaks; and (ii) identify whether certain industry or characteristic-sorted portfolios are affected earlier or later in the breakpoint cycle. Some breaks (e.g., 1973, and 2008) are very broad and affect stocks across multiple industries and investment styles. Other breaks are more specific to individual styles or industries and so do not have the same broad-based effects.

Inspecting the speed at which different portfolios are affected by breaks, we find that Financials, Telecommunication, Retail, Services, Steel, Chemicals, Oil, and Construction are generally among the first industries to be affected by breaks to risk premia. Moreover, the lead-lag relation varies across breaks with Financials playing a leading role during the 1929 market crash and Global Financial Crisis, while Telecommunication stocks were leading during the dotcom crash and Oil stocks were leading in 1973. The speed of information diffusion has increased over time as the lead-lag delay time between the first and last affected industries has clearly been reduced. Style portfolios also differ in how rapidly they are affected by breaks: momentum portfolios are generally among the earliest to be affected with loser stocks leading winner stocks. Similarly, large stocks tend to be affected earlier by breaks than small stocks, growth stocks generally move earlier than value stocks, firms with weak profitability move earlier than firms with robust profitability, and firms with conservative investments are among the last ones to be affected by breaks.

Our paper is related to a number of recent studies providing empirical evidence that cross-sectional risk premia associated with a broad array of firm-level characteristics vary considerably through time, reaching unusually high levels of volatility during economic crises and periods with elevated distress in financial markets. Freyberger et al. (2020) and Gu et al. (2020) document significant time variation in the mapping from a variety of firm-level predictors to expected returns. Gagliardini et al. (2016) find that risk premia are large and volatile in crisis periods and deviate considerably from the path implied by a constant-parameter model. Ang and Kristensen (2012) use a nonparametric approach to estimate and track time variation in the factor loadings of conditional CAPM or multi-factor models. Adrian et al. (2015) propose regression-based estimators of dynamic asset pricing models that capture time-variation in beta loadings and risk premia.[4] Using a present value model setup, Smith and Timmermann (2021) examine how breaks in regression coefficients affect time-series predictability of returns. Relative to that study, we use cross-sectional information to study instability in the risk premia of a range of both classic and more recently proposed investment style characteristics. We analyze which types of firm characteristics are associated with the greatest exposure to break risk and also show how the timing of the breaks varies across characteristics and industries. Moreover, we examine

[4]Such instability is mirrored across a broad range of asset classes and investment styles; using a century of data on six asset classes, Ilmanen et al. (2019) find considerable evidence of time variation in single-factor returns and volatility for value, momentum, carry, and defensive investment strategies.

how cross-sectional heterogeneity in break sensitivities across stocks can be used to form a break risk factor which we demonstrate is priced and highly significant.

The outline of the paper is as follows. Section 2 introduces our methodology, including the return regressions and prior specifications. Section 3 presents our data and empirical evidence of breaks. Section 4 constructs our cross-sectional break risk factor and compares it with existing risk factors from the finance literature. Section 5 focuses on the timing and effect of breaks in return regressions conducted for different portfolios of stocks sorted by industry or investment style. Section 6 concludes. Web appendices contain technical details and analyses of out-of-sample return predictability and portfolio allocation implications.

2. Methodology

This section introduces our panel regression approach to modeling discrete and pervasive shifts in the risk premium process. We justify our assumption of discrete, pervasive shifts or "breaks" in return premia in three ways. First, a key feature of our approach is that it allows us to identify economically large and long-lasting regime shifts as opposed to smaller and more local variation in risk premia. Focusing on breaks that are pervasive allows us to fully exploit the rich information available in the cross-section of stock returns. Second, and consistent with the idea of discrete shifts in risk premia, the changes that we identify empirically are associated with important economic events and coincide with large shifts in aggregate valuation measures such as the dividend-price ratio of the market portfolio. From an asset pricing perspective, large movements in valuation ratios is exactly what one would expect when risk premia shift. Third, we use economically motivated priors to ensure that the variation in risk premia falls within ranges that are economically plausible.[5]

We follow recent studies and estimate risk premia directly in a single step from regressions of firms' stock returns on a set of stock or firm characteristics. For characteristics that can be directly measured without error, this single-step regression approach avoids errors-in-variables problems. Stock betas and volatility measures, are, however, estimated in a first step and for these variables the error-in-variables problem remains.

[5] Pástor and Stambaugh (2001) identify breaks in the equity premium process and use transition regimes to link adjacent regimes.

We next explain the details of our Bayesian panel break approach which builds on the framework of Fama and French (2020) who demonstrate that stacking Fama-Macbeth regressions across time gives rise to a factor model representation.[6] We generalize this framework to allow for structural breaks that capture factor risk premia which undergo discrete shifts at unknown times.

2.1. Estimating time-varying risk premia

Suppose we observe a panel of monthly stock returns r_{it}, measured in excess of a risk-free rate, on $i = 1, \ldots, N_t$ firms over a sample $t = 1, \ldots, T$.[7] Moreover, let X_{it-1} denote a vector of firm or stock characteristics for firm i observed at time $t-1$. Characteristics could include observable features such as firm size, book-to-market ratio, investment, and profitability or estimated stock characteristics such as (factor) betas or return momentum.

Fama and French (2020) demonstrate that, when stacked across t, cross-sectional regressions of returns on lagged firm characteristics become factor models that can be estimated using time-series information. Building on this insight, consider the regression model

$$r_{it} = \alpha_i + r_{zt} + \lambda_t' X_{it-1} + \epsilon_{it}, \qquad \epsilon_{it} \sim N(0, \sigma_i^2). \tag{1}$$

From Fama and French (2020), the slope estimates λ_t are portfolio returns that can be interpreted as factors with pre-specified time-varying factor loadings (characteristics) and r_{zt} is the month-t return on a regular portfolio comprising the left-hand-side assets with weights summing to one when all explanatory variables are set to zero. This return component is therefore common to all stocks.[8] Finally, α_i captures any mispricing of asset i.[9]

The model in Equation (1) and conventional time series factor models both attempt

[6]A related literature finds evidence of breaks in expected equity returns. For example, Pástor and Stambaugh (2001) find 15 structural breaks in estimates of the U.S. equity premium from a data set spanning approximately 150 years. Bekaert et al. (2002) identify common breaks in return models and link them to global equity market integration.

[7]Our panel approach can easily accommodate variation in the number of stocks at time t, N_t.

[8]To obtain this component, we employ the common correlated effects framework of Pesaran (2006), effectively extracting r_{zt} from the cross-sectional average return.

[9]In a model without the intercept, α_i, Fama and French (2020) note that the time series average of ϵ_{it} will capture mispricing of asset i. To enable us to capture shifts in mispricing, we explicitly include α_i and impose that ϵ has mean zero.

to explain variation in returns. However, there are also important differences between the two approaches. The time series approach uses factors that are prespecified, e.g., from sorts of stocks on book-to-market equity, size, investment, profitability or prior returns and optimizes over the factor loadings which are assumed to be time-invariant. Conversely, estimates of Equation (1) optimize over the common return component (r_{zt}) and the factor returns λ_t so as to minimize the sum of squared residuals given the prespecified time-varying factor loadings.

The time-series average return on a factor is often used to estimate its risk premium. For example, the historical mean (excess) return on the market portfolio is commonly used as an estimate of the equity risk premium. However, if risk premia remain constant within certain blocks of time ("regimes") but can shift across regimes, then risk premia should be computed only on the data from the same regimes.[10] To capture possible time variation in risk premia, we therefore generalize the model in (1) to allow any subset of the factor risk premia, mispricing parameters (alphas), and volatilities to shift an unknown number of times (K) at unknown locations $\tau = (\tau_1, \ldots, \tau_K)$, producing $K+1$ separate regimes.

We initially assume that the breaks are common and affect all assets at the same time, but subsequently relax this assumption. The assumption that breaks to return premia have a pervasive effect on the cross-section of stock returns effectively allows us to use the full cross-section of returns to identify breaks in the risk premium process, vastly increasing the power of our approach. It also ensures that we only identify breaks to the risk premium process that are truly common.

Our panel break model for stock returns thus takes the following form:

$$r_{it} = \alpha_{ik} + r_{zt} + \lambda_k' X_{it-1} + \epsilon_{it}, \qquad \epsilon_{it} \sim N(0, \sigma_{ik}^2), \qquad t = \tau_{k-1} + 1, \ldots, \tau_k. \tag{2}$$

Here λ_k denotes the expected risk premia that are constant within the kth regime, while α_{ik} denotes the degree of mispricing of asset i in state ("regime") k. Our baseline model uses six lagged characteristics (X_{it-1}) – market beta, size, book-to-market, momentum, investment, and profitability – and estimates variation in the associated risk premia across regimes.

[10] Pástor and Stambaugh (2001) estimate time variation in the U.S. equity risk premium as the average of market excess returns within regimes that are separated by structural breaks.

Given our large cross-section of stocks, estimating a full covariance matrix in each regime is not possible. We therefore adopt a common factor structure to absorb dependence across stocks and assume that the remaining residuals in Equation (2) are uncorrelated. While this may seem a strong assumption, the model that we take to the data includes the common factor r_{zt} to absorb common variation in returns.[11] In fact, as we demonstrate below, the assumption of uncorrelated residuals – conditional on including our common factor r_{zt} – is supported by the data. Moreover, using the approach of Pesaran (2006) we also extend our baseline model to include latent common factors that absorb any remaining correlation in the residuals: $\epsilon_{it} = \gamma_i' f_t + u_{it}$.

To capture changes to cross-sectional risk premia in Equation (2), we use a Bayesian panel break methodology that accounts for uncertainty about breaks.[12] Our approach builds on and extends that of Smith and Timmermann (2021) who examine how breaks in regression coefficients affect time-series predictability of returns in a present value setting. Conversely, building on Fama and French (2020) our analysis here identifies breaks to pooled cross-sectional risk premia that load on firm-specific characteristics.

2.2. *Prior distributions*

Before continuing with the analysis, we next explain our choice of priors which follows conventional practice and specifies Gaussian distributions over the slope coefficients and conjugate inverse gamma priors over the residual variances.[13]

The choice of priors should be guided by asset pricing theory and reflect what is economically plausible in terms of the magnitude of any deviations from the underlying factor pricing model. Throughout our paper, benchmark returns are either excess returns or returns on zero-investment (long-short) portfolios. In this case, conventional asset pricing models imply that $\alpha_k = (\alpha_{1k}, \ldots, \alpha_{Nk}) = 0_N$ in the kth regime (Huberman et al. 1987). Centering α_k a priori at zero, the specification of σ_α reflects the prior belief that the pricing

[11] Bai and Ng (2002) estimate that just two factors is sufficient to capture variation in the cross-section of U.S. stock returns.

[12] Frequentist approaches, such as Bai and Perron (1998) and Baltagi et al. (2016), ignore break uncertainty and may therefore compromise small-sample inference (Pástor and Stambaugh 2001).

[13] For a detailed description of the prior choices, see Appendix B.

model holds. Setting $\sigma_\alpha = 0$ corresponds to a dogmatic belief that the pricing model holds with absolutely no mispricing. Conversely, setting $\sigma_\alpha = \infty$ reflects a prior belief that any degree of mispricing is equally likely. Small values of σ_α reflect prior beliefs that are skeptical about the existence of mispricing but do not rule it out entirely; larger values reflect stronger prior beliefs that there may be some mispricing.

Further, we choose our prior to ensure that an economically unreasonable high Sharpe ratio is unlikely since this would give rise to an approximate arbitrage opportunity by generating high expected returns without being exposed to much risk (Shanken 1992).[14] This scenario could arise if a high intercept estimate, α_{ik}, coincides with a low idiosyncratic volatility, σ_{ik}. Our prior places very little weight on this scenario by linking the intercept to the residual volatility (MacKinlay 1995; Pástor and Stambaugh 1999; Pástor 2000).[15] Following Pástor and Stambaugh (1999), our baseline analysis adopts a moderate prior belief by setting σ_α equal to 5%. We apply the same prior belief that the α_{ik} values are centered at zero across all regimes, i.e., that the degree of mispricing is constant. This does not rule out that some assets may be more mispriced in one regime and less mispriced in another because residual volatilities are allowed to vary across regimes.

Finally, our prior assumes that breaks occur, on average, every twenty years, though we also consider a ten-year prior. The prior on the slope coefficients λ_k is Gaussian. The prior hyperparameter σ_λ controls the degree of shrinkage applied: the smaller this hyperparameter, the more the slopes get pulled toward zero. We specify a moderate degree of shrinkage by setting σ_λ equal to 0.08 (Wachter and Warusawitharana 2009).

[14] Dybvig (1983) and Grinblatt and Titman (1983) use residual variances to study how much any given asset can depart from a factor model. Shleifer and Vishny (1997) argue that high volatility can introduce limits to arbitrage and thus cause a given asset to be mispriced.

[15] The Gaussian prior on the intercept is conditional on the residual volatility and thus the variance of the intercept combines the residual variance and the prior variance σ_α^2. Since the prior on α_{ik} is centered at zero, a low residual variance will shrink the intercept estimate towards zero, making a value far from zero highly unlikely. As the residual variance increases, the intercept is pulled less strongly toward zero and thus intercept estimates further away from zero become more likely.

3. Instability in risk premia

This section introduces our returns data and presents empirical evidence on the presence of pervasive breaks to the risk premia of the Fama-French factors and momentum. We also examine shifts in the mispricing parameters (alphas) and in the return volatility parameters.

3.1. Data

We use monthly data on a total of $N = 23,664$ stocks observed between January 1950 and June 2018 sourced from CRSP, Compustat, and I/B/E/S. Our sample includes stocks listed on the NYSE, AMEX and NASDAQ. Stocks are only included if they have a market value on CRSP at the end of the previous month and a value for common equity in the firm's financial statement.

Data are compiled on 94 firm characteristics detailed in Green et al. (2017). Table A1 of the Web Appendix lists the variables and the corresponding acronyms.[16] We relate stock returns to characteristics measured at the end of the previous month and assume that annual (quarterly) characteristics are available in month $t-1$ if the firm's fiscal year (quarter) ended at least six (four) months before month $t-1$.[17]

3.2. Break Locations

Our empirical analysis focuses on a six-factor model obtained by regressing firm-level excess stock returns on an intercept, market beta ($\hat{\beta}$), size ($SIZE$), book-to-market (BM),

[16]This table corresponds to Table 1 of Green et al. (2017) and is only included for reference. We are grateful to Jeremiah Green for making available on his website SAS code to extract the data from CRSP, Compustat and I/B/E/S.

[17]A more detailed explanation of the characteristics is provided in the Appendix of Green et al. (2017). Characteristics are cross-sectionally winsorized at the 1st and 99th percentiles of their monthly observations. The I/B/E/S statistical period date and CRSP monthly end date are used to align I/B/E/S and CRSP data in calendar time.

momentum (MOM), investment (INV), and profitability (PRF):

$$r_{it} = \alpha_{ik} + r_{zt} + \lambda_{MKT,k}\hat{\beta}_{it-1} + \lambda_{SIZE,k}SIZE_{it-1} + \lambda_{BM,k}BM_{it-1}$$
$$+ \lambda_{MOM,k}MOM_{it-1} + \lambda_{INV,k}INV_{it-1} + \lambda_{PRF,k}PRF_{it-1} + \epsilon_{it}. \tag{3}$$

Measurement of the six characteristics follows Green et al. (2017) so that market beta is estimated using weekly returns and equal-weighted market returns for the three-year period ending in month $t-1$ (with at least 52 weeks of returns), size is the natural logarithm of market capitalization measured at the end of month $t-1$, book-to-market value is the book value of equity divided by the prior fiscal year-end market capitalization, momentum is computed as the 11-month cumulative return from month $t-12$ through month $t-2$, investment is computed as annual change in gross property, plant, and equipment plus annual change in inventories all scaled by lagged total assets, and profitability is computed as revenue minus cost of goods sold minus SG&A expense minus interest expense divided by lagged common shareholders' equity.

This six-factor model is widely used in empirical work which makes it important to investigate the stability of the associated risk premia. Subsequently, we also consider evidence of instability in the expected return premia of a much larger model that includes all 94 characteristics from the data set of Green et al. (2017).

Figure 1 displays the posterior probabilities of the number (top window) and location of breaks (bottom window) affecting the parameters of the six-factor model. Approximately 75% of the posterior weight is assigned to a model with four breaks with most of the remaining 25% roughly evenly distributed among models with three and five breaks, respectively. Given the strong evidence of four breaks, our empirical analysis focuses on this model, but it is important to bear in mind that our Bayesian approach accounts for uncertainty about both the number of breaks and their location.[18] Detailed discussion of our formal definition of breaks is provided in Appendix D.

The location of each of the four breaks is estimated quite accurately. The four posterior mode break dates are July 1972, October 1981, June 2001, and October 2008 with around

[18]Only 1.2% of the posterior probability is assigned to one break, and 2.2% to two breaks. The probability of no breaks is zero down to the third decimal.

75% of the probability assigned to one particular month.[19]

3.3. Breaks in expected return premia

We next consider how the risk premia vary across the five regimes identified by the four breaks displayed in Figure 1. The solid black lines in Figure 2 display the evolution in the equity, value, size, momentum, investment, and profitability risk premia, i.e., the values of the λ_k parameters in Equation (3). In addition, the solid green line in the top left panel shows the equity risk premium obtained from a single-factor (CAPM) model. Following Pástor and Stambaugh (2001), the red dotted lines in each panel further show the posterior standard deviation of the risk premia estimated from the 6-factor model. These standard deviations are quite stable across regimes and vary in a fairly tight band around 1%.

Starting with the single factor CAPM, the equity risk premium varies from 5.9 to 6.7% in the two regimes prior to 1981, declines to a slightly lower range between 5.2 and 6.2% in the next two regimes, before falling to 3.3% after 2008. These are economically plausible values and suggest a marked decline in the equity risk premium after the GFC. The equity risk premium obtained from the six-factor model (solid black line in top left panel) evolves along a similar path, although it shows a smaller decline in the final regime.[20]

Next, consider the evolution in the risk premium associated with the book-to-market ratio (top right corner). This declines monotonically from 3.8% per year prior to 1972 to 0.6% in the period after the GFC. Hence, over the course of our sample, the value risk premium has declined by more than four-fifths of its initial level, suggesting a sizeable reduction in the amount by which returns on value stocks have outpaced growth stocks.

The size premium (middle left panel) shows a similar erosion from 4% per year prior to 1972 to 1.9% after 1981, followed by a further reduction to 0.7% after the GFC. Hence, the size premium seems largely to have disappeared over the sample.

[19] Figure A1 in the web appendix shows results based on a prior of a 10-year break frequency as opposed to the 20-year prior used here. Using the 10-year prior on the break frequency, we detect the same break dates as under the 20-year prior plus one additional break in the late-1990s, corresponding to the collapse of Long Term Capital Management and the Asian Financial Crisis. Most of the risk premia in this short-lived regime are temporarily elevated, so the overall effect on our results from changing the prior is marginal.

[20] Unlike Pástor and Stambaugh (2001) we do not impose a smoothness condition which imposes that the equity risk premium gradually transitions between regimes.

The momentum premium (middle right panel) behaves very differently. Starting at 4.6% per annum in the first regime, this premium drops to 1.6% over the course of the next two regimes before reversing course and increasing to 3.5% after 2008.

The investment and profitability risk premia are notably higher during the middle decades in our sample but have come down markedly in recent years. Specifically, the investment premium (bottom left panel) starts out at 1.6% prior to 1973, increases sharply to 6.2% in 1973 and exceeds 5% until 2001. At this point, the investment premium drops to 0.9% before declining further to a statistically insignificant level (0.3%) after 2008. The profitability risk premium (bottom right panel) starts out at 2.3% prior to 1973, declines to 0.8% in the second regime only to rise above 6% from 1982 to 2001. However, the profitability risk premium then declines quite sharply and finishes at 2.5% in the final regime.

We conclude from these findings that the market equity, value, and size risk premia all have undergone secular declines over the nearly seven decades covered by our sample. The reductions are largest for the size and value premia which, at the end of our sample, are close to zero. Conversely, after declining sharply in the early seventies, the momentum risk premium has subsequently risen steadily and is now close to its original value in the early sample. The investment and profitability risk premia increase markedly during the middle portion of our sample but weaken substantially after 2001. In the final (post-2008) regime, the investment risk premium is insignificantly different from zero while the profitability premium remains significant.

To formally evaluate the empirical validity that our factor model leaves no significant cross-sectional dependence among the idiosyncratic shocks, we estimate average pairwise correlations between residuals and compute the test for cross-sectional dependence (CD) proposed by Pesaran (2021) which, under the null of no dependence, has a standard Normal distribution. For our data, the CD statistic is 1.72 so we cannot reject the null hypothesis of no cross-sectional dependence remaining in the residuals.[21] One might be concerned with the test's ability to detect cross-sectional dependence if negative and positive correlations have an offsetting effect. As it turns out, the vast majority of correlations are positive so this effect is unlikely to be severe in our setting. To alleviate any remaining concerns,

[21] The CD test might also be viewed as a test against weak dependence. For large panels ($N > 10$) like ours, weak dependence is unlikely to cause any serious problems for inference (Pesaran 2015).

however, we further employ the CD_{lm} test of Breusch and Pagan (1980) which uses squared correlations. The CD_{lm} statistic is 1.85, so again we cannot reject the null hypothesis of no cross-sectional dependence remaining in the residuals. While the CD_{lm} test can exhibit considerable size distortions in settings with large N and short T, our setting has large N *and* large T so any size distortions of the test are likely to be small.

As a further robustness check, we estimate a version of our model that allows for a latent common factor in residuals: $\epsilon_{it} = \gamma_i' f_t + u_{it}$. Reassuringly, the baseline results are robust to this change, implying that the common factor r_{zt} successfully absorbs the majority of cross-sectional dependence in return variation. Specifically, the CD statistic is reduced from 1.72 to 1.67, the CD_{lm} statistic is reduced from 1.85 to 1.73, and the average pairwise correlation is reduced from 0.17 to 0.15. The estimated break dates and risk premia remain almost identical when we add this factor.

3.4. Formal tests for time-varying and declining risk premia

Fama and French (2021) find that the value premium has diminished considerably since 1991.[22] Constructing six portfolios sorted on size and book-to-market, they report that the annualized value premium fell from 4.3% (1963-1991) to 0.6% (1992-2019) for large caps and from 7% to 4% for small caps. They cannot reject the null hypothesis that the risk premium is zero in the second subsample, but also cannot reject that the value premium is constant across the two subsamples. However, their tests likely have low power as they use just a handful of portfolios and monthly risk premia tend to be highly volatile.

Exploiting information in a large cross-section of individual stocks, as we do here, circumvents this problem and increases our ability to detect shifts in risk premia. To examine whether our estimates imply that risk premia have vanished, the upper panel of Table 1 displays the final regime's six-factor risk premium estimates (expressed as annualized percentages) and corresponding t-statistics (in brackets below) from our panel break model that regresses firm-level excess returns on market beta, size, value, momentum, investment, and profitability as displayed in Equation (3). In the final regime (2008-2018) the value

[22] Schwert (2003) and Linnainmaa and Roberts (2018) also report that the value premium has declined over time.

premium (0.63%) is not significantly different from zero. Similarly, at 0.70% and 0.31% per year, we cannot reject the null that the size and investment premia have gone to zero in the final regime. Conversely, with t-statistics of 4.21, 3.02, and 2.27, respectively, we strongly reject the null that the market equity (4.68%), momentum (3.47%) and profitability risk premia (2.48%) equal zero in the last regime. These results demonstrate that our approach can be used to test which risk premia remain significant at the end of the sample versus which ones are sufficiently small so as to be insignificantly different from zero.

To more directly compare our findings to those in Fama and French (2021), we next impose a single break at the same time (1991) as that assumed by Fama and French (2021) and use our methodology to estimate risk premia. The results, displayed in the middle panel of Table 1 show that the value premium declined from an annualized 3.36% (1950-1991) to 1.53% (1992-2018). In contrast to the results in Fama and French (2021), using Bayes factors we find overwhelming evidence in favor of a significant change in the value premium before and after 1991.[23] This demonstrates the added power that comes from using the full cross-section to test for changes in risk premia.

Our finding of stronger evidence in favor of the break in 1991 relative to that found by Fama and French (2021) could be driven by our use of Bayes factors to test the null hypothesis of no break as opposed to our use of a larger cross-section. To address this possibility, we first compute the Bayes factor when imposing the 1991 break on the 3×2 portfolios used by Fama and French (2021). This Bayes factor is 2.42, implying little or no evidence in favor of the break. Second, we implement a conventional Chow test by estimating the model on the full cross-section of stocks with a break dummy that equals zero for the data up to 1991 and changes to unity in 1992. The resulting p-value for the associated F-statistic equals 0.006, so a conventional stability test strongly rejects the null that the value premium is constant across the two subsamples. These results support our assertion that the value premium has declined since 1991 and show that it is our use of a large cross-section of returns that yields additional power to draw this conclusion.

[23] Bayes factors are constructed from the marginal likelihood of each model computed using the method of Chib (1995) and are the preferred Bayesian model comparison approach as they integrate over all parameters in the model and inherently penalize model complexity. Bayes factors between 1 and 3 are inconclusive, values between 3 and 20 indicate positive evidence in favour of our baseline model, while values greater than 20 indicate strong evidence (Kass and Raftery 1995). The Bayes factor of 179.87 reported in the table therefore represents very strong evidence against the null of unchanged risk premia.

Alquist et al. (2018) report that the size effect diminished shortly after its publication. Using the same Bayes factor approach with the full cross-section of stocks to test for a single break in the size premium occurring at 1981, again we find overwhelming evidence in favor of the break. Specifically, the size premium declined from an annualized 4.20% (1950-1981) to 0.65% (1982-2018).

These tests show that risk premia have changed over time but do not reveal whether there has been a systematic downward trend. To examine this point, we separately test whether each of the six risk premia monotonically decline over the five regimes. To do this, we use the Monotonic Relation test developed by Patton and Timmermann (2010) which is nonparametric, does not require a functional form (i.e. linear), and is easy to implement using bootstrap methods. Under the null, the risk premium is constant or weakly increasing across regimes, while under the alternative it is monotonically decreasing. When the bootstrap p-value is less than 0.05, we conclude that the risk premium is significantly monotonically decreasing.

Results from this test are displayed in the lower panel of Table 1. There is clear evidence of significant monotonically decreasing value and size risk premia (p-value below 0.05) across our five regimes. However, the equity, momentum, investment, and profitability risk premia are not significantly monotonically decreasing, in line with Figure 2.[24]

3.5. Breaks vs. time-varying parameters

Our approach assumes that changes in model parameters are rare but discrete. This perspective allows us to more sharply identify the locations at which the largest changes took place.[25] Depending on which events led to the change in the parameters, at other times we might expect parameter changes to be more gradual.

To test whether a time-varying parameter model with smoothly-evolving parameters might better approximate the underlying data generating process compared with our break-

[24]Studies that suggest the equity premium has declined over time include Blanchard (1993), Jagannathan et al. (2001), and Fama and French (2002).

[25]Jochmann et al. (2013) also find that the parameters of their return prediction models sometimes change very rapidly.

point approach, we estimate the following specification:[26]

$$r_{it} = \alpha_{it} + r_{zt} + \lambda_{MKT,t}\hat{\beta}_{it-1} + \lambda_{SIZE,t}SIZE_{it-1} + \lambda_{BM,t}BM_{it-1}$$
$$+ \lambda_{MOM,t}MOM_{it-1} + \lambda_{INV,t}INV_{it-1} + \lambda_{PRF,t}PRF_{it-1} + \epsilon_{it} \quad (4)$$

with $\epsilon_{it} \sim N(0, \sigma^2)$, and the parameters, $\theta_t = (\alpha_t, r_{zt}, \lambda_t)$, follow a random walk

$$\theta_t = \theta_{t-1} + u_t, \quad (5)$$

in which $u_t \sim N(0, Q)$ and $Q = \text{Diag}(\phi_1, \ldots, \phi_6)$ is a diagonal matrix so the state innovations are conditionally independent. We further assume that the initial value is Normally distributed $\theta_0 \sim N(\theta, Q)$.

To measure the strength of evidence in favor of our breakpoint specification relative to this time-varying parameter specification, we next compute a Bayes factor. The Bayes factor (83.19) suggests strong evidence in favor of our discrete break specification using standard threshold values. To alleviate concerns that this conclusion may be influenced by our assumption that the innovations are uncorrelated in the time-varying parameter model, we re-estimate the model allowing for cross-sectional dependence. The Bayes factor relative to this model is notably lower (27.23), illustrating the importance of allowing for cross-sectional dependence when modeling the underlying data generating process. Nonetheless, the evidence in favor of our discrete breakpoint approach relative to the slow-moving coefficients in the time-varying parameter model remains strong even after accounting for cross-sectional error dependence in the time-varying parameter model.

That model parameters sometimes change very rapidly in a way that is well approximated by discrete breaks is confirmed by inspecting five-year rolling window average estimates of factor risk premia. For example, fluctuations in the size premium tend to be quite sharp, rather than slow moving. Moreover, the risk premia estimated from the time-varying parameter model sometimes change very sharply, e.g., by 150 basis points over one or two months for the momentum factor. These observations support our formal Bayes factor test which strongly favors breakpoints as opposed to time-varying parameters.

[26] Cogley and Sargent (2005) and Primiceri (2005) propose popular time-varying parameter specifications.

3.6. Aggregate and idiosyncratic volatility

The top panel of Figure 3 graphs the aggregate volatility obtained from our Bayesian panel breakpoint model in Equation (3), estimated as the standard deviation of r_{zt} in each regime. Aggregate volatility starts just below 15% per year, rises to 17.1% in 1972, before monotonically declining throughout the remainder of the sample, reaching 14.4% in the final regime (2008-2018), its lowest value of the sample. The posterior standard deviation of this aggregate volatility - shown in a dotted line at the bottom of the panel - varies in a range between 2.2% and 4.5%, with variation tending to be lower in the longer-lived regimes.

Our approach also allows the volatility of the idiosyncratic error term ϵ_{it} to vary across regimes. To see how the average idiosyncratic volatility evolves over time, the lower panel of Figure 3 graphs the value-weighted average of firm-level residual volatility estimates through our sample, expressed as an annualized percentage. In the first regime (1950-1972), idiosyncratic volatility is very low, amounting to just 9.8% per year. Average idiosyncratic volatility then nearly doubles in 1972, before further rising to 29.1% per year in 1981 and to 39.1% in 2001.[27] After 2008, idiosyncratic volatility comes down substantially, declining to 25%. The posterior standard deviation of the residual volatility mostly follows a parallel path, rising from 3.0% in the first regime to 13.2% in the final regime.

3.7. Mispricing

To gain insights into how any mispricing has evolved over time, Table 2 evaluates the cross-sectional distribution of α estimates. For each of the five regimes, we report the average posterior mean and standard deviation along with various percentiles of the annualized percentage α estimates from regressions of firm-level stock returns on market beta, size, value, momentum, investment, and profitability as displayed in Equation (3). The final column reports the proportion of individual firm-level alpha estimates that are significantly different from zero at the 5% level, using a two-sided test. In each panel, the bottom row shows the same statistics obtained from a model without breaks fitted to the full sample.

[27] Consistent with these findings Campbell et al. (2001) report that firm volatility has increased markedly from 1962 to 1997.

All alpha estimates use full sample information and so could not have been exploited in real time for improved investment performance. The regime-specific alpha estimates, as they use shorter samples, are more strongly affected by estimation error than the constant-parameter estimates shown in the bottom row. In practice, this means that the cross-sectional range of alpha estimates within each regime is somewhat wider than is normally the case.

With this caveat in mind, first consider the top panel (all stocks). In the full sample, the mean alpha estimate is 0.40%, or 40 basis points (bps) per annum with an inter-quartile range from -0.67% to 2.24% and a standard deviation of 2.85. Moving to the individual regimes, we find stronger evidence of mispricing in the early parts of our sample: the mean alpha estimate is around 2.5% per year in both the first (1950-1972) and third (1981-2001) regimes and the 75th percentile is more than twice as high in these regimes as its average, full-sample value. In these early regimes, sizeable proportions (24% and 21%) of the alpha estimates are significantly different from zero.[28]

Evidence of mispricing in individual stocks has been markedly reduced over time, however, and the mean alpha estimates are negative, at -0.25% and -0.60% per year, in the final two regimes. Although the range of alpha estimates is wider in these regimes than they are in the full sample, this can to a large extent be attributed to the greater effect of sampling error in the shorter-lived regimes. Indeed, the proportion of stocks whose alpha estimates are significantly different from zero is much smaller in the final two regimes – six and four percent, respectively – than in the full sample (17%).[29]

We would expect to find stronger evidence of mispricing in the six-factor model among the smallest, most illiquid stocks that are harder to trade. To see if this is indeed the case, the middle and bottom panels of Table 2 show separate results for larger stocks and micro caps. Consistent with our expectation, the interquartile range of alpha estimates is far wider for micro caps (-18.98%; 12.79%) than for the larger stocks (-0.52%; 1.95%). The percentage of stocks with significant alpha estimates is also larger for micro caps than for the larger stocks.

[28]Because many, possibly correlated, alpha test statistics are being considered here, caution should be exercised when interpreting this evidence due to the associated multiple hypothesis testing problem.

[29]Table A2 in the web appendix shows, for each regime, percentiles of the distribution of the posterior standard deviations of the α estimates. Posterior standard deviations of the α estimates tend to be notably higher in certain regimes such as the 2001-2008 period, highlighting the importance of accounting for estimation error in models with unstable parameters.

We conclude from these findings that there is substantial *ex-post* evidence of time-variation in mispricing for individual stocks during our sample and that (i) the mispricing is much stronger during the early parts of our sample, declining significantly after 2001; and (ii) mispricing is stronger for micro caps than for large stocks.

3.8. Which model parameters are affected by instabilities?

Our empirical analysis up to this point uncovers strong evidence that alphas, risk premia, and idiosyncratic volatilities change across the five regimes identified by our model. However, while we have inspected the magnitude of the shifts in these parameters across regimes, we have not formally tested whether all parameters change at the break dates or whether they are unaffected by regime shifts.

To address this point, we next conduct formal hypothesis tests that disentangle which parameters are most affected by instabilities. Specifically, we estimate several restricted versions of the baseline model that allow for breaks in (i) mean coefficients (α and λ) only, (ii) idiosyncratic volatility (σ) only, (iii) α only, and (iv) λ only. To gauge the strength of evidence in favor of our general baseline model relative to each restricted model, we again compute Bayes factors. The results, displayed in Table 3 for the full sample, i.e., across all breaks, as well as on a break-by-break basis, show overwhelming evidence that all four breaks are broad-based and affect both the mean and volatility parameters. Focusing on the mean coefficients, there is also strong evidence that all four breaks hit both the risk premia (λ) and pricing errors (α).

We conclude that there is strong support for discrete regime shifts in the parameters of the simple six-factor return regression model in Equation (3). Moreover, these shifts are broad-based, economically large, and highly statistically significant.

3.9. Breaks and Macroeconomic Risks

Studies such as Lettau et al. (2008) argue that variation in macroeconomic risk helps explain movements in the equity risk premium. Using quarterly data from 1952:1 to 2002:4, these authors identify a structural break in 1992 at which point volatility declines, and they find a striking correlation between movements in macroeconomic risk and the stock market.

To see if a similar relationship holds for our data, we next examine if low frequency movements in macroeconomic risk are related to low frequency movements in the market equity risk premium identified by our CAPM estimates. Computing the average real uncertainty measure from Jurado et al. (2015) and Ludvigson et al. (2021) within the regimes identified by our baseline model, along with our CAPM equity risk premium estimate (the green line in the top-left panel of Figure 2), we find a 0.63 correlation (across regimes) between the two series.[30] Our CAPM equity premium estimate is also highly correlated with low frequency movements in the dividend-price ratio. The average dividend-price ratio within regimes identified by our model has a 0.28 correlation with our CAPM equity risk premium estimate.[31]

We next address whether exposure to such regime shifts is itself a source of risk that is priced in the cross-section of equity returns.

4. Break Risk Factor

The empirical evidence in the previous section shows that risk premia associated with stock or firm characteristics such as market betas, size, book-to-market value, return momentum, investment, and profitability are affected by pervasive and economically large breaks. Exposure to this type of instability in risk premia introduces a separate source of risk in individual stock returns as well as returns on portfolios focusing on particular investment styles. For example, investors holding small value stocks will be exposed to the risk that size and value premia change in a manner that makes their return distribution more difficult to estimate and predict than if risk premia were constant. Break risk matters particularly to long-term buy-and-hold investors who do not rotate their portfolio allocations very frequently, but can also be important to short-term investors because of the challenges associated with detecting breaks and updating estimates of risk premia in real time.

[30] Recursive, real-time estimates of our break probabilities are also positively correlated with the monthly real (0.13 correlation), macroeconomic (0.17), and financial (0.19) uncertainty measures taken from Jurado et al. (2015) and Ludvigson et al. (2021). These uncertainty measures tend to spike around our posterior mode break dates, as do our real-time break probability estimates.

[31] Our CAPM equity risk premium estimate has a similar positive, and even more pronounced, correlation with the earnings-price ratio (0.33).

These arguments suggest that instability in the risk premium process is itself a source of risk that could give rise to a break risk factor. This is economically plausible because the breaks identified by our approach occur during economic and financial crises. Stocks more exposed to major macroeconomic events and financial crises might plausibly be expected to earn higher returns as compensation for risk exposure to “bad states”.

4.1. Individual stocks’ exposure to instability risk

To establish whether instability risk is economically important, we must demonstrate that (i) regime shifts are pervasive and affect the returns of multiple stocks or portfolios; (ii) exposure to instability risk is priced in the cross-section and stocks with greater exposure to this type of risk earn higher returns, on average, than stocks with low exposure, assuming that instability risk does not hedge against other sources of risk.

The first point (pervasiveness) is indirectly established by the fact that we use a panel regression approach to identify common breaks in style risk premia. Because our approach penalizes large models with many parameters, it is highly unlikely to identify regime shifts that only affect a small subset of stocks. To further strengthen this point, we provide formal evidence in Section 5 that a wide set of industry and style-sorted portfolios are affected by changes in regimes.

To address the second point, we need a measure of how much individual stocks are affected by breaks which we can use to sort stocks into portfolios with high and low break sensitivities. Moreover, we need to be able to compute this measure in real time before performing the portfolio sorts.

To measure individual stocks’ sensitivity to instability risk, we build on a literature that links large changes in consumption growth and heightened macroeconomic uncertainty, both features of the break dates identified by our empirical analysis, to variation in aggregate valuation measures such as the price-dividend ratio. For example, disaster risk models such as Barro (2009), Gabaix (2012), Martin (2013), and Wachter (2013) imply that assets whose prices fall when a disaster occurs have a higher expected return because of their higher exposure to disasters. This is similar to the mechanism in our analysis where stocks with a higher exposure to break risk earn a higher risk premium. Similarly, Berkman et al.

(2011) find that their crisis severity index is positively correlated with the earnings-price ratio and dividend yield, while Lettau and Van Nieuwerburgh (2008) show that breaks to the steady state dividend growth rate can lead to parameter instability in regressions of returns on the lagged dividend-price ratio.

Using these insights, we estimate a panel break model that relates individual stock returns to the lagged value of the aggregate log dividend-price ratio, dp_{t-1}:[32]

$$r_{it} = \alpha_{ik} + \beta_{ik} dp_{t-1} + \epsilon_{it}, \qquad t = \tau_{k-1} + 1, \ldots, \tau_k. \tag{6}$$

Next, using a 10-year warm-up estimation period we generate out-of-sample return forecasts from Equation (6) estimated with and without breaks. For each stock, i, and each month in the sample, t, we then compute the difference between forecasts from the panel model with breaks ($\hat{r}_{it,Brk}$) and without breaks ($\hat{r}_{it,NoBrk}$):

$$BRK_{it} = \hat{r}_{it,Brk} - \hat{r}_{it,NoBrk}, \qquad i = 1, \ldots N, \qquad t = 121, \ldots, T. \tag{7}$$

BRK_{it} is larger for stocks with greater exposure to break risk, and we refer to this as stock i's break risk characteristic (at time t). Finally, as we next describe, we examine if differences in such exposures translate into differences in risk premia.

4.2. Fama-MacBeth Regressions

We evaluate the ability of our break risk measure in Equation (7) to explain the cross-section of returns by estimating cross-sectional regressions each month

$$r_{it} = r_{zt} + \lambda_{BRK,t} BRK_{it-1} + \lambda_{2t}' X_{it-1} + \epsilon_{it}, \tag{8}$$

where X_{it-1} contains the five Fama-French factors plus momentum. Next, following the Fama-MacBeth methodology, we use the time-series estimates of $\lambda_{BRK,t}$ and λ_{2t}' to evaluate

[32] Empirically, Paye and Timmermann (2006) and Rapach and Wohar (2006) find evidence of breaks in the slope coefficient of the dividend-price ratio in return regressions such as Equation (6). Smith and Timmermann (2021) also provide evidence of breaks in the relation between stock returns and the lagged dividend-price ratio using data on individual stock returns but do not address whether these breaks are more important to particular types of stocks ("styles").

the mean and standard deviation of these slope coefficients.

The first column of the top panel of Table 4 displays the results. The break risk factor obtains nearly the same significance as the investment variable in explaining the cross-section of returns and its t-statistic is approximately one-and-a-half times larger than that of the size, book-to-market, momentum, and profitability variables. Average returns are also higher for firms highly exposed to break risk than for those with the smallest exposure.

To corroborate that our results are not overly sensitive to the proposed measure of break risk exposure, columns 2-5 in Table 4 present results using alternative proxies of the break risk factor. Our second measure uses the root-squared difference between forecasts produced by panel models fitted with and without breaks. The third, fourth and fifth columns use the difference at each point in time in the intercept, slope and volatility parameters, respectively, estimated from panel models with and without breaks. All five measures are highly statistically significant.[33]

Following Novy-Marx (2013), the bottom panel of Table 4 reports results from the same analysis on break risk measures that have been demeaned by industry. The results are broadly similar, except the t-statistic of every break risk measure is increased, so that adjusting the risk measure by industry obtains even more power to explain the cross-section of expected returns.

These results demonstrate the robustness of our findings. From herein we focus on the break risk factor measured by the difference between the forecasts produced by the panel models with and without breaks in Equation (7).

4.3. Sorts on break sensitivity

Running Fama and MacBeth (1973) regressions on individual stocks places considerable emphasis on micro-cap stocks that make up a sizable share of the number of stocks but only account for a small fraction of the total market capitalisation. Such regressions may also be sensitive to outliers and impose a potentially misspecified parametric relation between

[33] All results use Newey and West (1987) heteroskedasticity-adjusted t-statistics. The third measure (based on the intercept) has the least power to explain the cross-section of expected returns but still obtains a significant t-statistic of 2.53.

the variables, compromising subsequent inference.

To alleviate this concern, we next construct value-weighted portfolios sorted according to our instability risk factor and provide a nonparametric test of the hypothesis that exposure to break risk predicts average returns in the cross-section. Table 5 displays results for these portfolios sorted on our break risk factor. The first row ("Low") shows results for the bottom quintile of stocks ranked by break sensitivity, while the fifth row ("High") shows results for the stocks most sensitive to breaks. Column one reports the average monthly return earned by each quintile portfolio, followed by the alpha and slope coefficients obtained from time-series regressions of the portfolio returns on the five Fama-French factors and momentum with t-statistics reported in brackets below.

Returns on the break-sorted portfolios increase monotonically with our risk factor and the high-sensitivity quintile portfolio earns a 0.28% higher average monthly return than the low-sensitivity portfolio, equivalent to an annualized return premium of 3.36% which is statistically significant at the 5% level with a t-statistic of 2.33.

Turning to the risk-adjusted performance from the six-factor regressions, once again we see monotonically increasing values of alpha as we move from the least to the most break-sensitive stocks. Moreover, the alpha estimate of both the least break-sensitive stocks (at -0.15% per month) and the most break-sensitive stocks (at 0.19%) are both significantly different from zero. At 0.34% per month or more than 4% annualized, this difference is also economically large.

To alleviate concerns about transaction costs raised by Novy-Marx and Velikov (2015) and Hou et al. (2020), we follow Chordia et al. (2020) and perform the same analysis omitting all stocks with a price below $3 or a market capitalisation below the 20th percentile of the NYSE capitalisation distribution. The bottom panel of Table 5 displays the results which, while marginally weaker, tell the same basic story.

These results provide further cross-sectional evidence of the existence of an economically important break risk factor. Stocks whose expected return processes are most sensitive to the instability in risk premia identified by our methodology earn both higher average returns (about 3% per year) and higher risk premia (about 4% per year) than stocks with the lowest sensitivity to breaks.

4.4. Break risk and other risk factors

The past two decades has seen an explosion in the number of factors that reportedly explain the cross-section of expected returns. Amidst this ‘factor zoo’ (Cochrane (2011)) it is important to address whether our proposed break risk factor remains significant even after accounting for the presence of other candidate risk factors.[34] To this end we first consider the relation between the break risk factor and existing risk factors. The upper panel in Table 6 reports pairwise correlations among a number of factors, including the market, book-to-market, size, momentum, investment, profitability, and break risk factors. Our break risk factor is relatively weakly correlated with the five Fama-French risk factors and momentum, with correlations ranging from -0.26 (momentum) to 0.28 (market).

The middle panel reports the maximum as well as the 10th, 25th, 50th, 75th and 90th percentiles of the correlations between our break risk characteristic in Equation (7) and the other 94 characteristics. These characteristic correlations are computed for each series in the cross-section and the table reports the average over the cross-section. The median (maximum) correlation is 0.10 (0.42), consistent with no other single characteristic or factor being able to explain the majority of the variation in break risk.

The five characteristics most strongly correlated with our break risk characteristic are, in descending order, idiosyncratic return volatility, return volatility, volatility of liquidity (share turnover), cash flow to debt, and cash flow volatility. Evidently break risk contains information related to both return and cash flow volatility. Interestingly, not even a combination of these five characteristics explains much of the variation in break risk. A regression of break risk on the five characteristics produces an R^2 of 0.24, supporting our claim that break risk contains genuinely new information that is not spanned by existing characteristics or risk factors.

[34]Using a high t-statistic threshold of three, Harvey et al. (2016) identify approximately 150 factors.

4.5. Risk Factors in Individual Regimes

Which risk factors are most important may vary over time. Our approach is ideally suited for addressing such time variation through panel break regressions

$$r_{it} = \alpha_{ik} + r_{zt} + \lambda_{BRK,k} BRK_{it-1} + \lambda_{2,k}' X_{it-1} + \epsilon_{it}, \qquad t = \tau_{k-1}+1, \ldots, \tau_k, \tag{9}$$

where $\lambda_{BRK,k}$ denotes the risk premium on our break risk factor and $\lambda_{2,k}$ captures the risk premium estimates on the remaining 94 characteristics in the kth regime.[35]

Table 7 reports the outcome of estimating Equation (9) on our panel of firm-level stock returns. For each regime identified by our model, we show the characteristics that earn significant risk premia using a t-statistic threshold of three as proposed by Harvey et al. (2016). The total number of selected characteristics in each regime is reported at the bottom of the table.[36]

In total, 24 different factors (out of 95) get selected at least once in our sample. Only the market risk factor gets selected in every regime. The size (market value) and book-to-market risk factors both get selected in the first three regimes, but not in the final, consistent with our findings in Figure 2 that risk premia on these factors are waning. The momentum risk factor is selected in the third and fourth regimes while neither of the investment and profitability risk factors get selected in any of the regimes.

Our proposed break risk factor gets selected in the last three regimes, i.e., the period from 1981-2018. This is strong evidence that the break risk factor is important in explaining cross-sectional variation in stock returns. In fact, besides the three Fama-French risk factors and our break risk factor, none of the other risk factors gets selected in more than a single regime, indicating that the explanatory power of these factors is not stable over time. Interestingly, the number of factors that gets selected in an individual regime peaks at 12 during 2001-2008 before dropping sharply to only three factors in the final regime. Only

[35] Smith (2018b) performs Bayesian model selection of the 94 characteristics, allowing for model uncertainty and multiple breaks in the set of characteristics that independently inform the cross-section of expected returns. Here, we further include our proposed break risk characteristic to evaluate whether it holds information about the cross-section of returns that is not spanned by the 94 characteristics.

[36] The break dates are aligned with those identified in our earlier six-factor model.

the market risk factor, momentum, and our break risk factor get selected after 2008.[37]

We conclude from this evidence that only five factors – market risk, size, book-to-value, momentum, and our new break risk factor – have consistent power over cross-sectional variation in stock returns for the majority of the sample. This is a new finding and illustrates the kind of insights our approach can be used to provide. In fact, as shown in the bottom panel of Table 7, a constant-parameter approach that uses the full data sample to select factors chooses 16 factors, failing to separate out the many factors whose effect on the cross-section of stock returns is confined to short sub-samples from those factors with a more robust effect.

5. Pervasiveness and timing of Breaks to Industry and Characteristics-sorted Portfolios

Cross-sectional returns data on individual stocks, the main focus up to this point, can be used to boost the power of our ability to detect breaks. Conversely, returns on more broadly diversified portfolios formed along industry, characteristics or "style" lines can be used to understand whether certain types of firms are more affected by break risk than others, helping us better interpret the economic sources and investment consequences of exposure to break risk.

Pursuing this idea, this section estimates our panel break model on a set of industry and characteristics-sorted portfolios. Next, using these portfolios, we introduce the noncommon breakpoint procedure developed by Smith (2018a) which allows breaks to hit any subset of series in the cross-section and at different times. This approach enables us to accomplish three tasks: (i) distinguishing between market-wide and industry or style-specific breaks; (ii) evaluating whether particular assets are hit earlier or later in the break cycle; and (iii) evaluating whether lead-lag relations vary through time. For instance, one might expect

[37] Green et al. (2017) acknowledge that the assumption of time invariance implicit in the majority of firm characteristic studies is unlikely to hold after 1980 because of "changes in the volume, nature, and costs of trading in stocks that occurred from 1980 to 2014, including Reg. FD, the decimalization of trading quotes, Sarbanes-Oxley, accelerated SEC filing requirements, auto quoting, and computerized long/short quantitative investment". Without using a formal test, they identify instability in the number of selected characteristics which falls from 12 to two after 2003. Our approach finds a similar reduction from 12 to three factors slightly later (after 2008).

that the oil industry played a leading role during the 1970s, telecommunications during the early-2000s, and financials/real estate during 2008.

5.1. *Break Risk for Industry and Style Portfolios*

We start by estimating our panel break model using monthly excess returns on 30 value-weighted industry portfolios and sets of 5×5 portfolios sorted on size and book-to-market, size and momentum, size and investment, or size and profitability. For the industry portfolios and the 5×5 portfolios sorted on size and either book-to-market or momentum, our data run from July 1926 through December 2019. This longer sample of portfolio returns provides a way to cross-validate the robustness of our findings on the effect of breaks on individual firms' returns. For the 5×5 portfolios sorted on size and either investment or profitability, the data begin in July 1963. Data are sourced from Ken French's website.

To identify differences and similarities in how breaks affect different types of stocks, our analysis is undertaken separately for the five sets of test portfolios using the specification in Equation (6). This allows us to address whether breaks are specific to particular investment styles or industries, or whether they are more pervasive and affect most or all portfolios.

First consider the evidence of breaks in the model fitted to the 30 industry portfolio returns. For the 1926-2019 sample, the mode (and mean) for the number of breaks is six, with approximately 88% of the probability mass distributed between five and six breaks, corresponding to a break occurring roughly once every fifteen years. The timing for most of the breaks is well defined with posterior probabilities concentrated around 1929, 1973, 2001, and 2008, thus coinciding with major economic events such as the Great Depression, the oil price shocks of the 1970s, the dotcom crash in the early-2000s, and the Global Financial Crisis. Reassuringly, in the sub-sample that overlaps with the individual stock returns data (1950-2018), the break dates identified for the industry portfolio returns are either the same or very close. Compared to the results for the individual stocks, the posterior probability mass for the break locations is more disperse, indicating that the effect of breaks on different industry portfolios was not confined to a single month but diffused gradually through time.

A similar number of breaks is identified for the 25 portfolios sorted on size and either book-to-market or momentum. For example, the model fitted on the portfolios sorted on size and book-to-market identifies seven breaks with similar locations to those for the industry portfolios.[38]

Having established the similarity in both the number and location of breaks across different portfolios, we next analyze which portfolios exhibit the greatest sensitivity to breaks. To this end, we rank portfolios by their sensitivity to breaks as measured by the mean squared difference between forecasts from models estimated with and without breaks.[39]

The top panel in Table 8 shows break sensitivity results for the top and bottom quintile of industries. Returns on telecommunication stocks exhibit the greatest sensitivity to breaks, followed by the utilities, oil, business equipment, and financial industries. Stocks in the wholesale, mining, textile, books and meals industries are least sensitive to breaks. Cyclical industries thus appear to be more sensitive to breaks than non-cyclical industries and the break sensitivities of the first group tend to be three to four times greater than those of the latter group of industries.

Among the 25 portfolios sorted on size and book-to-market ratio (second panel in Table 8), small firms' returns are most sensitive to breaks and big firms least sensitive. Differences in break sensitivity are economically large with small firms' break sensitivity being six to seven times larger than that of large firms. Though size matters more to break sensitivity than book-to-market value does, there is also a clear relation between firms' book-to-market ratios and their break sensitivity. Conditional on firm size, value firms are more sensitive to breaks than growth firms and there is a near-monotonically decreasing relation between book-to-market ratio and break sensitivity.

Similar findings hold for the stocks sorted on size and momentum (third panel in Table 8). Conditional on firm size, "loser" stocks with the smallest prior returns are more sensitive to breaks than "winner" stocks with a near-monotonic decreasing relation between prior returns and break sensitivity. Conditional on firm size, firms with conservative investments and robust profitability tend to be more sensitive to breaks in their risk premia than aggressive-investment firms with weak operating profits (bottom two panels), consistent

[38] This finding is *not* automatic since we estimate our panel break model separately for the industry returns and the 5×5 characteristics sorted portfolios and so the break detection could be very different.

[39] Our results are robust to using other sensitivity measures such as the standard deviation of the estimated intercept, slope coefficient or residual variance across regimes.

with these types of firms being riskier and having higher required returns than their peers (Novy-Marx 2013; Fama and French 2015).

These findings suggest that firms normally thought of as being riskier (small firms with high book-to-market ratios, conservative investments and robust profitability) have greater exposure to breaks in their return processes. Firms with poor prior-year return performance also tend to be more exposed to break risk which could be related to the occasional resurgence in the returns of "loser" stocks documented by Daniel and Moskowitz (2016).

5.2. Market-wide versus Characteristics-specific breaks

We next evaluate whether the breaks are market-wide or specific to certain industries or styles such as size, value, momentum, investment or profitability using (excess) returns on 50 value-weighted portfolios (10 univariate decile sorts on each of size, value, momentum, investment, and profitability).

Adopting the methodology developed by Smith (2018a), we allow any subset of assets $1 \leq N_k \leq N$ to be affected by the kth break occurring at the common time τ_k. This is accomplished by generalizing Equation (6) to

$$r_{it} = \alpha_{ik} + \beta_{ik} dp_{t-1} + \epsilon_{it}, \qquad t = \tau_{k-1} + 1, \ldots, \tau_k \tag{10}$$

in which $\beta_{ik+1} = \beta_{ik}$ for those portfolios that are not hit by the kth break. Conversely, the common break assumption in the baseline model in Equation (6) restricts all portfolios to be hit by breaks ($N_k = N$ for all k).

Starting with the style-sorted portfolios, Figure 4 displays the estimated break dates for the model in Equation (10). In ranked order, portfolios 1 through 10 track decile portfolios ranked on return momentum (winners followed by losers), portfolios 11 and 20 represent the highest and lowest decile of book-to-market-sorted portfolios (value and growth, respectively), and decile portfolios 21 and 30 contain the smallest and biggest firms sorted on market capitalization. Finally, deciles 31 and 40 contain the most and least profitable firms (robust and weak), while deciles 41 and 50 contain the firms with the lowest and highest investments (conservative and aggressive), respectively. Our sample period goes back to

1926 so that, in addition to the four post-war breaks identified in the baseline analysis, we detect a further three breaks in 1929, 1933, and 1940.

The figure nicely illustrates that some breaks are very broad and affect all style-sorted portfolios while other breaks have a more limited impact. For example, three breaks (in 1929, 1973, and 2008) are common across all investment styles for which data are available;[40] one break (1933) is specific to just one style (size) while the remaining three breaks affect multiple styles, but not all five. Moreover, conditional on a break affecting a given investment style, almost all of the decile portfolios within that style are affected by the break. The breaks we identify are, thus, systematically linked to the style characteristics considered here as they affect stocks across the entire characteristics spectrum.

Applying the same approach to the industry portfolios, we find that almost all industries are affected by each of the breaks. Moreover, while the two earliest breaks affect 25 and 26 of the industries, respectively, the last two breaks affect 29 and 30 of the industry portfolios, suggesting that the breaks have become more pervasive over time. Firms in different industries are likely to have non-zero loadings on the style factors which helps explain why the vast majority of industries are affected by each of the breaks even when some style portfolios are not impacted by all breaks.

5.3. Speed of adjustment to breaks

Studying the speed with which different types of stocks react to breaks can provide insights into the underlying economic drivers of such breaks. Indeed, stocks with different style- or industry characteristics may react more or less rapidly to breaks due to the gradual dissemination of information about breaks which is likely to take time to uncover and process. Hou (2007) reports that slow information diffusion across sectors is a primary driver of lead-lag dynamics in return predictability, causing the lead-lag relation between big and small firms to occur primarily within industries. The effect is caused by a slow reaction to negative information. The lead-lag effect is larger for firms that are smaller, less competitive, and neglected. Hong et al. (2007) find that the returns of industries such as

[40] Data on the investment and profitability-sorted portfolios only begin in 1963, so the effect of the 1929 break on these styles cannot be analyzed.

retail, services, commercial real estate, metal, and petroleum lead the aggregate market by up to two months. Similarly, Croce et al. (2019) report evidence that the lead-lag relation across firms varies through time.[41]

These findings suggest that information diffusion across markets is gradual and that the aggregate stock market responds to information in industry returns with a lag. Generalizing the model in Equation (10) to allow the timing of breaks to vary across assets, we have

$$r_{it} = \alpha_{ik} + \beta_{ik} dp_{t-1} + \epsilon_{it}, \qquad t = \tau_{k_i - 1} + 1, \dots, \tau_{k_i} \tag{11}$$

where now τ_{k_i} denotes the time at which the ith portfolio is hit by the k_ith break.[42] The common break assumption in the baseline model in Equation (6) restricts all portfolios to be hit at the same time as $\tau_{k_i} = \tau_k$ for all i and k. By relaxing this assumption, the noncommon break model in Equation (11) captures the possibility of shifts in the lead-lag pattern in which individual return series are affected by breaks.

Figure 5 displays the timing of the noncommon breaks across the 30 industries for four of the most economically interesting break dates, namely 1929, 1973, 2001, and 2008. The leading industries identified by our approach are broadly aligned with those identified by Hong et al. (2007) as Financials, Telecommunication, Retail, Services, Steel, Chemicals, Oil, and Construction are the first industries to be affected by breaks to the return process. Some of the leading industries, such as Oil, Financials, and Telecommunications are also most sensitive to risk as can be seen from Table 8.

Allowing the lead-lag relations to vary through time turns out to be empirically important. For instance, Financials had a leading role during the 1929 Wall Street Crash (top left window) and the Global Financial Crisis (bottom right), while Telecommunication stocks were the first to be affected by the break associated with the dotcom crash (bottom left), and Oil stocks were affected earlier than other sectors by the break associated with the oil price shock of 1973 (top right).

The speed of information diffusion across different industries, as measured by the delay

[41] Croce et al. (2019) find that the telecommunications industry became more leading from 1995 to 2000, real estate during the early-2000s, and finance after 2005. Consumer goods leads national output by about one month, manufacturing lags by about two months, and business equipment lags consumer goods by nearly three quarters.

[42] For full details of the model and estimation we refer the reader to Smith (2018a).

between the first and final industry hit by a break, has increased over time. The average lead-lag delay across the first four industry breaks is 8.25 months while it equals 3 months across the final three breaks.

We next undertake a similar analysis across the 50 style-sorted portfolios, i.e., 10 univariate sorts on each of size, value, momentum, profitability, and investments. Using the same methodology and focusing on the same four breaks as in Figure 5, Figure 6 reveals several interesting patterns. First, momentum portfolios tend to be among the earliest to be affected by breaks, with "loser" stocks moving before "winner" stocks. Second, size-sorted portfolios tend to be affected before stocks sorted on book-to-market ratio, with large stocks moving before small stocks. Stocks sorted on book-to-market tend to move slowest–with growth stocks generally moving before value stocks–and are even not hit altogether in the case of the break associated with the Dotcom bubble. Firms with weaker profitability were affected slightly earlier by the major breaks in our sample than firms with more robust profitability. Stocks of firms with an aggressive investment style tend to move relatively late in the break cycle but slightly earlier than more conservatively investing firms.

In summary, our analysis uncovers a number of new insights. First, we show that far from being stable, the lead-lag patterns in portfolio returns vary considerably over time and are related to the cause of the event triggering the break. Second, we show that stocks with low prior-year returns tend to be affected before stocks with high prior-year returns, that large caps are affected before small caps (consistent with Lo and MacKinlay (1990)), and that value stocks tend to be affected later than growth stocks. Finally, weak-profitability firms with conservative investments move slightly earlier than firms with robust profitability and more aggressive investments.

5.4. Industry timing premium

Our finding that industries and investment styles are affected at different speeds by breaks in risk premia begs the question whether firms that are hit earlier by breaks earn a "timing premium" relative to those that are hit later. Stocks whose returns move earlier tend to be more important for the price discovery process and should be more highly correlated with the market, justifying a positive timing premium. Consistent with this, Croce et al. (2019)

find that firms in leading industries pay an annualized return that is 4% higher on average than that paid by firms in lagging industries, with 1.5-2% being a pure timing premium on advance information. The pure timing premium captures cross-sectional heterogeneity in the timing of exposure to shocks and is isolated by accounting for cross-sectional heterogeneity in exposure to shocks, as pointed out by Bansal et al. (2005). Similarly, Savor and Wilson (2016) show that firms scheduled to report earnings earlier in the cycle earn an abnormal return of almost ten percent per year.

To examine this point, we recursively estimate the noncommon breaks model in Equation (11) on the 30 industry portfolio returns, in which the coefficients are unit-specific to absorb cross-sectional heterogeneity in exposures while allowing cross-sectional heterogeneity in the timing of the breaks and thus isolating a pure timing premium on advance information. Next, we sort the industry portfolios into quintiles based on the timing of the final breakpoint detected. A zero-cost investment strategy that goes long in the top (leading) and short in the bottom (lagging) quintile portfolios earns an annualized alpha of 1.3% which is statistically significant–with a t-statistic of 2.91–even after controlling for the market, size, value, momentum, investment, and profitability factors.

6. Conclusion

We present new evidence of instability in the mapping from characteristics such as firm size, book-to-market ratio, return momentum, investment, and profitability to expected returns, with the market equity risk, size, and value premia undergoing marked reductions over time. The breaks we identify line up closely with major economic shocks, including the oil price shocks in the seventies and the Global Financial Crisis in 2008.

We show that individual firms display very different degrees of sensitivity to instability in the risk premium process and use this to form a break risk factor that goes long in the most break-sensitive stocks and shorts the least break-sensitive stocks. This break risk factor obtains similar or even stronger significance than conventional size, value, momentum, investment, and profitability factors in Fama-MacBeth regressions.

Our evidence reveals that the impact and lead-lag timing of instability risk vary significantly across firms in different industries and with different size, value, momentum, investment, or profitability characteristics. Stocks with poor past returns ("losers"), large market capitalization, and low book-to-market ratios tend to be affected earlier by breaks than stocks with high past returns, small market capitalization, and high book-to-market ratios. Firms in the telecommunication, utility, oil, business equipment and financial sectors are most affected by break risk, while firms in the meals, books, textiles, mining and wholesale industries are least impacted. Similarly, small value stocks are more strongly affected by break risk than large growth stocks as are small stocks with low prior-year returns compared with large stocks with high prior-year returns.

Results from an out-of-sample analysis reported in a web appendix show that our panel break model can be used to generate more accurate return forecasts than alternative constant-parameter and time-varying parameter benchmarks. When these forecasts are used by a moderately risk averse mean-variance investor to form portfolios, this leads to a rotation out of industry portfolios that are hit early in the breakpoint cycle, such as oil after 1973, telecommunications after 2001, and financials after 2008, and results in gains in annual certainty equivalent returns around two percent. Over the seven decades covered by our sample, the major shift we identify in risk premia is associated with a substantial decline in the optimal allocation to small caps and value stocks.

The breaks we uncover are all associated with major economic shocks and financial market distress which thus appear to have a long-lasting impact and give rise to new regimes with significantly altered risk premia. Notably, size and value risk premia are insignificantly different from zero in the period after 2008. This pattern is quite different from the mechanism in disaster risk models in which risk premia settle back to their historical mean once the disaster probability returns to normal levels. Similarly, compared with long-run-risk models, our results suggest that the risk premium process can be quite stable for long periods of time but is interrupted by large, pervasive shifts triggered by episodes of economic and financial distress. Although these episodes are relatively rare, their long-lasting impact on risk premia means that they have an important effect on cross-sectional return predictability patterns, investment performance and portfolio choice.

Acknowledgements

We thank an anonymous referee for many constructive comments and suggestions on the paper. We are grateful for suggestions on an early version of this paper from Bryan Kelly, Dacheng Xiu, and seminar participants at the 2018 SoFiE Summer School at University of Chicago and the March 2019 UK Inquire Group meeting in Windsor. We are also grateful for comments from Gurdip Bakshi as well as conference and seminar participants at the North American Winter Meeting of the Econometric Society 2021, the SoFiE 2021 meetings, the Stanford Institute for Theoretical Economics 2021, Boston University, and Temple University. Linyan Zhu provided excellent research assistance. Any remaining errors are our own.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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Table 1: Risk premium tests

	Equity	Value	Size	Momentum	Investment	Profitability
Positive risk premium tests (Final regime: 2008-2018)						
Risk premium	4.68	0.63	0.70	3.47	0.31	2.48
t-stat	(4.21)	(0.72)	(0.45)	(3.02)	(0.89)	(2.27)
Single breakpoint tests						
Bayes factor (1991)		179.87				
Risk premium (1950-1991)		3.36%				
Risk premium (1992-2018)		1.53%				
Bayes factor (1981)			162.43			
Risk premium (1950-1981)			4.20%			
Risk premium (1982-2018)			0.65%			
Monotonic relation tests						
	0.16	0.01	0.03	0.19	0.17	0.14

Table 1: Risk Premium Tests. The upper panel of this table displays the final regime's risk premium estimates (expressed as annualized percentages) and corresponding t-statistics (in brackets below) from the Bayesian panel break approach when regressing firm-level excess returns on market beta, value, size, momentum, investment, and profitability as displayed in Equation (3). The middle panel displays the results of two separate single breakpoint tests: a break in the size premium at 1981 and a break in the value premium at 1991. Bayes factors express the strength of evidence in favor of the break – values greater than 150 represent overwhelming evidence in favor of the break Kass and Raftery (1995). We also report pre- and post-break risk premium estimates. The lower panel displays p-values from Patton and Timmermann (2010)'s Monotonic Relation tests when testing separately whether each of the six factor risk premia monotonically decline across the five regimes identified by the baseline model. p values lower than 0.05 imply significant evidence in favor of monotonically declining risk premia.

Table 2: Cross-sectional Distribution of α Estimates

Regime	Mean	St.dev.	5%	10%	25%	Median	75%	90%	95%	sig.
					All stocks					
1950:01-1972:07	2.61	1.40	-3.52	-1.80	0.50	2.53	4.59	7.85	9.70	0.24
1972:08:-1981:10	-1.38	2.32	-14.73	-7.91	-2.82	-0.02	1.78	4.00	5.79	0.18
1981:11-2001:06	2.54	3.37	-11.67	-4.42	0.50	2.79	5.92	9.59	13.82	0.21
2001:07-2008:10	-0.25	5.10	-21.02	-10.73	-2.25	1.42	4.00	8.41	12.97	0.06
2008:11-2018:06	-0.60	5.67	-20.04	-9.84	-1.68	0.99	3.30	7.76	12.80	0.04
Full sample	0.40	2.85	-6.90	-4.89	-0.67	0.42	2.24	4.57	7.10	0.17
					Larger stocks (Micro-caps excluded)					
1950:01-1972:07	2.37	1.00	-2.68	-1.40	0.55	2.30	4.52	6.87	8.32	0.28
1972:08:-1981:10	-1.05	1.41	-10.98	-7.03	-2.65	-0.00	1.69	3.62	4.94	0.13
1981:11-2001:06	2.79	1.57	-7.55	-3.06	0.60	2.91	5.70	8.72	11.49	0.22
2001:07-2008:10	0.20	2.11	-14.68	-8.30	-1.88	1.41	3.65	7.31	10.33	0.05
2008:11-2018:06	0.03	2.07	-14.65	-7.44	-1.47	0.94	3.12	6.64	9.90	0.04
Full sample	0.72	1.06	-5.92	-3.60	-0.52	0.40	1.95	4.04	6.25	0.15
					Micro-caps					
1950:01-1972:07	4.21	4.93	-28.44	-14.02	-10.92	-6.12	14.40	20.00	33.11	0.36
1972:08:-1981:10	-9.20	8.04	-45.33	-42.18	-29.04	-24.03	11.03	17.52	30.13	0.24
1981:11-2001:06	-1.21	13.22	-67.82	-46.86	-29.51	-20.14	25.31	39.87	50.07	0.34
2001:07-2008:10	-10.44	20.77	-111.85	-86.95	-52.21	-32.69	33.74	53.82	87.12	0.10
2008:11-2018:06	-15.76	21.22	-142.33	-107.24	-56.20	-32.38	31.11	56.12	62.18	0.07
Full sample	-4.84	8.02	-44.33	-34.31	-18.98	-9.38	12.79	19.89	33.05	0.23

Table 2: Cross-sectional distribution of α estimates. The top panel of this table displays, for each of the five regimes, the cross-sectional average and standard deviation of the posterior mean α_i estimates, as well as the 5th, 10th, 25th, median, 75th, 90th, and 95th percentiles of the α_i estimates from our Bayesian panel break approach when regressing firm-level excess returns on market beta, size, value, momentum, investment, and profitability as displayed in Equation (3). All values are in annualized percentage terms. The final column reports, for each regime, the proportion of stocks that have α_i estimates that are significantly different from zero at the 5% level using a two-sided test. The final row of each panel displays corresponding results for the full sample using the constant-parameter model. All results use a prior standard deviation of α of 5%. The middle and lower panels report results without micro-caps and for only micro-caps. Micro-caps are defined as stocks with a price less than $3 or a market capitalization below the 20th percentile of the NYSE capitalization.

Table 3: Which Model Parameters are Affected by Breaks? Bayes Factors

	BF_{mean}	BF_{σ}	BF_{λ}	BF_{α}
All breaks	154.28	214.33	171.80	219.13
Jul 1972	139.71	235.17	198.95	176.32
Oct 1981	168.28	242.43	187.60	230.01
Jun 2001	183.60	189.01	132.24	265.52
Oct 2008	211.12	191.76	98.75	218.11

Table 3: Parameters affected by breaks: Bayes factors. This table displays Bayes factors that indicate the strength of evidence in favor of our baseline model relative to each of four restricted models, including models that allow breaks only in (i) mean coefficients, that is, α and λ (corresponding Bayes factor is denoted BF_{mean}), (ii) volatility (BF_{σ}), (iii) risk premia (BF_{λ}), and (iv) α (BF_{α}). Results are displayed for the full sample, that is across all breaks (top row), and for each individual break (rows 2-5). Bayes factors are computed from the marginal likelihood of our baseline model and that of the restricted model. Marginal likelihoods are computed using the method of Chib (1995). The strength of evidence in favor of our baseline model relative to the restricted model is evaluated using the standard thresholds detailed in Kass and Raftery (1995): values greater than 20 indicate strong evidence in favor of the baseline model.

Table 4: Fama-Macbeth Regressions of Returns on Break Risk Factor

Independent variable	Break risk measures				
	(1)	(2)	(3)	(4)	(5)
	Slope coefficients ($\times 10^2$) and (test-statistics)				
BRK	0.57	0.52	0.28	0.52	0.50
	(4.42)	(4.15)	(2.53)	(4.08)	(4.01)
BETA	0.95	1.04	0.82	0.77	0.90
	(11.87)	(10.66)	(10.88)	(12.04)	(10.97)
log(B/M)	0.26	0.22	0.20	0.30	0.31
	(3.14)	(3.08)	(2.89)	(4.22)	(3.86)
log(ME)	-0.13	-0.10	-0.11	-0.14	-0.11
	(-3.00)	(-3.65)	(-3.44)	(-2.75)	(-2.99)
$PR1YR$	0.78	0.59	0.56	0.60	0.65
	(3.29)	(3.55)	(2.87)	(4.12)	(3.22)
INV	-0.53	-0.44	-0.46	-0.57	-0.52
	(-4.46)	(-4.05)	(-4.84)	(-3.89)	(-5.00)
PRF	0.20	0.24	0.22	0.18	0.29
	(2.71)	(2.88)	(2.54)	(2.36)	(3.18)
	Results demeaned by industry				
BRK	0.70	0.59	0.34	0.60	0.58
	(5.12)	(4.56)	(2.78)	(4.58)	(4.51)
BETA	0.93	1.01	0.77	0.78	0.94
	(11.08)	(10.89)	(10.85)	(12.09)	(11.42)
log(B/M)	0.28	0.23	0.27	0.30	0.35
	(3.32)	(3.02)	(2.95)	(4.23)	(3.65)
log(ME)	-0.14	-0.12	-0.07	-0.19	-0.14
	(-3.05)	(-3.66)	(-3.22)	(-2.76)	(-3.22)
$PR1YR$	0.62	0.55	0.62	0.51	0.72
	(3.22)	(3.53)	(2.99)	(3.88)	(3.62)
INV	-0.60	-0.38	-0.42	-0.57	-0.51
	(-4.75)	(-3.87)	(-4.54)	(-3.94)	(-4.96)
PRF	0.18	0.24	0.21	0.19	0.24
	(2.70)	(2.92)	(2.45)	(2.55)	(3.03)

Table 4: Fama-Macbeth regressions of returns on break risk factor. This table displays the coefficients and Newey and West (1987) heteroscedasticity-adjusted test-statistics (in brackets below) from Fama-Macbeth regressions of firms' returns on our break risk factor (BRK). The first measure of the break risk factor (column 1) is computed at each time for each firm as the difference between forecasts produced from the Bayesian panel models with and without breaks using the dividend-price ratio as the predictor. The second measure (column 2) is the root squared difference between these forecasts. The third, fourth, and fifth measures (columns 3-5) are the difference at each point in time between the intercept, slope, and volatility estimates, respectively, from the panel models with and without breaks. We control for market beta, book-to-market [log(B/M)], size [log(ME)], past performance measured over the previous year ($PR1YR$), investment, and profitability. The bottom panel presents results from the same analysis in which the break risk measure has been demeaned by industry.

Table 5: Return Performance of Portfolios of Stocks Sorted on Break Sensitivity

Portfolio	r	α	MKT	SMB	HML	MOM	INV	PRF
				All stocks				
Low	0.22	-0.15	1.05	0.01	0.01	0.01	0.00	-0.01
	(2.12)	(-2.23)	(22.06)	(1.37)	(3.34)	(1.35)	(2.05)	(-0.52)
2	0.26	-0.06	0.99	0.00	0.05	0.00	0.00	-0.01
	(2.06)	(-2.12)	(30.04)	(1.70)	(2.88)	(0.85)	(1.48)	(-0.44)
3	0.34	-0.01	1.00	0.02	-0.02	-0.00	0.01	0.01
	(2.54)	(-1.35)	(32.52)	(2.00)	(-0.87)	(-1.11)	(1.79)	(1.40)
4	0.44	0.04	1.02	0.04	0.01	0.02	-0.02	0.00
	(1.98)	(1.08)	(23.74)	(1.29)	(2.03)	(1.71)	(-2.01)	(1.03)
High	0.50	0.19	1.04	-0.00	-0.02	-0.00	0.01	0.01
	(2.33)	(2.27)	(20.10)	(-1.58)	(-2.57)	(-0.65)	(1.32)	(0.99)
High-low	0.28	0.34	-0.01	-0.01	-0.03	-0.01	0.01	0.02
	(2.33)	(3.13)	(-1.08)	(-1.90)	(-1.18)	(-0.87)	(1.66)	(0.76)
				Without micro-caps				
Low	0.15	-0.12	0.90	0.00	0.01	0.00	0.00	-0.01
	(2.38)	(-2.23)	(18.70)	(1.62)	(2.46)	(1.47)	(2.09)	(-0.89)
2	0.22	-0.08	1.00	0.01	0.04	0.01	0.00	0.00
	(2.17)	(-2.44)	(33.32)	(1.76)	(2.95)	(1.22)	(1.60)	(0.57)
3	0.26	-0.03	0.91	0.01	-0.02	-0.01	0.00	0.02
	(2.52)	(-1.42)	(29.87)	(2.05)	(-1.30)	(-0.97)	(1.33)	(2.01)
4	0.35	0.05	1.06	0.04	0.05	-0.01	0.01	0.01
	(2.17)	(0.98)	(22.78)	(1.26)	(2.07)	(-1.54)	(1.02)	(0.85)
High	0.39	0.16	0.94	-0.00	-0.00	0.01	0.01	0.00
	(2.38)	(2.21)	(22.01)	(-1.98)	(-2.50)	(1.12)	(1.45)	(0.60)
High-low	0.24	0.28	0.04	-0.00	-0.01	0.01	0.01	0.01
	(2.30)	(3.08)	(1.06)	(-1.80)	(-1.42)	(1.44)	(0.75)	(1.45)

Table 5: Return performance of portfolios of stocks sorted on break sensitivity. This table displays monthly value-weighted average excess returns to quintile portfolios sorted according to our break risk factor measured through the difference in the forecasts from the panel models with and without breaks using the dividend-price ratio as the predictor. We also report coefficients and test-statistics (in brackets below) estimated from time-series OLS regressions of quintile portfolio returns on the market (MKT), size (SMB), value (HML), momentum (MOM), investment (INV), and profitability (PRF) factors sourced from Ken French's website. The bottom panel presents results for the same analysis removing all stocks with a price less than $3 or a market capitalisation below the 20th percentile of the NYSE capitalisation.

Table 6: Break Risk Correlations

	mrkt	bm	mve	mom	inv	prf	brk
				Correlations with Factors			
mrkt	1	0.24	0.32	-0.34	-0.37	-0.19	0.28
bm		1	0.13	-0.42	0.67	0.08	0.24
mve			1	-0.15	-0.09	-0.34	0.18
mom				1	-0.02	0.09	-0.26
inv					1	-0.02	-0.14
prf						1	-0.07
brk							1
				Correlations with Characteristics			
	10%	25%	50%	75%	90%	max	
brk	0.01	0.05	0.10	0.25	0.36	0.42	
R^2	0.24						

Table 6: Break risk correlations. The upper panel of this table displays the correlations amongst a number of factors, namely, the market (mrkt), book-to-market (bm), size (mve), momentum (mom), investment (inv), profitability (prf), and our break risk factor (brk). The middle panel reports the maximum and the 10th, 25th, 50th, 75th, and 90th percentiles of the correlations between our break risk characteristic and the 94 characteristics considered by Green et al. (2017). The lower panel reports the R^2 from a regression of our break risk characteristic on the five characteristics with which it is most strongly correlated, namely, in descending order: idiosyncratic return volatility, return volatility, volatility of liquidity (share turnover), cash flow to debt, and cash flow volatility.

Table 7: Characteristics that are Significant in Different Regimes

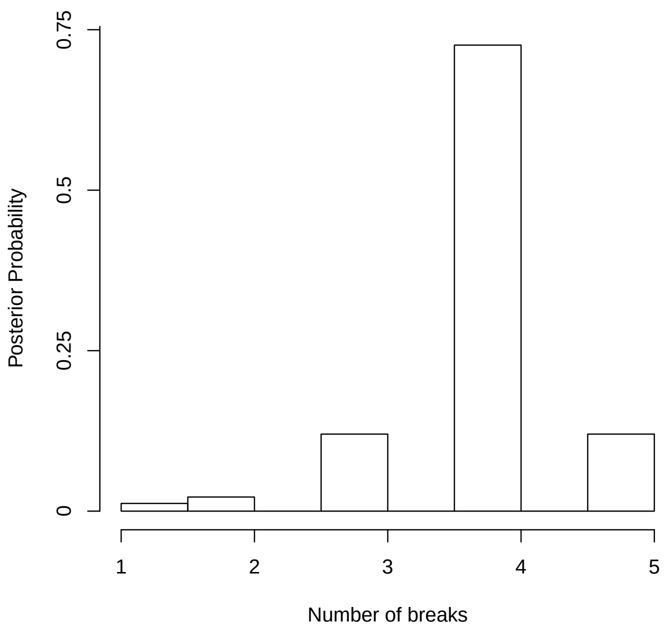
	1980:01-1981:10	1981:11-2001:06	2001:07-2008:11	2008:12-2018:06	
			Panel break model		
	beta	beta	beta	beta	
		brk	brk	brk	
	mve	mve	mve		
	bm	bm	bm		
			mom1m	mom1m	
	sgr				
	retvol				
	turn				
	baspread				
	aeavol				
	agr				
		rdmve			
		roaq			
		cashpr			
		lgr			
		gma			
		hire			
			herf		
			ps		
			salerec		
			std˙dolvol		
			ear		
			chcsho		
			chatoia		
Total	9	10	12	3	
			Constant-parameter model		
	beta	brk	mve	bm	mom1m
	retvol	baspread	aeavol	agr	rdmve
	roaq	lgr	hire	herf	ear
	chatoia				
Total	16				

Table 7: Characteristics that are significant for the cross-section of expected returns in different regimes. The upper panel of this table reports, for each regime identified by our panel break model, the characteristics that are significant using a t-statistic threshold of three when regressing firm-level excess stock returns on the 94 characteristics of Green et al. (2017) and our break risk factor. The total number of selected characteristics is reported at the bottom of the table. The posterior mode break dates occur at October 1981, July 2001, and November 2008. The characteristic definitions correspond to those in Table A1 except for brk which denotes our break risk factor. The lower panel reports which characteristics are selected from the constant-parameter model using a t-statistic threshold of three.

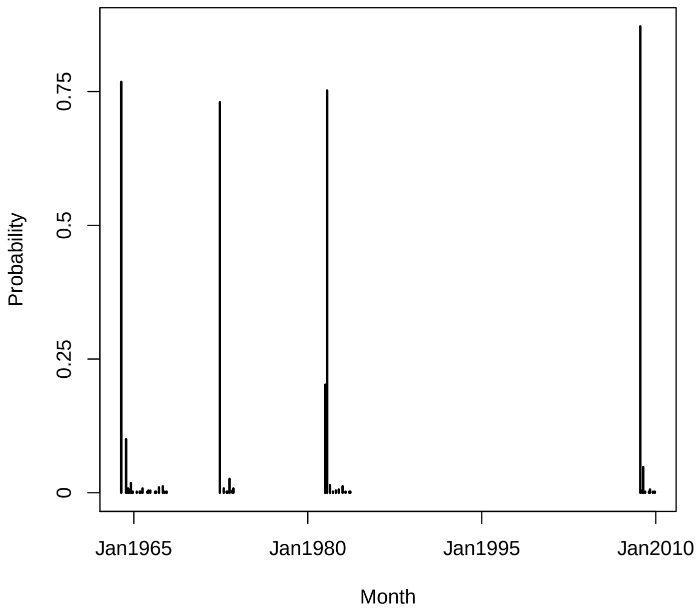
Table 8: Portfolios Most and Least Affected by Break Risk

Portfolio	Size of break rank	MSFD	Portfolio	Size of break rank	MSFD
		Industries			
Telcm	1	0.0222	Whlsl	25	0.0059
Util	2	0.0169	Mines	26	0.0052
Oil	3	0.0145	Textls	27	0.0045
Buseq	4	0.0141	Books	28	0.0033
Fin	5	0.0139	Meals	29	0.0028
Hlth	6	0.0137	Other	30	0.0022
		Size and book-to-market			
SMALL HiBM	1	0.0528	ME3 LoBM	21	0.0067
ME2 HiBM	2	0.0461	ME4 LoBM	22	0.0059
SMALL BE4	3	0.0399	BIG BE3	23	0.0049
ME2 BE4	4	0.0368	BIG BE2	24	0.0036
SMALL BE3	5	0.0290	BIG LoBM	25	0.0033
		Size and momentum			
SMALL LoPRIOR	1	0.0205	BIG PRIOR2	21	0.0031
ME2 LoPRIOR	2	0.0189	ME3 PRIOR4	22	0.0027
SMALL PRIOR2	3	0.0165	ME4 HiPRIOR	23	0.0025
ME2 PRIOR2	4	0.0148	BIG HiPRIOR	24	0.0018
ME2 PRIOR3	5	0.0141	BIG PRIOR4	25	0.0016
		Size and investment			
SMALL LoINV	1	0.0477	BIG INV3	21	0.0050
SMALL INV2	2	0.0386	ME4 HiINV	22	0.0037
ME2 LoINV	3	0.0335	ME4 INV4	23	0.0029
ME2 INV3	4	0.0318	BIG INV4	24	0.0023
ME2 INV4	5	0.0301	BIG HiINV	25	0.0021
		Size and profitability			
SMALL HiOP	1	0.0415	BIG OP3	21	0.0050
SMALL OP4	2	0.0387	BIG OP4	22	0.0046
SMALL OP3	3	0.0363	ME4 LoOP	23	0.0039
ME2 HiOP	4	0.0325	BIG OP2	24	0.0028
ME2 OP4	5	0.0301	BIG LoOP	25	0.0026

Table 8: Portfolios most and least affected by break risk. This table lists the upper and lower twenty percent of portfolios according to the magnitude of the total impact of breaks on their respective return forecasts (with 1 denoting the largest impact) for each of our five test assets. This magnitude is captured by the mean squared forecast difference ('MSFD') between panel regressions with and without breaks of excess portfolio returns on the lagged aggregate dividend-price ratio as displayed in Equation (6). We report results for 30 industry portfolios (top panel) and 5×5 portfolios sorted on (i) size and book-to-market (second panel), (ii) size and momentum (third panel), size and investment (fourth panel), and size and profitability (bottom panel).

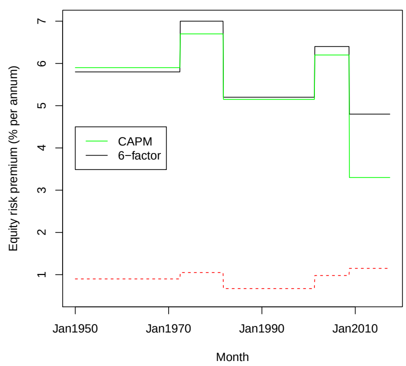


(a) Posterior model probabilities

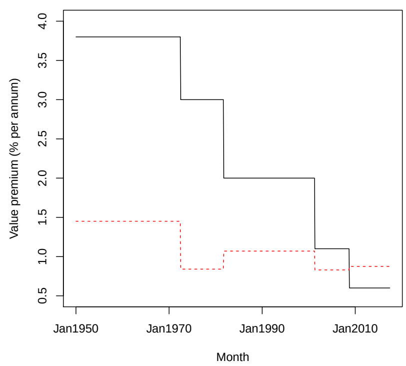


(b) Posterior break location probabilities

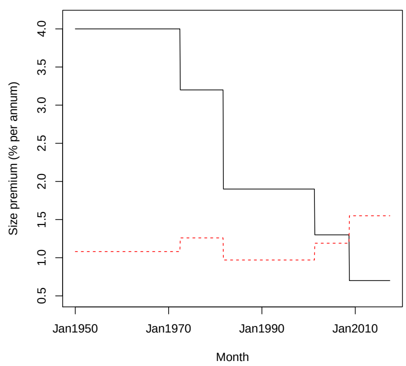
Figure 1: This figure displays the posterior distribution of (i) the number of breaks and (ii) break locations estimated from our Bayesian panel break model when regressing firm-level excess stock returns on lagged market beta, size, value, momentum, investment, and profitability as displayed in Equation (3).



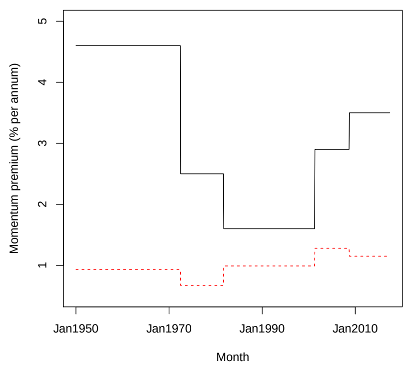
(a) Equity premium



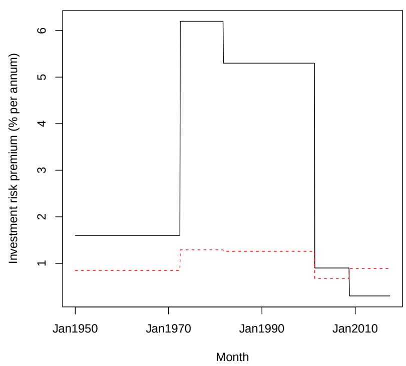
(b) Value premium



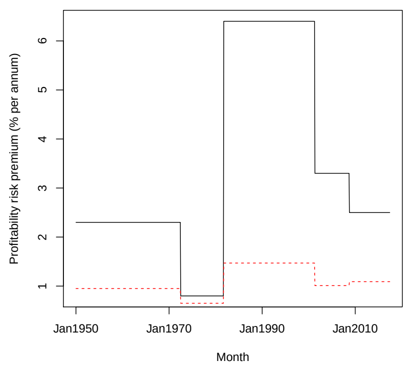
(c) Size premium



(d) Momentum premium

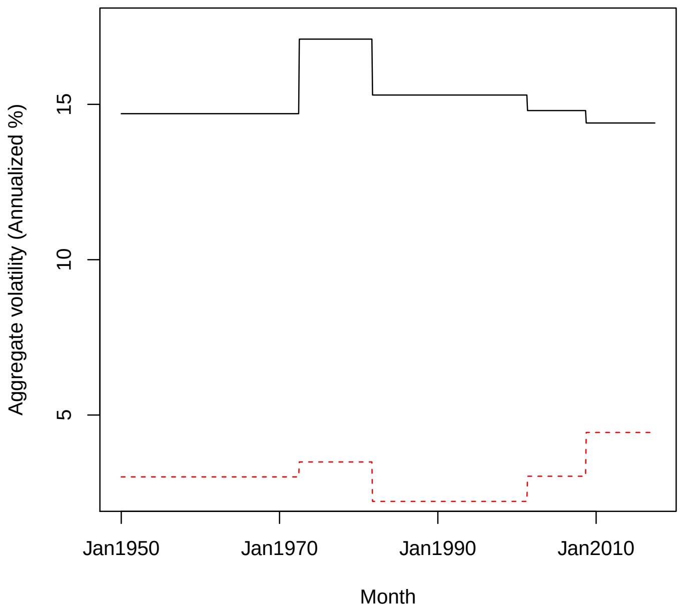


(e) Investment premium

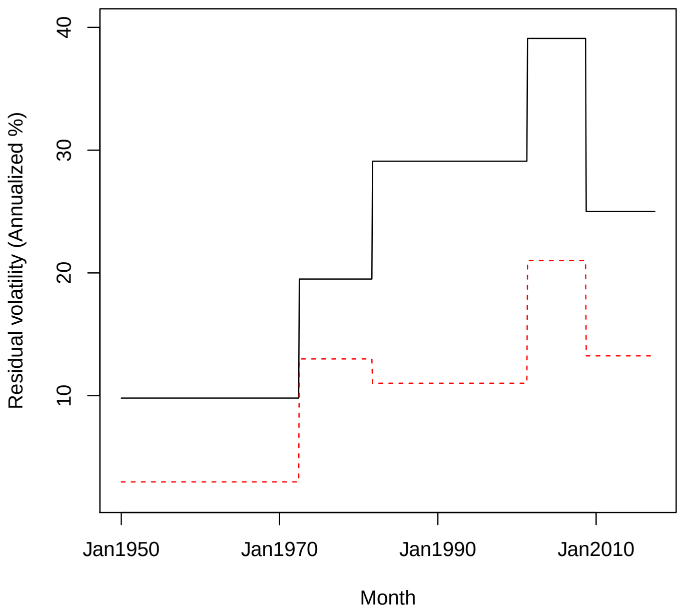


(f) Profitability premium

Figure 2: The solid black lines graph the posterior mean estimates of time-varying risk premia from our Bayesian panel break model when regressing firm-level excess stock returns on lagged market beta, size, book-to-market, momentum, investment, and profitability in a multivariate regression as displayed in Equation (3). The red dashed lines plot their corresponding posterior standard deviations. The solid green line in the top left window graphs the equity premium posterior mean estimates from a corresponding CAPM panel break regression that only includes market betas as regressors.



(a) Aggregate volatility



(b) Idiosyncratic volatility

Figure 3: The solid black line in the top panel of this figure graphs the aggregate volatility estimates from our Bayesian panel break approach when regressing firm-level excess stock returns on lagged market beta, size, value, momentum, investment, and profitability as displayed in Equation (3). The red dashed line plots the posterior standard deviation. The aggregate volatility is estimated as the standard deviation of r_{zt} in each regime, expressed as an annualized percentage. The lower panel graphs the value-weighted average of firm-level posterior mean residual volatility estimates (expressed as an annualized percentage) from the same model.

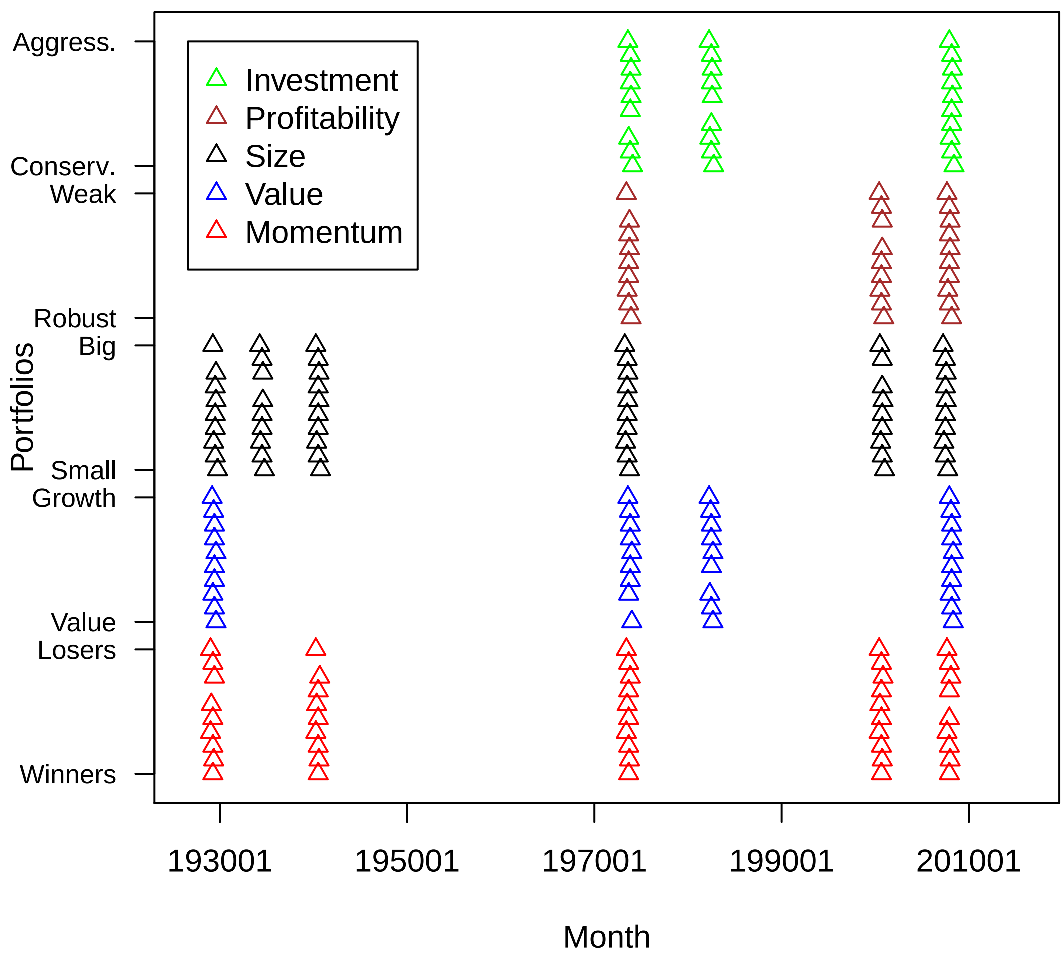
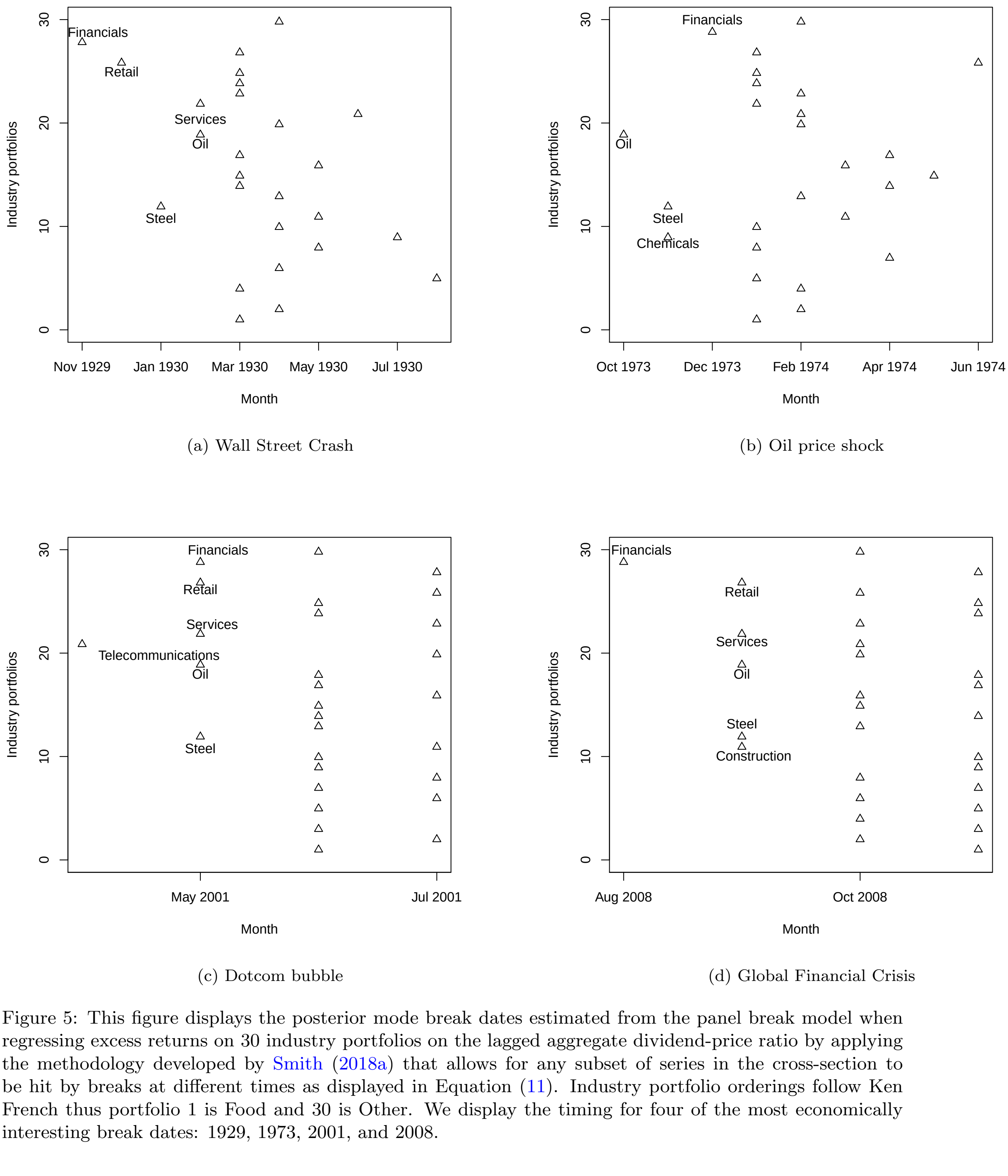


Figure 4: This figure displays the posterior mode break dates estimated from the Bayesian panel break model when regressing the excess returns on 50 portfolios on the lagged aggregate dividend-price ratio as displayed in Equation (10) by applying the methodology developed by Smith (2018a) that allows for any subset of series in the cross-section to be hit by breaks. The 50 portfolios include 10 univariate sorts on each of momentum (red), book-to-market (blue), size (black triangles), profitability (brown), and investment (green).



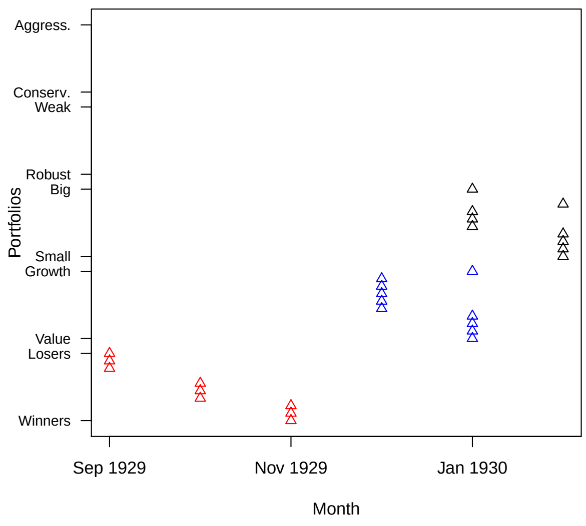
(a) Wall Street Crash

(b) Oil price shock

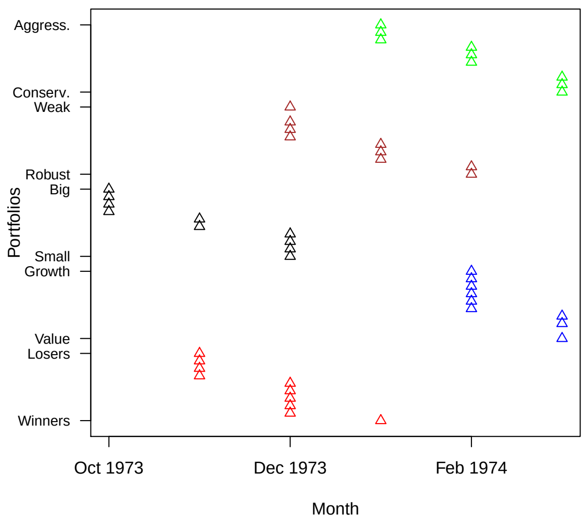
(c) Dotcom bubble

(d) Global Financial Crisis

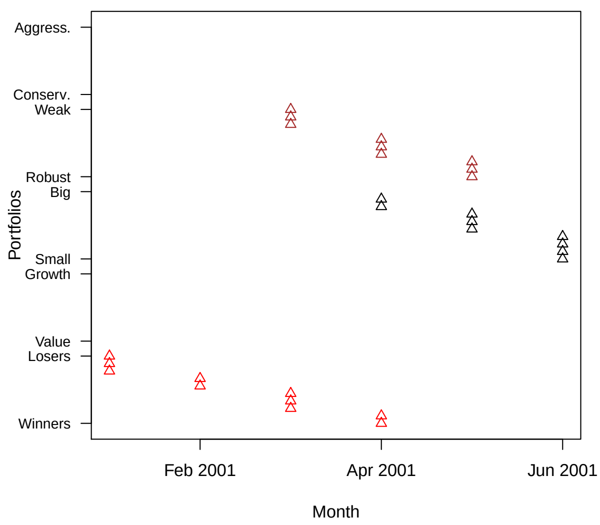
Figure 5: This figure displays the posterior mode break dates estimated from the panel break model when regressing excess returns on 30 industry portfolios on the lagged aggregate dividend-price ratio by applying the methodology developed by Smith (2018a) that allows for any subset of series in the cross-section to be hit by breaks at different times as displayed in Equation (11). Industry portfolio orderings follow Ken French thus portfolio 1 is Food and 30 is Other. We display the timing for four of the most economically interesting break dates: 1929, 1973, 2001, and 2008.



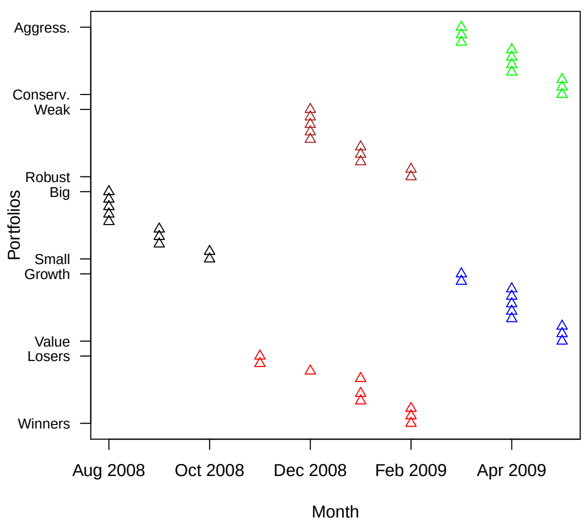
(a) Wall Street Crash



(b) Oil price shock



(c) Dotcom bubble



(d) Global Financial Crisis

Figure 6: This figure displays the posterior mode break dates estimated from the panel break model when regressing excess returns on 50 style portfolios – 10 univariate sorts on each of momentum (red), book-to-market (blue), size (black triangles), profitability (brown), and investment (green), sourced from Ken French's website – on the lagged aggregate dividend-price ratio by applying the methodology developed by Smith (2018a) that allows for any subset of series in the cross-section to be hit by breaks and at different times as displayed in Equation (11). We display the timing for four of the most economically interesting break dates: 1929, 1973, 2001, and 2008.

Appendix A. Likelihood function

This appendix specifies the likelihood function used to estimate our model. To this end, we introduce some notations. Our panel break approach allows the intercepts, slope coefficients, and variances to shift following a break. Recalling that τ_k refers to the date for the kth break, the duration of the kth regime is denoted $l_k = \tau_k - \tau_{k-1}$ and consists of observations $\tau_{k-1}+1, \ldots, \tau_k$. Let $\alpha_k = (\alpha_{1k}, \ldots, \alpha_{Nk})$, $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_{K+1})$, $\lambda_k = (\lambda_{k,1}, \ldots, \lambda_{k,J})$, $\boldsymbol{\lambda} = (\lambda_1, \ldots, \lambda_{K+1})$, $\sigma_k^2 = (\sigma_{k1}^2, \ldots, \sigma_{kN}^2)$, $\boldsymbol{\sigma^2} = (\sigma_1^2, \ldots, \sigma_{K+1}^2)$ denote the parameters in the individual regimes and collect all parameters in $\boldsymbol{\theta} = (\boldsymbol{\alpha}, \boldsymbol{\lambda}, \boldsymbol{\sigma^2})$. Finally, let $\boldsymbol{X_{t-1}}$ denote the observations on the J characteristics for the N stocks at time $t-1$ and define $\boldsymbol{X} = (\boldsymbol{X_1}, \ldots, \boldsymbol{X_{T-1}})$. The likelihood of the data can then be written as[43]

$$p(\boldsymbol{r} \mid \boldsymbol{X}, \boldsymbol{\theta}, \tau) = \prod_{i=1}^{N} \prod_{k=1}^{K+1} (2\pi\sigma_{ik}^2)^{\frac{l_k}{-2}} exp\left[\sum_{t=\tau_{k-1}+1}^{\tau_k} \frac{(r_{it} - \alpha_{ik} - r_{zt} - \lambda_k' X_{it-1})^2}{-2\sigma_{ik}^2}\right]. \tag{A.1}$$

Appendix B. Priors

Next, we provide details of the prior distributions used by our model.

Appendix B.1. Prior on the regime durations

Following Smith and Timmermann (2021), we place a Poisson prior distribution over the regime durations

$$p(l_k \mid \gamma_k) = \frac{\gamma_k^{l_k} e^{-\gamma_k}}{l_k!}, \qquad k = 1, \ldots, K+1, \tag{B.1}$$

in which the Poisson intensity parameter γ_k has a conjugate Gamma prior distribution

$$p(\gamma_k) = \frac{d^c}{\Gamma(c)} \gamma_k^{c-1} e^{-d\gamma_k}, \qquad k = 1, \ldots, K+1. \tag{B.2}$$

[43] For expositional ease we suppress r_{zt} herein.

A prior belief that a break occurs, on average, every 20 years is achieved by setting c=480 and d=2.

Appendix B.2. Priors on regression coefficients

For regimes $k = 1, \ldots, K+1$ and firms $i = 1, \ldots, N$, we specify an inverse gamma prior on the idiosyncratic residual variances

$$p(\sigma_{ik}^2) = \frac{b^a}{\Gamma(a)} \sigma_{ik}^{2^{-(a+1)}} exp\left(-\frac{b}{\sigma_{ik}^2}\right), \tag{B.3}$$

and a Gaussian prior on the intercepts, conditional on the variances

$$p(\alpha_{ik} \mid \sigma_{ik}^2) = 2\pi^{\frac{-1}{2}} (\sigma_{ik}^2)^{\frac{-1}{2}} (\sigma_\alpha^2)^{\frac{-1}{2}} exp\left(\frac{\alpha_{ik}^2}{-2\sigma_{ik}^2 \sigma_\alpha^2}\right), \tag{B.4}$$

in which a and b are the prior hyperparameters of the residual variance and σ_α^2 reflects the prior belief about the degree of mispricing. To achieve a prior residual variance equal to the variance of the return data, the prior hyperparameter a is set equal to 2 and b is set equal to the variance of the return data across all i and t.[44]

Risk premium estimates have a Gaussian distribution. For regimes $k = 1, \ldots, K+1$

$$p(\lambda_k) = \left(2\pi^{\frac{-J}{2}} \mid V_\lambda \mid^{\frac{-1}{2}}\right) exp\left(\frac{\lambda_k' V_\lambda^{-1} \lambda_k}{-2}\right), \tag{B.5}$$

in which $V_\lambda = 1_J \sigma_\lambda^2$.

Multiplying the likelihood function by the priors yields the posterior distribution. Inference is performed on the posterior distribution which is approximated using Markov chain Monte Carlo methods.

[44] For the out-of-sample analysis, for this calculation we use only the return data available at the time the model is estimated to avoid look-ahead bias.

Appendix C. Model Estimation

Model estimation comprises three steps. First, the parameters in regimes $k = 1, \ldots, K+1$ are estimated from their full conditional distributions using a Gibbs step

$$
\begin{aligned}
\sigma_{ik}^2 \mid \cdot &\sim IG(\tilde{a}_{ik}, \tilde{b}_{ik}), \qquad i = 1, \ldots, N, \\
\alpha_{ik} \mid \cdot &\sim N(\rho_{ik}, s_{ik}^2), \qquad i = 1, \ldots, N, \\
\lambda_k \mid \cdot &\sim N(\mu_k, \Sigma_k),
\end{aligned}
\tag{C.1}
$$

in which

$$
\Sigma_k^{-1} = V_\lambda^{-1} + \sum_{t=\tau_{k-1}+1}^{\tau_k} \boldsymbol{X_{t-1}} \boldsymbol{X_{t-1}}', \tag{C.2}
$$

$$
\begin{aligned}
\mu_k &= \Sigma_k \sum_{t=\tau_{k-1}+1}^{\tau_k} \boldsymbol{X_{t-1}} r_t, \\
s_{ik}^{-2} &= \sigma_\alpha^{-2} + l_k, \qquad i = 1, \ldots, N \\
\rho_{ik} &= s_{ik}^2 \sum_{t=\tau_{k-1}+1}^{\tau_k} r_{it}, \qquad i = 1, \ldots, N \\
\tilde{a}_{ik} &= a + l_k/2, \qquad i = 1, \ldots, N \\
\tilde{b}_{ik} &= \frac{1}{2}\left(2b + \sum_{t=\tau_{k-1}+1}^{\tau_k} r_{it}^2 - \mu_k' \Sigma_k^{-1} \mu_k\right), \qquad i = 1, \ldots, N
\end{aligned}
$$

where r_t denotes the excess stock returns on the N firms at time t. The second and third steps estimate the break locations and number of breaks, respectively, in the same manner as in Smith and Timmermann (2021) but use Equation (C.2) to compute the acceptance probabilities.

Appendix D. Formal definition of breaks

Our model is estimated using a reversible jump Markov chain Monte Carlo algorithm (Green 1995). This approach repeatedly attempts to 'jump' between models with different numbers of breaks. With a sufficient number of iterations, the posterior model probabilities and corresponding break locations are approximated by the proportion of iterations spent at each number and timing of breaks.

We now formally define what constitutes a breakpoint. For each jump, whether to accept the move (and thus introduce a different number of breaks) is determined by a Bayes factor, the preferred Bayesian model comparison method.

Suppose we attempt to jump from K to K^* breaks. The Bayes factor is a likelihood ratio of the model with K^* breaks and the model with K breaks. The posterior probability of model K, M_K, having observed the data (r, X) is

$$\Pr(M_K \mid r, X) = \frac{\Pr(r, X \mid M_K)\Pr(M_K)}{\Pr(r, X)}, \tag{D.1}$$

the elements of which can be approximated using the marginal likelihood approach of Chib (1995).

The probability of accepting the jump from K breaks to K^* breaks is reflected in the Bayes factor

$$BF_{M_K, M_{K^*}} = \frac{\int \Pr(\theta_{K^*} \mid M_{K^*})\Pr(r, X \mid \theta_{K^*}, M_{K^*})d_{\theta_{K^*}}}{\int \Pr(\theta_K \mid M_K)\Pr(r, X \mid \theta_K, M_K)d_{\theta_K}} = \frac{\Pr(M_{K^*} \mid r, X)\Pr(M_K)}{\Pr(M_K \mid r, X)\Pr(M_{K^*})}. \tag{D.2}$$

Assuming equal prior model probabilities, $\Pr(M_K) = \Pr(M_{K^*})$, the Bayes factor will equal the ratio of posterior probabilities of the respective models.

Two advantages of the Bayes factor approach are, first, that it automatically penalizes model complexity to guard against overfitting, and thus does not rely on ad hoc penalty terms. Second, it does not depend on a single set of parameters as it integrates over all parameters in each model with respect to their priors, thus accounting for parameter uncertainty.

Appendix E. Out-of-sample Return Forecasts and Portfolio Implications

This appendix analyzes the out-of-sample accuracy of the return forecasts generated by our panel break model and examines some investment implications of these forecasts.

Appendix E.1. Accuracy of out-of-sample return forecasts

We begin by evaluating the out-of-sample forecast accuracy of our panel break model and comparing it to a range of alternative specifications that either are simpler versions of our general specification – allowing us to identify the features of our model that are particularly important – or use a different approach to capture time variation in expected returns. Specifically, we compare our approach to four benchmarks: a univariate time series break model, a constant-parameter panel model, a time-varying parameter model featuring small changes to the parameters every period, and the (time series) historical average.[45]

Using a warm-up period of ten years, forecasts are generated by recursively estimating each month with historically available data our model and the benchmark forecasting models based on the specification in Equation (6). Forecasts from our model incorporate any uncertainty surrounding the number and timing of breaks as well as parameter uncertainty. Market portfolio forecasts are constructed as the value-weighted average of the portfolio-level forecasts.

To evaluate whether any improved predictive accuracy is statistically significant, we use the test statistic of Clark and West (2007) that accounts for our forecasting models being nested which can lead conventional test statistics to have nonstandard distributions. Against the four benchmarks, we find that the panel break model performs significantly better out-of-sample at the 10% critical level for between 25 and 27 of the 31 industry portfolios (including the market portfolio). Our panel break model also produces significantly better return forecasts for between 20 and 22 of the 26 portfolios sorted on size and value

[45] The time series break model is estimated using the Bayesian algorithm of Chib (1998). The constant-parameter panel model is our baseline model that precludes breaks, and the time-varying parameter model is that set out in Equation (4). The priors in each of these three benchmarks are specified such that they correspond to those in the baseline model. Consistent with our panel break model, the time-varying parameter model shows considerable evidence of parameter instability and a notable downward drift in the risk premium estimates of the equity, value, and size premia.

and for between 22 and 23 of the 26 portfolios sorted on size and momentum. Across all 83 portfolios and four benchmark models (332 cases), return forecasts from our model never significantly underperform.

Appendix E.2. Investment Implications

We next explore the economic significance of our model's return forecasts for a risk-averse mean-variance investor who allocates her portfolio every month between the riskless asset and a risky portfolio constructed from each set of test portfolios. In each month t, the risky portfolio is constructed as the vector of weights ω_t chosen to maximize the expected utility from the return on the risky portfolio next month, $r_{p,t+1}$:

$$E[U(r_{p,t+1} \mid A)] = r_{f,t} + \omega_t' \hat{r}_{t+1} - \frac{A}{2}\omega_t' \hat{S}_t \omega_t. \tag{E.1}$$

Here $r_{f,t}$ denotes the risk-free rate in month t, $\hat{r}_{t+1}$ denotes the vector of return forecasts for month $t+1$ computed using information available at month t, $\hat{S}_t$ denotes the covariance matrix that is estimated using the residuals from the return prediction model at month t, and A denotes the risk aversion coefficient which is set equal to three following Campbell and Thompson (2008). We constrain the portfolio weights to sum to one and rule out any short selling or leverage.

Compared to the optimal portfolio weights based on historical averages of the moment estimates, the average industry allocations based on our out-of-sample panel break return forecasts are substantially higher for the smoke, telecommunications, services, and financial industries. Conversely, the weights are lower for beer, healthcare, autos, and business equipment.[46] Certainty equivalent returns of the panel break model are about 2% per annum higher than that of the alternative benchmarks.

Undertaking a similar investment exercise on the 25 (5×5) portfolios sorted on size and value, we compute portfolio allocations across the five portfolios comprising (i) the smallest stocks and (ii) stocks with the highest book-to-market ratios, on average, for the first and final decades of our out-of-sample period. Average allocations to the five smallest

[46] A full set of results is presented in Web Appendix Table A3.

stock portfolios declined from 40% to just 6% from the first to the final decade. Similarly, average allocations to the highest book-to-market ratio (value) stock portfolios declined from 42% to 4%. These shifts in allocations are driven by the systematic decline in the size and value premia identified in our empirical analysis.[47]

For 5 × 5 portfolios sorted on both size and book-to-market and size and momentum, we find utility gains in the neighborhood of 2% per annum relative to the four benchmarks. The panel break model could therefore have been used in real time to generate return forecasts that, when implemented in a simple investment strategy, produce sizeable economic gains.

Finally, for 5 × 5 portfolios sorted on size and investment, utility gains relative to the four benchmarks range between 1.1 and 2.2% per annum, averaging 1.62%. For the 5 × 5 portfolios sorted on size and profitability, certainty equivalent returns range between 1.3 and 1.9%, averaging 1.47% per annum.

Appendix E.3. Rotation of Portfolio Allocations

To better understand what generates the utility gains associated with our model's return forecasts, we next consider how the portfolio weights change around break points. To this end, Table A4 reports the average allocation in three-year windows before and after the three most recent breaks in our sample. For each set of test assets, we limit the results to the five portfolios whose portfolio allocations are most strongly affected by these three breaks. For the industry portfolios (top panel), weights were significantly reduced for oil and chemical stocks after the 1973 oil price shock while the allocations to financial, services, and telecommunication stocks came down significantly following the break associated with the end of the dotcom bubble. Finally, financial, services and oil stocks all saw reduced allocations after the break associated with the GFC. Figure A2 complements these findings by showing 36-month trailing moving average estimates of the portfolio allocations to the industry whose portfolio allocation is most strongly affected by each of the breaks.

A similar rotation is seen among the style-sorted portfolios (second through fifth panels of Table A4): Following all three breaks, we see a large reduction in the allocation to large

[47] We find a similar shift away from the smallest stocks for the 25 portfolios sorted on size and momentum.

stocks with low prior returns. Moreover, the 1973 break induces a sharp reduction in large growth stocks, while conversely the 2001 and 2008 breaks lead to a significant decline in the allocation to large value stocks. The last two breaks also see a sizeable reduction in the allocation to the stocks of firms with conservative investments and robust profits.

These results demonstrate significant rotation in the optimal portfolio weights around the time of the breaks identified by our panel break methodology.

Table A1: Firm Characteristic Acronyms and Definitions

Acronym	Definition	Acronym	Definition
absacc	Absolute accruals	***mom1m***	1-month momentum
acc	Working captial accruals	***mom36m***	36-month momentum
aeavol	Abnormal earnings announcement volume	***ms***	Financial statement score
age	no. years since first Compustat coverage	***mve***	Size
agr	Asset growth	***mve_ia***	Industry-adjusted size
baspread	Bid-ask spread	***nanalyst***	Number of analysts covering stocks
beta	Beta	***nincr***	Number of earnings increases
bm	Book-to-market	***operprof***	Operating profitability
bm_ia	Industry-adjusted book-to-market	***orgcap***	Organisational capital
cash	Cash holdings	***pchcapx_ia***	Industry-adjusted Δ% in capital exps.
cashdebt	Cash flow to debt	***pchcurrat***	Δ% in current ratio
cashpr	Cash productivity	***pchdepr***	Δ% in depreciation
cfp	Cash-flow-to-price ratio	***pchgm_pchsale***	Δ% in gross margin - Δ% in sales
cfp_ia	Industry-adjusted cash-flow-to-price ratio	***pchsale_pchinvt***	Δ% in sales - Δ% in inventory
chatoia	Industry-adjusted Δ in asset turnover	***pchsale_pchrect***	Δ% in sales - Δ% in A/R
chcsho	Δ in shares outstanding	***pchsale_pchxsga***	Δ% in sales - Δ% in SG&A
chempia	Industry-adjusted change in employees	***pchsaleinv***	Δ% sales-to-inventory
chfeps	Δ in forecasted EPS	***pctacc***	Percent accruals
chinv	Δ in inventory	***pricedelay***	Price delay
chmom	Δ in 6-month momentum	***ps***	Financial statements score
chnanalyst	Δ in number of analysts	***rd***	$R\&D$ increase
chpmia	Industry-adjusted Δ in profit margin	***rd_mve***	$R\&D$ to market capitalisation
chtx	Δ in tax expense	***rd_sale***	$R\&D$ to sales
cinvest	Corporate investment	***realestate***	Real estate holdings
convind	Convertible debt indicator	***retvol***	Return volatility
currat	Current ratio	***roaq***	Return on assets
depr	Depreciation/$PP\&E$	***roavol***	Earnings on volatility
disp	Dispersion in forecasted EPS	***roeq***	Return on equity
divi	Dividend initiation	***roic***	Return on invested capital
divo	Dividend omission	***rsup***	Revenue surprise
dy	Dividend to price	***salecash***	Sales to cash
ear	Earnings to announcement return	***saleinv***	Sales to inventory
egr	Growth in common shareholder equity	***salerec***	Sales to receivables
ep	Earnings to price	***secured***	Secured debt
fgr5yr	Forecasted growth in 5-year EPS	***securedind***	Secured debt indicator
gma	Gross profitability	***sfe***	Scaled earnings forecast
grCAPX	Growth in capital expenditures	***sgr***	Sales growth
gr1tnoa	Growth in long-term net operating assets	***sin***	Sin stocks
herf	Industry sales concentration	***sp***	Sales to price
hire	Employee growth rate	***std_dolvol***	Volatility of liquidity ($ trading volume)
idiovol	Idiosyncratic return volatility	***std_turn***	Volatility of liquidity (share turnover)
ill	Illiquidity	***stdcf***	Cash flow volatility
indmom	Industry momentum	***sue***	Unexpected quarterly earnings
invest	Capital expenditures	***tang***	Debt capacity / firm tangibility
IPO	New equity issue	***tb***	Tax income to book income
lev	Leverage	***turn***	Share turnover
mom12m	12-month momentum	***zerotrade***	Zero trading days

Table A1: Firm characteristic acronyms and definitions. This table provides acronyms and definitions for the 94 firm characteristics considered in our study, and corresponds to Table 1 of Green et al. (2017).

Table A2: Cross-sectional Distribution of σ_α Estimates

Regime	5%	10%	25%	Median	75%	90%	95%
			All stocks				
1950:01-1972:07	0.65	1.12	1.63	1.88	3.12	5.85	8.21
1972:08:-1981:10	0.97	1.35	2.21	2.98	4.49	6.87	9.76
1981:11-2001:06	0.73	1.24	1.66	1.97	3.76	6.11	8.49
2001:07-2008:10	1.43	1.89	3.02	4.27	6.08	8.91	11.46
2008:11-2018:06	0.90	1.34	2.03	2.67	4.21	6.59	9.34
Full sample	0.42	0.84	1.15	1.36	2.47	3.92	5.87
			Larger stocks (Micro-caps excluded)				
1950:01-1972:07	0.49	0.87	1.32	1.48	2.85	4.67	7.68
1972:08:-1981:10	0.86	1.27	2.01	2.67	3.90	6.09	8.42
1981:11-2001:06	0.60	1.03	1.32	1.65	3.32	5.48	7.21
2001:07-2008:10	1.17	1.46	2.65	3.81	5.29	7.44	9.89
2008:11-2018:06	0.70	1.12	1.75	2.27	3.99	5.28	8.01
Full sample	0.29	0.70	0.95	1.20	2.10	3.22	4.97
			Micro-caps				
1950:01-1972:07	1.20	2.13	2.73	3.57	4.41	8.15	9.89
1972:08:-1981:10	1.41	1.75	3.25	4.08	6.17	8.77	12.36
1981:11-2001:06	1.18	2.17	3.16	4.05	5.44	8.00	12.19
2001:07-2008:10	2.44	3.36	4.87	5.34	8.22	13.06	18.06
2008:11-2018:06	1.50	1.99	2.87	4.14	5.32	8.94	13.04
Full sample	0.83	1.34	1.69	2.17	3.67	6.24	8.76

Table A2: Cross-sectional distribution of σ_α estimates. The top panel of this table displays, for each of the five regimes, the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the posterior standard deviation of the α_i estimates from our Bayesian panel break approach when regressing firm-level excess returns on market beta, size, value, momentum, investment, and profitability as displayed in Equation (3). All values are in annualized percentage terms. The final row of each panel displays corresponding results for the full sample using the constant-parameter model. All results use a prior standard deviation of α of 5%. The middle and lower panels report results without micro-caps and for only micro-caps. Micro-caps are defined as stocks with a price less than \$3 or a market capitalization below the 20th percentile of the NYSE capitalization.

Table A3: Allocations across portfolio sorts

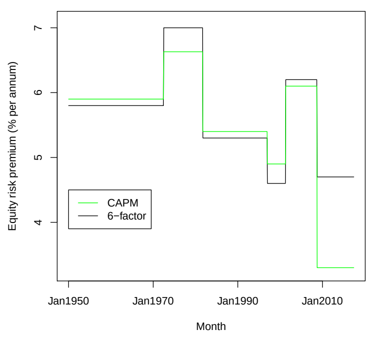
Portfolio	Brk					Hist avg				
					Industries					
food	0.00					0.01				
beer	0.16					0.23				
smoke	0.15					0.09				
books	0.02					0.00				
hlth	0.00					0.06				
chems	0.06					0.14				
elceq	0.01					0.02				
autos	0.00					0.07				
oil	0.06					0.04				
telcm	0.06					0.03				
servs	0.34					0.15				
buseq	0.07					0.11				
paper	0.00					0.02				
fin	0.06					0.00				
					Size and book-to-market					
	SMALL	ME2	ME3	ME4	BIG	SMALL	ME2	ME3	ME4	BIG
LoBM	0.04	0.01	0.00	0.00	0.00	0.03	0.03	0.03	0.03	0.02
BE2	0.03	0.02	0.02	0.00	0.00	0.02	0.04	0.04	0.03	0.02
BE3	0.07	0.04	0.04	0.02	0.00	0.05	0.04	0.04	0.04	0.03
BE4	0.07	0.07	0.05	0.03	0.02	0.05	0.05	0.05	0.04	0.03
HiBM	0.14	0.13	0.10	0.06	0.04	0.07	0.06	0.05	0.05	0.05
					Size and momentum					
	SMALL	ME2	ME3	ME4	BIG	SMALL	ME2	ME3	ME4	BIG
LoPRIOR	0.11	0.13	0.08	0.05	0.05	0.05	0.02	0.01	0.01	0.00
PRIOR2	0.09	0.07	0.05	0.05	0.02	0.07	0.04	0.04	0.02	0.01
PRIOR3	0.04	0.03	0.03	0.02	0.02	0.07	0.04	0.03	0.03	0.02
PRIOR4	0.05	0.03	0.02	0.01	0.00	0.07	0.05	0.04	0.04	0.03
HiPRIOR	0.02	0.01	0.02	0.00	0.00	0.08	0.06	0.06	0.06	0.04

Table A3: Allocations across portfolio sorts. The top panel of this table reports the weight allocations, averaged across the out-of-sample period, to the 30 industry portfolios. We display allocations obtained from our panel break model (Brk) model displayed in Equation (6) and the prevailing mean (Hist avg). Industries that are assigned less than 0.01 weight by both models are omitted. The middle panel displays the allocations across the 25 portfolios sorted on size and book-to-market. The lower panel displays the allocations across the 25 portfolios sorted on size and momentum.

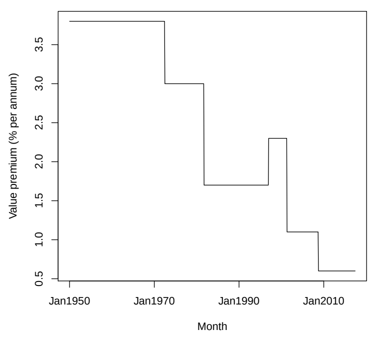
Table A4: Portfolio Allocations Around Breaks

Portfolio	1973		2001		2008	
	pre	post	pre	post	pre	post
Industries						
fin	0.04	0.02	0.07	0.03	0.07	0.02
servs	0.24	0.27	0.28	0.16	0.18	0.12
telcm	0.07	0.08	0.16	0.03	0.05	0.05
oil	0.14	0.01	0.04	0.05	0.08	0.02
chems	0.09	0.02	0.01	0.02	0.03	0.00
Size and momentum						
BIGLoPRIOR	0.07	0.02	0.01	0.00	0.03	0.00
BIGPRIOR2	0.00	0.00	0.05	0.02	0.04	0.00
BIGPRIOR3	0.04	0.02	0.08	0.03	0.05	0.00
ME4LoPRIOR	0.11	0.07	0.23	0.12	0.13	0.01
ME4PRIOR2	0.14	0.01	0.06	0.02	0.04	0.01
Size and book-to-market						
BIGLoBM	0.03	0.02	0.04	0.01	0.01	0.00
BIGBE2	0.00	0.00	0.05	0.02	0.01	0.00
BIGBE3	0.01	0.00	0.02	0.00	0.04	0.02
BIGBE4	0.08	0.08	0.14	0.05	0.08	0.03
ME4BE2	0.19	0.04	0.08	0.03	0.03	0.00
Size and investment						
BIGLoINV			0.11	0.05	0.04	0.02
BIGINV2			0.07	0.03	0.02	0.00
BIGINV4			0.09	0.04	0.03	0.01
ME4LoINV			0.10	0.05	0.07	0.03
ME4INV2			0.06	0.02	0.02	0.01
Size and profitability						
BIGHiOP			0.12	0.01	0.02	0.00
ME4HiOP			0.14	0.04	0.05	0.02
ME4OP4			0.10	0.03	0.03	0.00
BIGOP3			0.09	0.04	0.06	0.02
BIGOP4			0.08	0.04	0.05	0.02

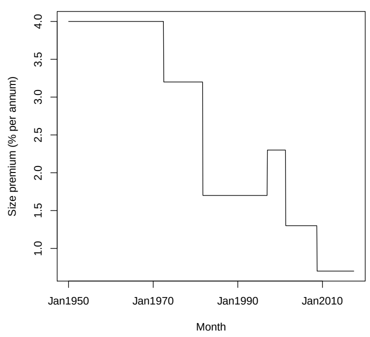
Table A4: Portfolio allocations pre- and post-breaks. This table displays real time allocations to various portfolio sorts averaged across the 36 months before and after the full sample posterior mode break dates in 1973, 2001, and 2008. Allocations are generated from recursively estimating the panel breakpoint model specification in Equation (6) using only data available at the time each forecast is made. Forecasts are generated separately for the five test assets: 30 industry portfolios (top panel) and 5 × 5 portfolios sorted on size and momentum (second panel), size and book-to-market (third panel), size and investment (fourth panel), and size and profitability (bottom panel). For each of the five test assets, allocations across the 30 (or 25) portfolios are constrained such that they sum to one and any short selling or leverage is precluded. For each of the five test assets, we report results for the five portfolios whose allocations are most affected by the breaks in 1973, 2001, and 2008.



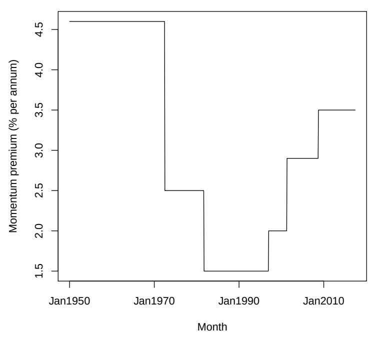
(a) Equity premium



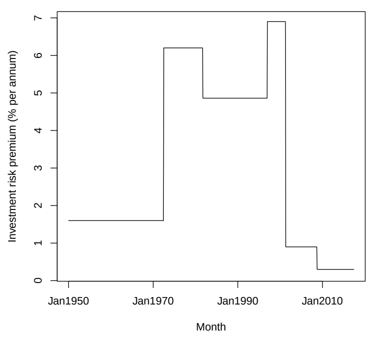
(b) Value premium



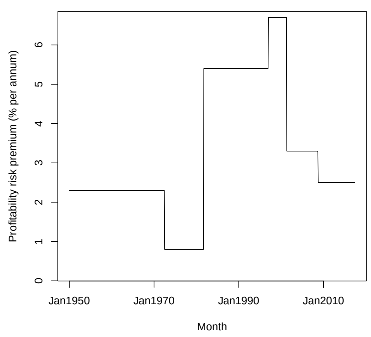
(c) Size premium



(d) Momentum premium

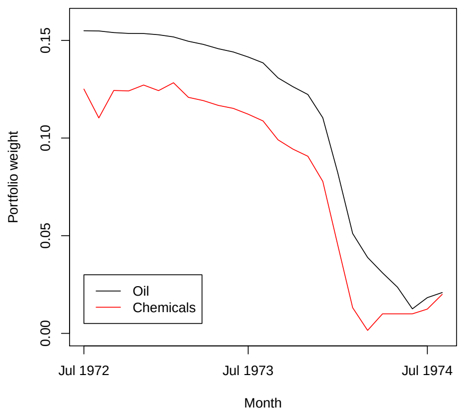


(e) Investment premium

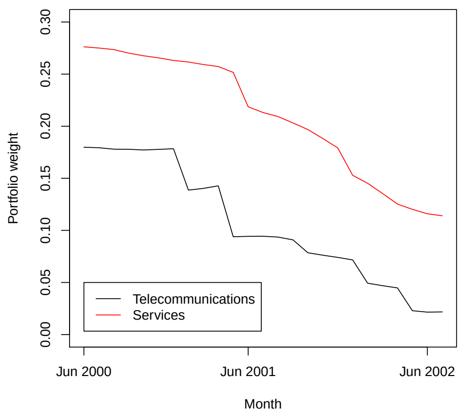


(f) Profitability premium

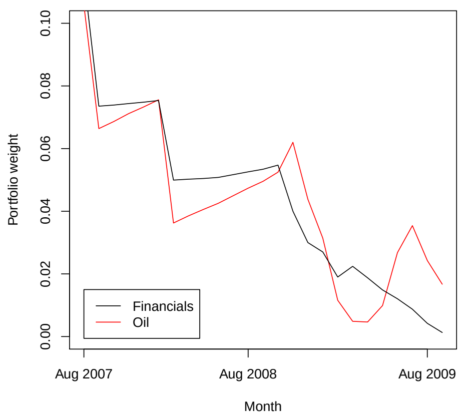
Figure A1: The solid black lines in this figure graph the posterior mean estimates of time-varying risk premia from our Bayesian panel break model when regressing firm-level excess stock returns on lagged market beta, size, value, momentum, investment, and profitability in a multivariate regression as displayed in Equation (3) but using a prior expected regime duration of 10 years rather than 20 years which is used in the baseline model. The solid green line in the top left window graphs the equity premium posterior mean estimate from a corresponding CAPM panel break regression that only includes market betas as regressors.



(a) Oil price shock



(b) Dotcom bubble



(c) Global financial crisis

Figure A2: This figure displays portfolio weights for a subset of industries around the break dates identified in 1973 (top window), 2001 (middle), and 2008 (lower). Specifically, we graph the 36-month trailing moving average of real-time monthly portfolio weights that are allocated between the 30 industries in the multi-asset portfolio. Allocations are generated from recursively estimating the panel breakpoint model specification in Equation (6) using only data available at the time each forecast is made. Allocations across the 30 portfolios are constrained such that they sum to one and any short selling or leverage is precluded. We display results for the industries whose portfolio allocations are most affected by each break.