Abstract

Why do stock prices fall more sharply than dividends around recessions? Stock prices are low when there is i), bad news about future cash flows or when ii), expected returns increase. If bad news about future cash flows drive prices down, stock prices should drop ahead of cash flows and the stock market “predicts” recessions. I document that stock prices and cash flows (as well as consumption and survey expectations of economic growth) fall almost contemporaneously, which is inconsistent with this type of explanation. This leaves me with the discount rate channel. Expected returns can rise because the amount of risk increases (economic uncertainty about cash flows goes up), or because the price of risk increases (investors become more risk averse). I find that stock price volatility increases substantially more than cash flow volatility during recessions. This result suggests that changes in the price of risk play a key role in explaining the data.
I. Introduction

Around U.S. recessions, dividends drop by an average of about 10%. The value that investors agree to pay for these companies falls even more remarkably by about 20%. These painful declines in asset prices happen fast; the average duration of recessions is less than one year. Why do stock prices fall twice as much as dividends when the economy is in a recession? All movements in stock prices that are not reflected in changes of today’s dividends must result from i) changes in expectations about future cash flows, or ii) changes in expected returns (Shiller, 1981; Campbell and Shiller, 1988). But how much of the additional 10% drop in stock prices around recessions can be attributed to which of these two channels?

Competing asset pricing theories make fundamentally different predictions (e.g., Bansal and Yaron, 2004; Campbell and Cochrane, 1999). If prices fall around recessions because investors expect lower future cash flows, one should observe that prices fall before the economy is in a recession. The stock market should “predict” recessions. Intuitively, if there is a predictable component in cash flows, forward-looking prices should reflect the bad times of tomorrow already today. Another explanation could be that expectations about future cash flows do not change, but expected returns shoot up during recessions such that future dividends get more heavily discounted. As a result, prices fall contemporaneously, but more than dividends. For that reason, I argue that timing and deepness of the fall in prices relative to cash flows provides information on the channels that drive asset prices. The goal of this paper is to pin down these theoretical predictions in greater detail and confront them with the empirical data.

I show that an important empirical issue that arises in this exercise is that stock prices are market-based data that are easily observed at the end of a period. In contrast, earnings, dividends, and consumption are all flow variables that are usually measured over an entire period, typically a year (to avoid seasonality). These are “time-aggregated” data. However, comparing end of period data with time-aggregated data gives rise to a time aggregation bias (e.g., Working, 1960; Taio, 1972; Breeden, Gibbons, and Litzenberger, 1989). By construction, time-aggregated data are a weighted moving average of past observations and as such
lag against end of period data. This bias is big. As an illustrative example, take the canonical consumption-based asset pricing model that features constant expected returns and unpredictable cash flows (Breeden, 1979). In this model, the price-dividend ratio is constant, no matter how bad the recession is. However, I show that if prices are measured end of period and dividends are time-aggregated - as is usually done in empirical applications - the price-dividend ratio will appear to anticipate future dividends and will strongly predict recessions. Thus, to be sure that I compare apples with apples in my empirical analysis, I convert end of period stock prices to time-aggregated prices such that the timing of prices corresponds closely to the timing of cash flows.¹

My empirical analysis focuses on quarterly U.S. data of stock prices, earnings, dividends, and consumption around recessions as defined by the NBER business cycle dating committee. The baseline results focus on the post-war period from 1950 to 2016. This sample allows me to study quarterly data, which is important to pin down the timing of the variables as precisely as possible. I find that stock prices, dividends, earnings, and consumption start falling contemporaneously with the beginning of recessions. Because prices drop more compared to dividends, the price-dividend ratio declines with the beginning of recessions as well. I interpret these results as direct evidence against the idea that cash flows and consumption have a predictable component such that stock prices anticipate recessions. However, end of period prices lead time-aggregated cash flows, such that it looks as if the end of period price-dividend ratio anticipates recessions. The comparison to the time-aggregated price-dividend ratio suggests, however, that this lead can be fully explained by the fact that prices and cash flows are measured at different points in time. I corroborate these findings based on market data by studying the forward term structure of expected economic growth as reported in the Survey of Professional Forecasters (SPF). I find that expected real GDP growth four quarters into the future does not change at all around recessions. Instead, all revisions in expected growth take

¹Dividends and earnings have a strong seasonal pattern, so it is not possible to construct non-time-aggregated versions of these variables.
place at very short horizons.²

To compare my empirical results to the theoretical counterfactual, I simulate “recessions” in the long-run risk model of Bansal and Yaron (2004). In this model, revisions about expectations of future cash flows take a central role. I show that the average recession is, by construction, also a period of predictable low growth. Because of the predictable component of cash flows, the (time-aggregated) price-dividend ratio starts dropping about one year ahead of recessions and is rather flat during recessions. This is about one year too early compared to the empirical data.³

Next, I turn to the discount rate channel to explain why prices drop so much during recessions. On the outset, there are at least two sources that could give rise to expected returns, a), the economy and cash flows are simply more risky during recessions, or b), the price of risk increases as investors get more risk averse. My event study setting allows me to estimate non-parametrically the volatility of stock prices, earnings, dividends, and consumption before and after the beginning of recessions. In line with a large literature (starting with Schwert, 1989; most recently Boguth and Kuehn, 2013; Bansal, Kiku, Shaliastovich, and Yaron, 2014; Tédongap, 2014; Jurado, Ludvigson, and Ng, 2015), I find that financial and macroeconomic uncertainty increases during recessions. Because I look at prices and cash flows separately, I can add to the literature by comparing the rise in volatilities between the different components of stock returns. The ratio of the recession variance over the pre-recession variance (which I call the “the recession variance ratio” in the following) is as large as four for stock prices, 2.7 for earnings and below two for dividends and consumption. In summary, the results suggest that stock prices get even more volatile compared to their own cash flows.

I apply a simple model to make some back of the envelope calculations to better understand the implications of these results. Changes in stock prices are the sum of innovations in dividends

² As reported in the Appendix, I do find interesting variation in longer horizon expected growth in the data. But these shifts in long horizon expectations are simply not systematically related to recessions. ³I get similar results for the recent recalibration of the long-run risk model in Bansal, Kiku, and Yaron (2012). The timing of the drop of the price-dividend ratio is very similar. Because the role of long-run risks is toned down, the price-dividend ratio drops somewhat less.
and innovations in expected returns. Intuitively, to get a stock price variance that increases more than cash flow variance, I need the variance of expected return innovations to increase by a huge factor of 5. This is in line with the idea that the price of risk must be larger during recessions, so that expected returns become more sensitive to economic shocks. The prime example of a model that features such a mechanism is the habit model by Campbell and Cochrane (1999).

To further compare my empirical results to the theoretical counterfactual, I also simulate “recessions” in the habit model. Cash flows are unpredictable and homoscedastic. All changes in prices come from changes in the price of risk. Indeed, stock prices fall contemporaneously with cash flows during recessions, similar as in the data. However, stock price volatility increases only by a factor of 1.1 during recessions. Even looking on the 20% largest recessions does only increase the stock price variance by a factor of 1.5. The long-run risk model (Bansal and Yaron, 2004) does feature time-varying cash flow volatility. However, because times of high volatility are not systematically related to times of low cash flows, recession variance ratios are 1.0. In short, leading asset pricing theories have serious difficulties to generate an increase in the variance of expected returns that is required to explain the stock market around recessions.

I provide several robustness checks. First, I show that my results do not just hold on average but also recession by recession for the period 1950-2016. I find that price-dividend ratios are in all cases lower after the beginning of a recession compared to before. Put differently, the stock market did not anticipate one single recession. Second, I document that my results are robust to an extended dataset of annual data that spans the period from 1871-2016. Stock prices also do not anticipate recessions in this sample. These results are, of course, less granular, but qualitatively and quantitatively similar to the baseline results that are based on quarterly data. Taken together, these findings suggest that my results are not driven by a few extreme observations but rather reflect a common feature of recessions.

**Literature:** This paper can be viewed as an event study-based test of macro finance asset pricing theories. While several papers have documented that expected returns are countercyc-
lical, e.g., Fama and French (1989), Ferson and Harvey (1991), Harrison and Zhang (1999), Lettau and Ludvigson (2009), Golez and Koudijs (2018), there are surprisingly few papers that focus on expected returns during specific kinds of “bad times” in the spirit of an event study. Lustig and Verdelhan (2012) show that realized future returns, as a proxy for expected returns, are higher during NBER recessions compared to normal times. For an international but annually sampled dataset, Muir (2017) documents that expected returns, as measured by the dividend yield, are higher during financial crises compared to “normal” recessions. Because fundamentals (drop in consumption, rise in volatility) are similar during financial crises and recessions, he concludes that leading asset pricing theories cannot explain risk premia during financial crises. I add to these previous findings by deriving the predictions of leading asset pricing models on the timing of prices, cash flows and the rise in volatility and by showing that these models also have difficulties in explaining “normal” recessions.

The analysis by Muir (2017) demonstrates that studying “bad times” in the spirit of an event study is helpful to differentiate between different channels that might drive stock prices. However, a potential concern of his analysis is that his conclusions are only valid if the dividend yield really forecast 100% future returns and 0% future cash flows, as he also discusses. Even though traditional dividend yield regressions point towards this interpretation (e.g., Campbell and Shiller, 1988), it is well known that changes in the estimation method (e.g., Binsberg and Koijen, 2010), variable definition (e.g., Larrain and Yogo, 2008; Jank, 2015), or the considered sample period (pre-1950: e.g., Chen, 2009; Golez and Koudijs, 2018; internationally: e.g., Rangvid, Schmeling, and Schrimpf, 2014) can lead to evidence that suggests that dividend yields also predict future dividends to some degree. I simply suggest to avoid the potential issues of dividend yield regressions by looking at changes of the dividend yield and its components before and after the beginning of a recession.

However, in order to study the timing of cash flows and stock prices with enough precision, one has to move to higher frequent data than annual, which brings me to the importance of the time aggregation bias. I show that end of period stock prices start dropping four quarters
before time-aggregated stock prices, earnings, dividends, consumption and the NBER declares
the beginning of a recession. This finding also explains the seemingly puzzling fact that a large
literature finds that monthly/quarterly stock returns are a good proxy for future business
conditions (e.g., Fama and French, 1989; Fama, 1990; Vassalou, 2003; Backus, Routledge,
and Zin, 2010; Campbell and Diebold, 2009), while at the same time another large literature
finds that dividend yields do not predict future dividends (e.g., Campbell and Shiller, 1988;
Cochrane, 2008; Muir, 2017). When looking at frequencies higher than one year, the time
aggregation bias in cash flow measures will make market-based data appear to be strongly
leading. When looking at lower frequencies, as is typically done in the case of dividend yield
predictability regressions, dividends might appear to be (close to) unforecastable. My results
suggest that stock prices help to “nowcast” cash flows (and consumption, or recessions) within
the horizon of about one year, simply because they are based on market prices and are time
aggregation bias free.

My paper adds to the ongoing discussion whether there is a predictable component in
consumption or not. The methods that are usually used to answer this question (e.g., variance
ratio tests or dividend yield regressions) have a large margin of error. As a result, with the
available methods and data, it is not possible to definitely reject that consumption has a long-
run predictable component that is sizeable in economic terms (see, for example, the discussions
in Hansen, Heaton, and Li, 2008, Marakani, 2009; Constantinides and Gosh, 2011; Beeler and
Campbell, 2012; Bansal, Kiku, and Yaron, 2012; Dew-Becker, 2017). My event study-based
tests show that dividends, earnings and consumption are not anticipated by stock prices around
recessions. This holds on average but also recession by recession. After accounting for the time
aggregation bias, the relationship between stock prices and cash flows around recessions is
better described contemporaneously. This is direct evidence that the business cycle is not well
described by changes in expected future cash flows. However, my results are by construction
silent on everything outside of the events, e.g., whether there might be shifts in expected cash
flows that drive stock prices at a considerable lower (or considerable higher) frequency.
Finally, a recent literature finds that stock returns are predictable at surprisingly short horizons. Bollerslev, Tauchen, and Zhou (2009) show that returns are predictable by the variance risk premium at horizons of less than one year. Bekaert, Engstrom, and Xu (2017) disentangle changes in the price of risk and cash flow uncertainty using a structural model. They conclude that changes in the price of risk are the main driver of conditional stock price variance. Martin (2017) uses option prices to derive the lower bound on expected returns at the daily frequency. He argues that expected returns must be highly volatile, particularly during bad times, to explain the data. In an extensive model comparison, he shows that leading asset pricing models have considerable difficulties to match with his findings. I come to the same conclusion by studying stock prices and cash flows around recessions directly.

Outline: The next section shows how stock prices and cash flows “should” respond to recessions according to well-known asset pricing theories. Section III provides the empirical counterparts; followed by some back of the envelope calculations on how discount rates behave during recessions in Section IV. Further results are provided in Section V, followed by the conclusion.
II. Recessions in Asset Pricing Models

How “should” stock prices respond to recessions? To answer this question, I simulate 10,000 years of artificial monthly data for three asset pricing models i), the canonical consumption-based asset pricing model (Breeden, 1979) ii), the long-run risk model as in Bansal and Yaron (2004) and iii), the habit model as in Campbell and Cochrane (1999). I then convert monthly data to the sum of 12 month dividends and 12 month consumption to get “time-aggregated” versions of these variables that are comparable to their empirical counterparts. Next, I compute quarterly log changes of these variables, because this is the highest frequency at which dividends and consumption are reported in my empirical dataset. NBER recessions are defined as:

“A recession is a period between a peak and a trough, and an expansion is a period between a trough and a peak. During a recession, a significant decline in economic activity spreads across the economy and can last from a few months to more than a year.”

Thus, I mimic the NBER business cycle dating committee by searching ex post for large local peaks in economic activity. I simply proxy economic activity by consumption in these models. More specifically, I search for all peaks in the simulated data and then mark the 25% largest peaks as the observation just before the beginning of a recession, to get “significant declines”. As a result, between 2%-3% of my simulated observations are “beginning of recessions”, which is comparable to the empirical data (3%). In the simulated data, similar to the empirical data, the duration of a “recession” varies. I then use local linear projections (Jorda, 2005) to estimate the cumulative average log change of the de-meaned price-dividend ratio, prices, dividends, and consumption in recession event time. The event window is set from 12 quarters before the beginning of recessions and ends 12 quarters after the beginning of recessions.


5Importantly, I do not want to predict recessions in the simulated or in the empirical data later on. Instead, in the spirit of Muir (2017), I want to study how stock prices behave given a drop in economic activity.
The Classic Consumption-based Model: In the classic model, future consumption is unpredictable and expected returns are constant. Realized returns are, of course, not constant. They are basically just the realized dividends the investor receives in each period. As is common in the literature, dividends are a leveraged consumption claim and thus dividends and consumption are correlated - which determines the equity premium in this model. I set consumption volatility to 2.5%.

Figure 1 summarizes the simulation results for the simple model. The figure shows the cumulative change of the price-dividend ratio, prices, dividends and consumption around recessions. I shift all variables by their own local peak (y-axis = 0) to make it easier to see the timing and the cumulative drop around recessions across variables. In this model, the price $P_t$ is:

$$P_t = D_t \times \frac{1 + E(\Delta D_{t+1})}{E(R_{t+1}) - E(\Delta D_{t+1})},$$

(1)

where $D_t$ is the dividend, $E(R_{t+1})$ is the expected return and $E(\Delta D_t)$ is expected dividend growth. Because expected returns and dividend growth are constant, log prices move 1:1 with changes in log dividends, $p_t = d_t + constant$. Thus, the log price-dividend ratio is constant. This, of course, only holds if prices and dividends are both measured exactly at the same point in time. The figure shows that if prices are measured at the end of a period (a quarter) and dividends are measured time-aggregated (the sum over the last year), the log price-dividend ratio makes wild swings even if the true price-dividend ratio is constant. This results simply from a timing mismatch. The figure also shows that using time-aggregated prices in the price-dividend ratio leads to a constant ratio and resolves the issue.

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This number is in line with recent empirical evidence provided by Dew-Becker (2017) and Kroencke (2017). Further simulation details are provided in the Appendix.

The y-axis will also be the same in all figures such that one can easily compare results between all simulated models and the empirical data later on.

Notice that $p_t$ and $d_t$ perfectly overlap in the figure and prices might be difficult to see.
Figure 1

Simulation of the Classic CCAPM

Prices (End of Period) / Dividends
Prices (Time Aggregated) / Dividends

Consumption (Time Aggregated)

Quarters Around Beginning of "Recessions" (x=0)
The Long-Run Risk Model: In the long-run risk model by Bansal and Yaron (2004), cash flows have three ingredients. Traditional one period consumption shocks (“short-run risk”) as in the simple model before, and in addition, a persistent component in consumption growth (“long-run risk”) and time-varying volatility. Interestingly, dividend growth only shares the persistent component (the long-run risk) of consumption risk and is, thus, to some degree predictable. I use the same model parameters as in Bansal and Yaron (2004), to make my results comparable to the literature.9

Figure 2 summarizes results for the long-run risk model. I find that the time-aggregated price-dividend ratio starts dropping about one year ahead of recessions. Intuitively, if one mimicks the NBER business cycle dating committee and searches for significant declines in economic activity (consumption), one identifies periods when long-run growth and short run growth happen to be low at the same time. The forward-looking investor, in turn, recognizes that future dividends will be lower and as a consequence stock prices decline many quarters before the recession actually starts. The picture also shows that the price-dividend ratio does not move much with the beginning of recessions. It is also instructive to see that the end of period price-dividend ratio looks similar to its counterpart in the simple model with constant expected cash flows (Figure 1). The mismatch in the timing of end of period prices and time-aggregated dividends obscures the differences between both models.

The long-run risk model also features time-varying volatility. However, in the long-run risk model, changes in volatility are, by construction, uncorrelated to short-run or long-run consumption risk. As a result, there is no systematic relationship between volatility and recessions (a fall in consumption). I will provide the numbers and discuss this aspect of the model in more detail later in the paper.

9 Further simulation details are provided in the Appendix.
Figure 2


- Prices (End of Period) / Dividends
- Prices (Time Aggregated) / Dividends

- Business cycle peak ↓

- Business cycle peak ↓

- Cumulative log change, max = 0

- Cumulative log change, max = 0

- Quarters Around Beginning of "Recessions" (x=0)

- Quarters Around Beginning of "Recessions" (x=0)
The Habit Model: Finally, I simulate the habit model by Campbell and Cochrane (1999). As in the simple model, consumption is an unpredictable standard i.i.d. process. However, the price of risk and expected returns are time-varying. Consumption is evaluated relative to a habit, which is a reference level of consumption that can be thought as a moving average of past realizations. As a result, expected returns are low after observing a “good run” of consumption shocks. This is by construction around the peak of the business cycle. However, expected returns rise when consumption comes closer and closer to the reference level, i.e., during “significant declines” in economic activity (consumption). Again, I use the same model parameters as in Campbell and Cochrane (1999), to make my results comparable to the literature.¹⁰

Figure 3 summarizes the simulation results for the habit model. It is easy to see that the price-dividend ratio drops contemporaneously with dividends and consumption, when all variables are measured with the same timing. This reflects the fact that expected future cash flows are constant, but stock prices fall more than cash flows because expected returns go up. End of period stock prices - which are frequently used in empirical research - lead dividends and consumption for many quarters. Getting the timing “wrong” makes dividends and consumption predictable. Even in the habit model.¹¹

¹⁰ Further simulation details are provided in the Appendix. Notice that Campbell and Cochrane (1999) and Bansal and Yaron (2004) use quite different consumption volatilities, which explains why the drop in consumption is so different in both models. There is, unfortunately, no “benchmark” calibration available that sets both models on equal grounds, which implies that I can only compare the models qualitatively but not quantitatively.

¹¹ Of course, if one is interested in predicting recessions in real time (and not in the economic mechanisms that push stock prices down), using end of period stock prices would be the “right” way to go.
Figure 3

Simulation of the Habits Model, Campbell and Cochrane (1999)

Prices (End of Period) / Dividends
Prices (Time Aggregated) / Dividends

Prices (End of Period)
Prices (Time Aggregated)
Consumption (Time Aggregated)
Dividends (Time Aggregated)

Quarters Around Beginning of "Recessions" (x=0)
Summary of the Simulation Experiment: If there is no change in expected future cash flows and expected returns are constant, the price-dividend ratio should be constant during recessions (Figure 1). If recessions are periods of lower than usual growth such that there is a predictable component in cash flows, the price-dividend ratio should fall several quarters ahead of the recession (Figure 2). A drop in the price-dividend ratio contemporaneously with fundamentals (dividends and consumption) is in line with a change in discount rates (Figure 3). The simulation experiment reveals that the timing of the drop in prices compared to cash flows around recessions is informative to disentangling different potential economic channels. However, for this exercise, it is important that all variables have the same timing.
III. The Stock Market Around Recessions

A. Data & Method

My baseline results focus on quarterly sampled data for the period from 1950 to 2016. Time-aggregated stock prices, earnings, and dividends are trailing sums over the past 12 months. Earnings and dividends are highly seasonable and for this reason it is common to look at trailing 12 month sums of these variables. The quarterly sampling of the “annual” data allows me to pin down the timing of the variables as precisely as possible. This baseline sample spans ten NBER business cycle peaks.\footnote{Peak date (duration in months): Q2-1953(10), Q3-1957(8), Q2-1960(10), Q4-1969(11), Q4-1973(16), Q1-1980(6), Q3-1981(16), Q3-1990(8), Q1-2001(8), Q4-2007(18). My results are not sensitive with regard to the event Q3-1981, which closely follows the previous recession (“double dip”), or any other single observation as I show later in the paper.} Results for an annual dataset that spans the period from 1871 to 2018 and 29 recessions is provided as an robust test later in the paper. For the period from (1871) 1950 to 1974, I use the data provided by Robert J. Shiller on his website.\footnote{Shiller (2000).} For the period from 1975 to 2016, I rely on prices, dividends, and earnings for the S&P 500 index as provided by the Thomson Reuters Datastream.\footnote{Series: S&PCOMP; datatypes: MV, DSDY, DSPE.} All stock market data are adjusted for inflation using the CPI.\footnote{Available from FRED (St. Louis Fed); series CPIAUCSL.}

I use local linear projections (Jorda, 2005) to estimate the de-meaned log change of the variables of interest:

\[
\Delta x_{t+h} = a_h + b_h \times D_{Beginning\ of\ Recession, t} + \zeta_{t+h},
\]

where \( \Delta x_{t+h} \) is the log change of price-dividend ratio, prices, dividend, earnings or consumption, \( D_{Beginning\ of\ Recession, t} \) is a dummy that is one in the quarter the NBER declares the business cycle peak (and a recession begins), and \( h \) is the event window and ranges from \( h = -12 \) to \( h = +12 \) quarters. The coefficient \( b \) is my estimate of the (de-meaned) log change. Standard errors are based on the full coefficient covariance matrix such that I account for
correlation between bs. I then sum up bs to get the cumulative response of my variables around recessions.

**B. The Timing of Stock Prices and Cash Flows**

Figure 4 shows the cumulative drop of prices and cash flows around recessions. I shift all variables by their own local peak (y-axis = 0) to make it easier to see the timing and the cumulative drop around recessions across variables. Earnings are scaled by 0.5 to make it easier to see how they compare to dividends in event time.\(^{16}\) I find that the time-aggregated price-dividend ratio (upper figure) starts dropping with the beginning of recessions. The 90% confidence bands indicate that the drop in the price-dividend ratio is precisely measured. The lower figure reveals that both components, prices and dividends, fall very much contemporaneously. The decline in dividends cumulates to about -10%, and to about -20% for prices. Together, this results in a cumulative decline in the price-dividend ratio of -10% (\(\triangle pd_t = \triangle p_t - \triangle d_t\)).

Dividends might be smoothed due to dividend policy (e.g., Lintner, 1956, Fama and Babiak, 1968, Brav, Graham, Harvey, and Michaely, 2005, Leary and Michaely, 2011). For that reason, the figure also provides the cumulative response of earnings. I find that earnings fall very much together with prices and dividends. End of period stock prices, which are often used in empirical analysis, indeed lead recessions by several quarters. The comparison to time-aggregated stock prices reveals that this large lead is simply driven by the time aggregation bias and not by an economically rooted mechanism.

Cash flows might be unpredictable before recessions but predictable afterwards.\(^{17}\) The median duration of the covered recessions is 10 months (min 6 months; max 18 months), i.e. “afterwards” starts after about one year. The time-aggregated and smoothed data reach their trough after 6 quarters, the end of period and not smoothed prices earlier; in line with the rather short duration of recessions. Looking at the quarters after the end of recessions (\(t=+6\))

\(^{16}\)One half is about the average payout ratio \((D/E = 0.48)\) in my sample.

\(^{17}\)Such a pattern would hint towards some kind of asymmetric long-run risk. I am not aware of such a version of the long-run risk model.
to $t=+12$), it is apparent that cash flows grow with average speed (or slightly above), as is the case before a recession starts ($t=-12$ to $t=-2$).\footnote{All variables are de-meaned, hence, horizontal lines mean that the variable grows with average speed.} This suggests that the drop in stock prices also does not reflect expected cash flows lower than usual after a recession occurred.

Table I shows cumulative log changes in the de-meaned variables of interest and provides detailed statistical inference. Coefficients at the left hand side are for all variables cumulated from quarter $t=-1$ up to quarter $t=-12$ before the beginning of recessions ($t=0$). The table reassures that the time-aggregated price-dividend ratio, or just time-aggregated prices, do not significantly decline ahead of recessions. Finally, the right hand side of the table reports the cumulative change starting with the beginning of recessions ($t=0$). The drop in all variables is highly significant for the first couple of quarters during recessions. As the start of the following expansion varies between recessions (between 0.5 - 1.5 years), longer horizon estimates get more and more imprecise, however.

In summary, these results speak against the idea that cash flows have a predictable component such that stock prices anticipate recessions. I also do not find evidence that recessions are followed by lower than usual cash flows. This suggests that prices fall more than dividends because expected returns increase as the economy falls into a recession.
Figure 4. The Stock Market Around NBER Recessions, 1950-2016

Stock Prices and Cash Flows Around Recessions

- Cumulative log change, max = 0
- Business cycle peak
- Prices (End of Period) / Dividends
- Prices (Time Aggregated) / Dividends
- 90% confidence band

Quarters Around Beginning of NBER Recessions (x=0)
Table I Linear Projections: Stock Market

This table shows cumulative log changes of the price-dividend ratio ($\Delta pd$), prices ($\Delta p$), dividends ($\Delta d$), and earnings ($\Delta e$) around the beginning of NBER recessions from 1950 to 2016. The data are sampled quarterly and the event window ranges from $h=-12$ to $h=+12$ quarters around the beginning of a recession ($h=0$). Estimates are based on local linear projections,

$$\Delta x_{t+h} = a_h + b_h \times D_{\text{Beginning of Recession}, t} + \zeta_{t+h},$$

where $D_{\text{Beginning of Recession}, t}$ is one at the beginning of a recession and zero otherwise. Cumulative changes of the (de-meaned) variables are measured as sums of the coefficients $b$; $t$-statistics ($t$) on cumulated effects are based on the full $b$ coefficient covariance matrix. Dividends and earnings are trailing 12 month sums, i.e., they are time-aggregated. Prices are as at the end of a quarter (end of period, E.o.P), or they are trailing 12 month means, such that they have the same timing as earnings and dividends and are time-aggregated data (T.A.).

<table>
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<th>Quarter</th>
<th>$\Delta pd_t$, E.o.P.</th>
<th>$\Delta pd_t$, T.A.</th>
<th>$\Delta p_t$, E.o.P.</th>
<th>$\Delta p_t$, T.A.</th>
<th>$\Delta d_t$, T.A.</th>
<th>$\Delta e_t$, T.A.</th>
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20
C. The Timing of Consumption

In this section, I use consumption data as a further proxy for investor “cash flows” and also to connect my results more deeply to consumption-based asset pricing models. Consumption data are taken from the NIPA, available on the website of the Bureau of Economic Analysis.\(^\text{19}\)

Reported consumption is not highly correlated with stock returns which gives rise to the equity premium puzzle (Grossman and Shiller, 1980, 1981; Hansen and Singleton, 1982, 1983; Mehra and Prescott, 1985). Savov (2011) argues that if there are measurement problems with officially reported consumption, the more simple measure of garbage might be a better approximation of true consumption. Indeed, he finds that garbage growth is highly correlated with stock returns. Kroencke (2017) provides a possible explanation of why garbage is more correlated with stock returns. If consumption is measured with an error, it is optimal for NIPA statisticians to filter reported consumption to smooth out measurement errors. However, filtering reduces the variance of reported consumption (reported consumption drops too little) and will introduce a lag compared to true but unobservable consumption (reported consumption lags market based data, e.g. stock prices).

Kroencke (2017) suggests that the true consumption estimation process might be approximated by a simple Kalman filter model which allows to compute the series of “unfiltered” NIPA consumption. Because the series of “unfiltered” NIPA consumption that is likely to be better suited to assess the drop and the timing of consumption during recessions, I report results for unfiltered consumption as well as reported consumption.\(^\text{20}\) Furthermore, I provide results for aggregate consumption, as measured by nondurables and services, as well as nondurables excluding services. There is evidence that nondurables are easier to measure than services and are accordingly less plagued by measurement problems (see, Wilcox, 1992; Kroencke, 2017).

Figure 5 and Table II provide the results. All consumption measures start falling with the

\(^\text{19}\)NIPA tables 2.3.4 and 2.3.5; lines “nondurable goods” and “services”; real per capita growth weighted by their nominal share. Capita numbers are from NIPA table 1.1.6.

\(^\text{20}\)Because garbage is not available at the quarterly frequency, I complement results on reported NIPA consumption with unfiltered NIPA consumption sampled at the quarterly frequency. Further details on the unfilter procedure are provided in the Appendix.
beginning of recessions. The figure also shows scaled dividends and earnings to allow for visual comparisons to stock market cash flows. Unfiltered consumption, particularly nondurables, fall contemporaneously with firm cash flows. The figure also suggests that consumption grows with average speed (or slightly above) after the end of a recession ($t=+6$ to $t=+12$) as is the case before recessions start ($t=-12$ to $t=-2$). This is once again in disfavor of the idea that stock prices anticipate low future consumption growth after recessions.

In summary, I find that consumption falls very much together with firm cash flows around recessions, which corroborates the results from the previous section.

**Figure 5.** Consumption Around NBER Recessions, 1950-2016

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21 The scaling of earnings and dividends can be interpreted as an adjustment for firm leverage, as is common in the asset pricing literature (e.g., Campbell and Cochrane, 1999; Bansal and Yaron, 2004); the larger scaling factor for earnings is in line with the average payout ratio.
Table II Linear Projections: Consumption Measures

This table shows cumulative log changes of aggregate consumption (services and nondurables) \( (\Delta c) \) and nondurable consumption \( (\Delta ndr) \) around the beginning of NBER recessions from 1950 to 2016. All consumption data are real per capita. The event window ranges from \( h=-12 \) to \( h=+12 \) quarters around the beginning of a recession \( (h=0) \). Estimates are based on local linear projections,

\[
\Delta x_{t+h} = a_h + b_h \times D_{Beginning of Recession,t} + \zeta_{t+h},
\]

where \( D_{Beginning of Recession,t} \) is one at the beginning of a recession and zero otherwise. Cumulative changes of the (de-meaned) variables are measured as sums of the coefficients \( b \); \( t \)-statistics \( (t) \) on cumulated effects are based on the full \( b \) coefficient covariance matrix. Consumption data are trailing 4 quarter sums, i.e. they are time-aggregated. Consumption data are as “reported” in the NIPA tables, or “unfiltered” as in Kroencke (2017). Details on the unfilter procedure are provided in the Appendix.

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<th>↓</th>
<th>after Beginning of Recession→</th>
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<tr>
<td>( t )</td>
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<td>0.00</td>
<td>-0.16 -0.59 -1.06 -1.91 -2.04 -1.38</td>
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<tr>
<td>( t )</td>
<td>1.47 1.20 1.04 0.76 0.21</td>
<td>0.05</td>
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<td>( \Delta c_t ), unfiltered, T.A.</td>
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<tr>
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<td>( \Delta ndr_t ), reported, T.A.</td>
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<tr>
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<tr>
<td>( t )</td>
<td>1.01 1.40 1.05 0.21 -1.06</td>
<td>-2.31</td>
<td>-2.66 -3.52 -4.55 -5.27 -3.58 -2.59</td>
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D. The Timing of Growth Expectations

In this section, I analyse changes in the forward term structure of real GDP growth forecasts from the Survey of Professional Forecasters (SPF). More specifically, I compare changes in the nowcast of current quarter growth of real GDP (nowcast vs past period real-time real GDP) with changes in the forecast of growth four quarters into the future (forecast Q4 vs forecast Q3). Thus, this exercise allows me to compare short-term revisions in growth expectations versus longer term revisions in growth expectations. However, to derive a meaningful interpretation, I have to assume i) that survey expectations of professional forecasters are close to the expectations that are reflected by market prices, and ii) that real GDP growth follows similar dynamics as real consumption growth and corporate cash flows, at least around the event window.

The point estimates of the cumulative change in expectations are provided in Figure 6. Measures of statistical significance are reported in Table III. First, focusing on the expected forward growth rate four quarters into the future (black line; the longest horizon available), I find that long-horizon expectations are virtually constant around recessions. Put differently, professional forecasters do not update long-horizon expected growth, neither before recessions (as suggested by the traditional long-run risk model) nor during recessions (as some modified version of a long-run risk model might suggest). These results further corroborate my earlier conjecture that the long-run risk model cannot explain the joint timing of stock prices and realized measures of cash flows around recessions. Second, expectations are heavily updated at the short end of the forward term structure of expected growth. Nowcasts significantly drop and are virtually in free fall with the beginning of recessions. Taken together, these result suggest that recessions are events that carry news about short-horizon cash flows but not longer

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22 The data come from the website of the Philadelphia Fed: https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/data-files/rgdp. Real GDP Forecasts are available since Q4 1968 and are provided up to four quarters into the future; this time period spans seven U.S. recessions. The SPF provides a nowcast and forecasts for the following four quarters.

23 The SPF also covers (nominal) corporate profit forecasts and real consumption forecasts as alternative measures of expected cash flows. I find that nominal corporate profit forecasts deflated by the GDP deflater behave very similar to real GDP in event time. I prefer real GDP against real consumption forecasts because the consumption time-series does not start before 1981 and is covered by less survey participants.
horizon cash flows. Third, one can see that revisions in the nowcast (and similar next quarter growth) drift slightly downward before the business cycle peak. Because real activity does not decline before the business cycle peak (by definition), these results suggest that forecasters might be too optimistic during boom phases. However, this pre-drift in short horizon revisions in expectations is only weakly significant (as indicated by Table III) and not consistently so for all short-term horizons.

**Further Results:** I provide further results on the forward term structure of expected growth in the Appendix. These results show that there is variation in longer horizon forward growth rates (as suggested by long-run risk models). However, these variations are unrelated to recessions and occur at a relative low frequency. Finally, I find that returns are more heavily correlated with revisions in short-horizon expectations compared to long-horizon expectations.
Figure 6. Term Structure of Real GDP Growth Forecasts Around Recessions
Table III Linear Projections: Term Structure of Real GDP Growth Forecasts

This table provides cumulative changes of expected real GDP log growth (%, annualized) as reported by the Survey of Professional Forecasters from 1969 to 2016. Expected log growth rates are computed as the difference between the log mean forecast at horizon k and the log mean forecast at horizon k-1; except the nowcast which is the first difference to log “real-time” real GDP of the previous quarter. Changes in expectations are measured as first differences of log expected growth rates. All information are provided by the Survey of Professional Forecasters at the website of the Philadelphia Fed (www.philadelphiafed.org, series “mean RGDP forecasts”). The event window ranges from h=-12 to h=+12 quarters around the beginning of a recession (h=0). Estimates are based on local linear projections as described in the previous table captions (Table I and II).

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<td>forecast Q4</td>
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<td>2.18</td>
<td>0.19</td>
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</table>
E. Recession Variance Ratios

The previous literature has documented that price and cash flow volatility is higher than usual during recessions (starting with Schwert, 1989; most recently Boguth and Kuehn, 2013; Bansal, Kiku, Shaliastovich, and Yaron, 2014; Tédongap, 2014). My event study setting allows me to supplement these earlier results with non-parametric estimates that are free of any parametric assumption on how volatility can change. Importantly, I compare the increase of volatility between cash flows and stock prices around recessions. I argue that the increase of price volatility compared to cash flow volatility allows to make conclusions on what drives discount rates.\footnote{Jurado, Ludvigson, and Ng (2015) recently proposed a procedure to estimate macroeconomic uncertainty (almost) model free. However, their estimates rely on a large cross-section of variables and does not identify differences between the increase in the volatility of stock prices and cash flows, which is key for my analysis.}

Stock price changes are the sum of cash flow innovations and expected return innovations. Intuitively, if price volatility increases more compared to cash flow volatility, this implies that expected return innovations become even more volatile compared to their own cash flows. Such a pattern is, for example, qualitatively in line with models where the price of risk can change (e.g., Campbell and Cochrane, 1999), such that expected returns become more sensitive to shocks.

Figure 7 and Table IV provide the conditional volatility of stock prices, dividends, and earnings in recession event time. Estimates are based on the sample standard deviation conditional on the quarter around recessions; multiplied by 2 to provide annualized values. To reduce noise in the figure, I cautiously smooth estimates around the two neighbouring observations \{-1, 0, +1\} using the weights \{0.25, 0.50, 0.25\}.

Before recessions, end of period (time-aggregated) stock prices have a volatility of around 10% (5%).\footnote{It is not possible to map the exact relationship between the variances of end of period and time-aggregated data for an arbitrary process. Working (1960) shows that the variance of a time-aggregated i.i.d. process is $2/3$ of the end of period counterpart; which is roughly in line with the figure.} Stock price volatility doubles during recessions to 20% (11%), which means that the ratio of the pre-recession variance (h=-5 to h=-2) to the post-recession variance (h=+1 to h=+4) quadruples (quintuples). Earnings volatility increases from 6% to 10%, which gives a considerable smaller recession variance ratio of 2.7. The conditional volatility of dividends
does not quickly respond to recessions, and is on average only slightly increased. I find that nondurable consumption volatility increases during recessions, however, the measured increase also does not result in variance ratios larger than 1.9. Aggregate consumption volatility shows very similar recession variance ratios of 1.5 (reported) and 1.6 (unfiltered). Evidence from the three measures of cash flows (earnings, dividends, and consumption) are somewhat inconclusive on the precise increase of volatility. Given the rise in earnings and consumption volatility, the flat volatility of dividends might be explained by a smoothing effect caused by the dividend payout policy at the firm level (Lintner, 1956, Fama and Babiak, 1968). Taken together, it seems to be safe to say that cash flow volatility increases during recessions, in line with the literature, but to a substantially lesser degree compared to stock price volatility.

Furthermore, the table provides results for the recession variance ratio from simulations of the long-run risk model and the habit model as discussed in Section II of the paper. Even though the long-run risk model as in Bansal and Yaron (2004) features time-varying volatility in cash flows, the model is set up such that volatility does not systematically change around recessions when economic activity drops. As a results, all simulated recession variance ratios are around 1.26 In the habit model by Campbell and Cochrane (1999), cash flows are homoscedastic. However, because the price of risk is linked to large drops in consumption, expected returns can get more sensitive to shocks during recessions. The table shows that the stock price variance indeed increases during recessions in the habit model, however, the effect is substantially smaller (recession variance ratio = 1.1) compared to the increase that can be measured in the empirical data (4). To see whether changes in my definition of simulated “recessions” change results, the table also provides results for the 20% largest recessions. In this case, the recession variance ratio increases to about 1.5.27 Even looking at the tails of the distribution does not generate enough discount rate volatility.

In summary, I find that stock price volatility increases substantially more than cash flow

---

26 Further discussion on this point is provided in the Appendix. I show that times of large changes in volatility are also not systematically related to consumption.

27 The Appendix provides figures for “large” recessions in the habit model that allow for further comparisons.
volatility. Thus, I conclude that an increase of the price of risk during recessions plays a key role to explain the data. The habit model by Campbell and Cochrane (1999) goes qualitatively in the right direction, but does not get quantitatively close to the data.

Figure 7. Stock Market Volatility Around NBER Recessions, 1950-2016
Table IV Stock Market and Consumption Volatility Around Recessions

This table reports the annualized volatility (%) of log changes of stock prices ($\triangle p_t$), earnings ($\triangle e_t$), dividends ($\triangle d_t$), and nondurable consumption ($\triangle ndr_t$) the year before the beginning of a recession (h=-5 to h=-2) and the year after the beginning of a recession (h=+1 to h=+4). The reported recession variance ratio is the squared ratio of the recession volatility (+1:+4) over the pre-recession volatility (-5:-2). The last four rows report the recession variance ratio from simulations of the classic model (with homoscedastic stock prices and cash flows), the long-run risk model (Bansal and Yaron, 2004) and the habit model (Campbell and Cochrane, 1999) as in Section II of the paper (Figures 1, 2 and 3). Habit “large rec.” provides results based on 20% of the largest recessions in the habit model (Figures A.2).

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<th>Cash flows</th>
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<td>E.o.P</td>
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<td>$\triangle d_t$</td>
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<td>T.A.</td>
<td>T.A.</td>
</tr>
<tr>
<td></td>
<td>$\triangle ndr_t$</td>
<td>T.A.</td>
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<tr>
<td></td>
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<td>post-recession vola.</td>
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<td>variance ratio, Habit “large rec.”</td>
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<td></td>
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<td>0.97</td>
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IV. Back-of-the-envelope Calculations

Expected returns can rise if a), the amount of risk in the economy increases (cash flow/consumption uncertainty increases) or b), the price of risk changes (risk aversion goes up). In this section, I show that the recession variance ratio (variance during recessions divided by the variance just before recessions) of stock prices compared to cash flows is informative to learn about the two channels.

Model: I adapt a simple model as presented in Cochrane (2005, Chapter 20). I assume that the economy is described by the following three equations:

\[ r_t = z_t + \sigma_r \xi_r,t, \]  
\[ z_t = b z_{t-1} + \sigma_z \delta_t, \]  
\[ \Delta d_t = \sigma_{d,t} \xi_{d,t}, \]

where \( z_t \) captures time-varying expected returns, \( r_t \) is the return, and \( \Delta d_t \) is dividend growth. All variables are de-meaned and in logs; \( \delta_t, \xi_{d,t} \) are standard normal shocks. As a result, the price-dividend ratio can only change when there are changes in expected returns (\( z_t \)). Return innovations, \( \xi_{r,t} \), are implied by the present-value relationship. Indeed, using the Campbell and Shiller (1988) present-value identity, Cochrane (2005) shows that:

\[ d_{t+1} - p_{t+1} = b (d_t - p_t) + \frac{\sigma_{\delta,t+1} \delta_{t+1}}{1 - \rho b}, \]
\[ r_{t+1} = (1 - \rho b) (d_t - p_t) + \left( \xi_{d,t} - \frac{\rho}{1 - \rho b} \sigma_{\delta,t+1} \delta_{t+1} \right), \]
\[ \Delta p_{t+1} = (1 - \rho b) (d_t - p_t) + \left( \xi_{d,t} - \frac{1}{1 - \rho b} \sigma_{\delta,t+1} \delta_{t+1} \right), \]

which implies that the stock price variance can be decomposed as:

\[ \sigma_{p,t}^2 = \sigma_{d,t}^2 + \sigma_{dp,t}^2 + 2\rho_{d,dp} \sigma_{d,t} \sigma_{dp,t} \]
\[ \sigma_{dp,t}^2 = \frac{\sigma_{d,t}^2}{(1 - \rho b)^2}. \] (9)

In words, the stock price variance reflects the variance of innovations in dividends, plus the variance of innovations in expected returns, plus a covariance term.

**Parameters:** I use almost the same model parameters as suggested by Cochrane (2005) and set \( b = 0.9, \rho = 0.96, \sigma_d = 0.10, \sigma_\delta = 0.017, \rho_{r,dp} = -0.7, \rho_{d,dp} = 0.14. \)\(^{28}\) I scale these annual parameters to monthly counterparts such that I can compute the change in prices and dividends for 12-month “end of period” and “time-aggregated” data observed at a quarterly frequency (in the same way as described in Section II).

**Shocks:** To mimic the behavior of the stock market during recessions, I assume that dividends are hit by a negative shock \((\sigma_{d,t}\varepsilon_{d,t})\) that totals to -10% and is evenly distributed over the four quarters from -2 to +1 around the beginning of a recession. Because of the time aggregation bias, it will appear as if dividends drop with the beginning of a recession. For all other observations, I set \(\sigma_{d,t}\varepsilon_{d,t} = 0\) to focus on recessions. Similarly, I assume that expected returns increase by 1.36% such that the price-dividend ratio drops contemporaneously by -10% \((0.10 = 0.0136/(1 - b\rho)).\)\(^{29}\)

**Results:** Figure 8 shows cumulative stock prices and dividends around recessions in this condensed model. Given the set of parameters and shocks, the model comes close to the empirical counterpart (Figure 4).

In the previous section of this paper (Figure 7, Table IV), I find that the variance of prices increases by a factor of four during recessions. The variance of cash flows, however, only increases by a factor between 2.7 (earnings) and 1.4 (dividends and consumption). How can it be explained that stock price volatility increases so dramatically?

---

\(^{28}\)These parameters are chosen to match with evidence from price-dividend ratio regressions.

\(^{29}\)For all other observations, I set shocks to expected returns such that the price-dividend ratio is constant.
Equation 8 suggests a simple answer. As shown in Table V, if the variance of dividends increases by 2.5 (which is about the upper bound of my estimates) the variance of prices should only increase by a factor of 1.6, holding all else equal. To push the recession variance ratio of stock prices up, discount rate shocks ($\sigma_{\delta,t}^2$) must be more volatile during recessions, or the covariance term must go up ($\rho_{d,dp} \sigma_{d,t} \sigma_{dp,t}$). The covariance term is not promising. The numerically maximum possible covariance I can achieve is by setting $\rho_{d,dp} = 1$. However, this parameter would imply a low correlation between returns and the price-dividend ratio, which is counterfactual to the data (e.g., Cochrane, 2005). In any case, the hypothetical scenario of $\rho_{d,dp} = 1$ would result in a recession variance ratio that is 2.8, i.e. still not close to 4. The more plausible route is to increase the variance of discount rate shocks $\sigma_{\delta,t}^2$ by a large factor of 5(!).

The habit model by Campbell and Cochrane (1999) is a prime example of a theory that features such a mechanism. As consumption drops towards the habit, relative risk aversion increases and expected returns get more sensitive to shocks (in this model, a change in the consumption surplus ratio). As a results, stock price volatility increases, even though cash flow volatility is constant by assumption. However, my simulation of recessions in the habit model (Table V) shows that the model only increases stock price volatility by a factor of 1.1 (1.5, if one looks at very “large” simulated recessions). This suggests that the large degree of discount rate volatility required to explain the data is arguably difficult to generate by leading asset pricing theories, including the habit model.

In summary, finding a way of linking investor preferences and expectations such that discount rates are highly volatile during recessions is key to get asset pricing theories closer to the data. Interestingly, volatile discount rates are also in line with recent empirical evidence elsewhere, e.g., Bollerslev, Tauchen, and Zhou (2009), Bekaert, Engstrom, and Xu (2017) and Martin (2017).
A Condensed Model of the Stock Market Around Recessions

Prices (End of Period) / Dividends
Prices (Time Aggregated) / Dividends

cumulative log change

Quarters Around Beginning of "Recessions" (x=0)
Table V Back-of-the-Envelope Calculation of Stock Market Variances

This table shows the recession variance ratio for dividend and stock prices in a condensed model. Stock price volatility has three components:

\[ \sigma_{p,t}^2 = \sigma_{d,t}^2 + \sigma_{dp,t}^2 + 2\rho_{d,dp}\sigma_{d,t}\sigma_{dp,t}, \]

where, \( \sigma_{d,t}^2 \) is the variance of dividends, \( \sigma_{dp,t}^2 = \sigma_{\delta,t}^2 / (1 - \rho b)^2 \) is the scaled variance of innovations in expected returns, \( \rho_{d,dp} \) is the correlation between dividend growth and the dividend yield. The recession variance ratio is the variance during recessions dividend by the variance before recessions. As is explained in the text, a large value for \( \rho_{d,dp} \) is not plausible and is only provided as point of reference.

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<th>Prices, ( \triangle p_t )</th>
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<td>before recessions</td>
<td>( \sigma_d ) .10</td>
<td>.10</td>
</tr>
<tr>
<td></td>
<td>( \rho_{d,dp} ) .14</td>
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<tr>
<td></td>
<td>( \sigma_\delta ) .017</td>
<td>.017</td>
</tr>
<tr>
<td>during recessions</td>
<td>( \sigma_d ) ( 0.10 \times \sqrt{2.5} )</td>
<td>( 0.10 \times \sqrt{2.5} )</td>
</tr>
<tr>
<td></td>
<td>( \rho_{d,dp} ) .14</td>
<td>.14</td>
</tr>
<tr>
<td></td>
<td>( \sigma_\delta ) .017</td>
<td>.017</td>
</tr>
<tr>
<td>recession variance ratio</td>
<td>2.5</td>
<td>1.6</td>
</tr>
<tr>
<td></td>
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<td>2.8</td>
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<td></td>
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<td>4.0</td>
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</table>
V. Further Results

A. Did Stock Prices Predict Any Recession? (1950-2016)

I show in Section III that average stock price do not drop ahead of recessions. They rather fall contemporaneously with cash flows and consumption. But does this results also hold for individual recessions? Figure 9 shows from left to right the cumulative price-dividend ratio, dividends and earnings recession by recession. Because I compare one variable across different recessions, the y-axis now shows the level as measured from the peak, i.e. one quarter before the beginning of a recession. It is easy to see that stock prices are always, recession by recession, higher before compared to after the beginning of a recession. Stock prices drop contemporaneously with cash flows. This also shows that the baseline results are not driven by one or two extreme observations. There is, of course, large variation in the degree of the drop, but the timing of prices and cash flows is arguably quite similar.

Figure 9. The Stock Market Around NBER Recessions, 1950-2016
B. Evidence From Annual Data Since 1871

The baseline results focus on the period 1950 - 2016 (ten recessions), because this allows me to study the data sampled at an quarterly frequency. Quarterly data are helpful to pinning down the timing of prices and cash flows as precise as possible. For a longer sample period, 1871 - 2016, I also analyse an annually sampled dataset that covers a total of 29 NBER recessions. There is an important trade-off involved when choosing between quarterly and annual data in event studies (see Morse, 1984). A recession can occur as early as in January or as late as in December. In the annual dataset, it is basically assumed that the recession happens always at the same point in time within the year, which will make observations less precisely measured. On the other hand, the number of recessions is increased, which means that more (but less precisely measured) observations are available.

Figure 10 show the results for the longer sample. The figure closely resamples the baseline results, although the picture is indeed less granular. I find that time-aggregated stock prices and cash flows drop around recessions contemporaneously. As in the quarterly data, end of period stock prices lead cash flows, which I can attribute to the time aggregation bias. I find that the significance levels of the linear projections are comparable to the quarterly dataset (reflecting the trade-off mentioned above).
Figure 10. The Stock Market Around NBER Recessions, 1871-2016

Stock Prices and Cash Flows Around Recessions: 1871 - 2016 (A)

- Prices (End of Period) / Dividends
- Prices (Time Aggregated) / Dividends
- 90% confidence band

Cumulative log change, max = 0

Business cycle peak ↓

Years Around Beginning of NBER Recessions (x=0)
C. Further Results (Appendix)

A bit surprising might be that the time-varying volatility channel of the long-run risk model does not show up during recessions. However, the volatility channel is simply not systematically linked to consumption growth. To further illustrate this point, the Appendix also shows sorts of time of volatility troughs. During these times, price-dividend ratios fall contemporaneously when volatility starts to rise. But now cash flows and consumption remain unchanged. Also the literature has developed many extensions of the Bansal and Yaron (2004)-model, I am not aware of a version of the long-run risk model that systematically generates high volatility at the same time as economic activity is low.

Regarding the habit model, I find that the increase in stock price volatility is much larger compared to what the habit model predicts. Looking into the simulation details, I find that stock market volatility increases more visible during large recessions. As I show in the Appendix, these large recessions also have a larger and more persistent effects on stock prices compared to the “normal” recessions in the data. In short, also the habit model goes into the right direction, it falls short in explaining the large increase in expected return volatility.

Finally, I show in the Appendix that parametric estimates of the conditional volatility of stock prices and cash flows corroborate the conclusion based on non-parametric estimates. The timing of the increase in volatilities is somewhat different to the non-parametric estimates; the measured increases in conditional volatilities is fairly similar.
VI. Conclusion

Why do stock prices fall so much around recessions? I find that stock prices move contemporaneously with dividends, earnings, and consumption. I interpret this finding as direct evidence against the idea that cash flows and consumption have a predictable component at the business cycle frequency. This suggests that stock prices drop because expected returns rise. Expected returns can rise when the amount of risk increases, or when the price of risk increases. I find that the variance of stock prices increases substantially more during recession than the variance of cash flows. This result indicates that the price of risk substantially increases during recessions. I provide evidence that innovations in expected returns must be highly volatile to generate sufficient high stock price volatility. I conclude that finding a way of linking investor preferences and expectations such that discount rates are highly volatile during recessions is key to get asset pricing theories closer to the data.
References


Appendix

Unfiltered NIPA Consumption

True consumption is unobservable. NIPA statisticians estimate consumption based on proxies that can be thought of as true consumption plus measurement error. The quite complex estimation procedure of NIPA consumption potentially drives a wedge between the properties of reported consumption and true consumption, such that empirical inference can be substantially affected (e.g., Wilcox, 1992). Indeed, Savov (2011) finds that garbage growth as a more simple measure of consumption is highly correlated with stock returns and substantially reduces the equity premium puzzle.

Kroencke (2017) suggests that if observable consumption is measured with error, it is optimal for consumption statisticians to filter the observed proxies of consumption to pin down the level of true consumption as precise as possible. Even if filtering is optimal for the purpose of estimating the level of consumption, it can be hazardous for other applications where measurement error cancels out anyway, e.g., when computing consumption covariances in asset pricing applications, or when averaging consumption over many events as in this study. Kroencke (2017) shows that the true and complex estimation procedure might be approximated by a simple Kalman-filter model:

\[
\hat{c}_t = \hat{c}_{t-1} + K (y_t - \hat{c}_{t-1}),
\]

(10)

where \( \hat{c}_t \) is the reported (or estimated) level of NIPA consumption, \( y_t \) is a noisy measure of the level of consumption (e.g., retail sales, or garbage) and \( K \) is the filter parameter. This equation can be reversed to:

\[
y_t = \hat{c}_t - (1 - K) \hat{c}_{t-1},
\]

(11)

which can be used to derive a series of “unfiltered” NIPA consumption. The filter parameter \( K \) is a signal to noise ratio. It is close to 1 if there is almost no measurement error, i.e. in this case consumption statisticians fully update. If there is (a lot of) measurement error, \( K \) should be (a lot) below 1. Kroencke (2017) shows that the new measure of unfiltered NIPA consumption has a large correlation with stock returns and matches other properties of the garbage series of Savov (2011), such that the equity premium puzzle can be substantially mitigated. Importantly, unfiltered NIPA consumption can be used when garbage data are not available, for example at the quarterly frequency, as in this study.

I use the same (constant) unfilter parameters as derived in Kroencke (2017), i.e. \( K = 0.58 \) for aggregate consumption (nondurables and services) and \( K = 0.71 \) for the easier to measure and thus less heavily filtered nondurable consumption series. I unfilter first, second, third, and fourth quarter consumption separately to avoid the time aggregation bias in the unfilter equation. In a second step, I then time aggregate all consumption data such that the timing is comparable to time-aggregated dividends and the other time-aggregated data.
Details on the Simulated Asset Pricing Models

Classic Model: For the classic model, I assume Epstein-Zin preferences with a coefficient of relative risk aversion of 15, and an elasticity of inter-temporal substitution of 1.5. In this setting, Epstein-Zin preferences avoid the risk-free rate puzzle; with respect to the equity premium, one would get comparable results using CRRA preferences.

Consumption follows an i.i.d. process. Following the evidence provides by Kroencke (2017), is set the (annual) volatility of consumption growth to 2.5% and the correlation to stock dividend growth to 0.60. I then use the log-linearization technique described in Beeler and Campbell (2012), and Bansal, Kiku, and Yaron (2012), to solve for stock prices, dividends, and returns.

Long-Run Risk Model: I use exactly the same model equations and parameters as in Bansal and Yaron (2004). The coefficient of relative risk aversion is 10 and the elasticity of inter-temporal substitution is 1.5; consumption growth volatility is set to 2.5%. The model is solved using the log-linearization technique described in Beeler and Campbell (2012), and Bansal, Kiku, and Yaron (2012). To simulate the model, I use the MATLAB function BKY_generate.m from Beeler and Campbell (2012). (I slightly modify the function to get prices. Otherwise, I use the same “equations and routines” which should make my results highly comparable to the literature.)

Habit Model: I use exactly the same model equations and parameters as in Campbell and Cochrane (1999). To simulate the model, I convert the Gauss programs used in Campbell and Cochrane (1999) to MATLAB. The GAUSS files are provided by John Cochrane on his website. By the conversion to MATLAB, I have to make some adjustments. First, to solve the price-dividend ratio, I use the GaussLegendre.m function provided by Pavel Holoborodko on his website. This numerical integration routine is much faster than the build-in routine. Second, as recommended by Wachter (2005), I use a much finer grid for the consumption ratio to solve the mode. More specifically, I use an upper segment of 50 equally spaced points between zero and maximum consumption surplus ratio and a lower segment of 450 logarithmically spaced points between the lowest value of the upper segment and exp(-300).
Descriptive Statistics from Model Simulations: I then simulate 10,000 years of artificial monthly data for all three models and proceed as described in Section II to get the results presented in Figures 1, 2, and 3. In addition, Table A.1 provides annualized descriptive statistics for consumption growth, dividend growth, stock price growth, and (total) stock returns in excess of the risk-free rate. All growth rates (returns) are simple computed and are based on monthly simulated observations, i.e. before any time-aggregation is applied to the data.

Table A.1 Descriptive Statistics from Model Simulations

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<th>dividend growth</th>
<th>price growth</th>
<th>excess returns</th>
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<tr>
<td>mean (×12, %)</td>
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<td>2.09</td>
<td>5.17</td>
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<td><strong>Long-Run Risks</strong></td>
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<tr>
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<td>2.96</td>
<td>6.88</td>
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<tr>
<td>standard deviation (×√12, %)</td>
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<td>11.38</td>
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</tr>
<tr>
<td><strong>Habits</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean (×12, %)</td>
<td>1.90</td>
<td>2.56</td>
<td>3.09</td>
<td>6.20</td>
</tr>
<tr>
<td>standard deviation (×√12, %)</td>
<td>1.50</td>
<td>11.22</td>
<td>15.27</td>
<td>15.30</td>
</tr>
</tbody>
</table>
Volatility Shocks in the Long-Run Risk Model

Figure A.1 shows the impact of changes in volatility on stock prices according to the long-run risk model by Bansal and Yaron (2004). The y-axis is the same as in all other comparable figures to facilitate comparisons. Dividend growth is flat around large changes of conditional volatility. This is the mirror image of Figure 2 and further illustrates that recessions (low economic activity) and time-varying volatility are unrelated in the long-run risk model. The figure also illustrates that prices move approximately 1:1 with changes in volatility and generate drops in prices that are relative mild in magnitude.

Figure A.1

This figure shows results for the simulated long-run risk model of Bansal and Yaron (2004) around times of volatility troughs. The simulation is the same as described in Section II of the main paper. The top figure shows the price-dividend ratio, the lower figure prices, dividends, long-run consumption and dividend growth, and the conditional variance.
Large Recessions in the Habit Model

Figure A.2 shows results for “large” recessions in the habit model by Campbell and Cochrane (1999). The results in the main paper (black lines in this figure) are based on the 25% highest local peaks in annual consumption (this converts to about 2.5% of all simulated observations). I want to check how sensitive my results are with respect to my definition of “simulated recessions”. For that purpose, I simply pick the 20% of the “largest” recessions (5% of the highest local peaks) and re-draw prices and the conditional volatility (red lines) in this figure. Looking at very large recessions reveals that prices drop deeper and the increase in the conditional volatility is more pronounced the stronger the recession is. The recession variance ratio (the variance one year before recessions dividend by the variance during recessions) is as large as 1.5 for the largest recessions (compared to 1.1 for all recessions). However, this number is still much less compared to the empirical data (4).

Figure A.2

This figure shows results for the simulated habit model of Campbell and Cochrane (1999). Black lines show the same results as described in Section II of the main paper. Red lines show results for 20% of the “largest” recessions.
**Further Results on the Forward Term Structure of Expected Growth**

Figure A.3 shows mean expected real GDP growth for the current quarter (nowcast) as well as the expected real GDP growth four quarters into the future (“forecast Q4”) as reported by the Survey of Professional Forecasters. In line with the event-time figure provided in the main paper, I find that short-horizon expectations drop during recessions whereas longer horizon expectations do not show such a consistent business cycle behaviour. However, it is also clear that longer horizon expectations change over time, but apparently not at the frequency of the business cycle.

Table A.2 provides further statistics for revisions (i.e., the first differences) in expected current quarter growth rates and expected growth rates up to four quarters into the future. The caption also provides some further details on the data construction. Mean revisions are on average close to zero. Standard deviations of revisions in expectations are large, and they are considerable larger at short horizons compared to longer horizons. Finally, Table A.2 provides simple regression of returns on revisions in expectations. I use time-aggregated stock returns and sums of the last four quarters of revisions in expectations in these regressions to better match the timing of the different variables. I find that short horizon revisions in expectations of real growth strongly correlate with stock market returns. This relationship is decreasing in the term structure of expectations.

**Figure A.3**

This figure shows forward expected real GDP growth. The nowcast refers to the current quarter expected growth rate whereas the forecast refers to the expected growth rate four quarters into the future. The data come from the Survey of Professional Forecasters and are available at the website of the Philadelphia Fed; the sample period is from Q4/1968 to Q4/2016. Further details on the variable construction are provided in the caption to table A.2.
Table A.2 Properties of Revisions in SPF Expected Real GDP Growth

Forward expected real GDP growth is computed as:

\[
E_t(\triangle \text{Real GDP}_{t+k}) = \log\left(\frac{E_t(\text{Real GDP}_{t+k})}{E_t(\text{Real GDP}_{t+k-1})}\right) \times 4,
\]

where \(E_t(\text{Real GDP}_{t+k})\) is the mean forecast of real GDP \(k\)-quarters into the future, as reported by the Survey of Professional Forecasters. Expected growth rates are annualized. In case of the nowcast, \(E_t(\text{Real GDP}_{t-1})\) is the “real-time” estimate of real GDP for the previous quarter as it was available at time \(t\). Revisions in expectations \(E_t(\triangle \text{Real GDP}_{t+k})\) are computed as first differences. The top panel provides the mean and the standard deviation of revisions in expectations along the forward term structure. The lower panel reports results from linear regressions of time-aggregated stock returns on the sum of the last four revisions in expectations of real GDP growth. The last line reports the simple correlation coefficient between time-aggregated stock returns and revisions in expectations of real GDP growth. The data come from the Survey of Professional Forecasters and are available at the website of the Philadelphia Fed; the sample period is from Q4/1968 to Q4/2016.

<table>
<thead>
<tr>
<th></th>
<th>Forecast</th>
<th>Nowcast</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Properties of revision in expectations, (\triangle E_t(\triangle \text{Real GDP}_{t+k}))</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean (p.a., %)</td>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td>standard deviation (p.a., %)</td>
<td></td>
<td>1.60</td>
<td>1.08</td>
<td>0.78</td>
<td>0.55</td>
<td>0.56</td>
</tr>
<tr>
<td>(R_t = a + b \times \triangle E_t(\triangle \text{Real GDP}_{t+k}) + e_t)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(b)</td>
<td></td>
<td>0.73</td>
<td>0.76</td>
<td>0.68</td>
<td>0.84</td>
<td>0.13</td>
</tr>
<tr>
<td>(t_{NW})</td>
<td></td>
<td>5.35</td>
<td>4.20</td>
<td>3.35</td>
<td>2.45</td>
<td>0.46</td>
</tr>
<tr>
<td>(R^2)</td>
<td></td>
<td>0.23</td>
<td>0.13</td>
<td>0.06</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td>(corr(R_t, \triangle E_t(\triangle \text{Real GDP}_t)))</td>
<td></td>
<td>0.48</td>
<td>0.36</td>
<td>0.24</td>
<td>0.20</td>
<td>0.04</td>
</tr>
</tbody>
</table>
Parametric Estimates of Conditional Volatility (1950-2016)

The baseline results on the conditional volatility of stock prices and cash flows are based on non-parametric estimates. Evidence on the change in the volatility for cash flows is inconclusive, in the sense that earnings volatility increases during recession while dividend volatility remains more or less constant. A potential concern could be that the non-parametric estimates are simply noisy and obscure the true pattern. Figure A.4 provides EGARCH(4,4,4) estimates of the conditional volatility. The figure suggests that the parametric method needs more time to catch the increase in volatility. In Figure 7, the non-parametric estimates of end of period stock prices jump immediately with the beginning of a recession. Otherwise, the pattern in the figure is very similar compared to the non-parametric estimates reported earlier.

Figure A.4. The Stock Market Around NBER Recessions, 1950-2016