The Time Varying Risk Puzzle. *

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Abstract

This paper shows that the correlation between discount rates on three major risky asset classes – equity, housing and corporate bonds – is approximately zero. I establish this new stylized fact – the time varying risk puzzle – by using new long-run data for 17 advanced economies. I confirm that asset valuations and macro-financial risk factors predict returns on individual asset classes, but I show that none of these variables have predictive power across asset classes. The absence of observed discount rate co-movement constitutes a major puzzle since all but a very select set of asset pricing models assume a joint pricing kernel and hence predict a high correlation of risk premia. My findings imply that time-varying discount rates are unlikely to be the key driver of asset price fluctuations. This puts into question prominent asset pricing models relating to time-varying risk aversion, disaster risk, and intermediary risk appetite. The absence of co-movement in the data is not fully attributable to asset-specific risk, investor heterogeneity or market segmentation. Instead, the data point to volatile expectations as the central source of asset price volatility, in line with behavioural models. The observed expectation volatility has real economic effects on a business cycle frequency. Elevated sentiment – or overoptimistic expectations – predict low future GDP growth, and sentiment reversals often mark the onset of financial crises.

Keywords: discount rates, risk premiums, return predictability, excess volatility, co-movement, sentiment, corporate bond spreads

JEL classification codes: G12, G17, G40, E32, E44, N20

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1. Introduction

Prices of risky assets fluctuate substantially over time. Much of this variation is difficult to square with changes in fundamentals such as dividends, rents or corporate default rates (Shiller, 1981; Greenwood and Hanson, 2013; Knoll, 2017). Instead, the dominant explanation for asset price volatility is time variation in discount rates – the idea that investors are sometimes less willing to bear risk, hence eliciting a low price of risky assets. Cochrane (2011) calls the understanding of why discount rates vary over time "the central organising question of current asset-pricing research".

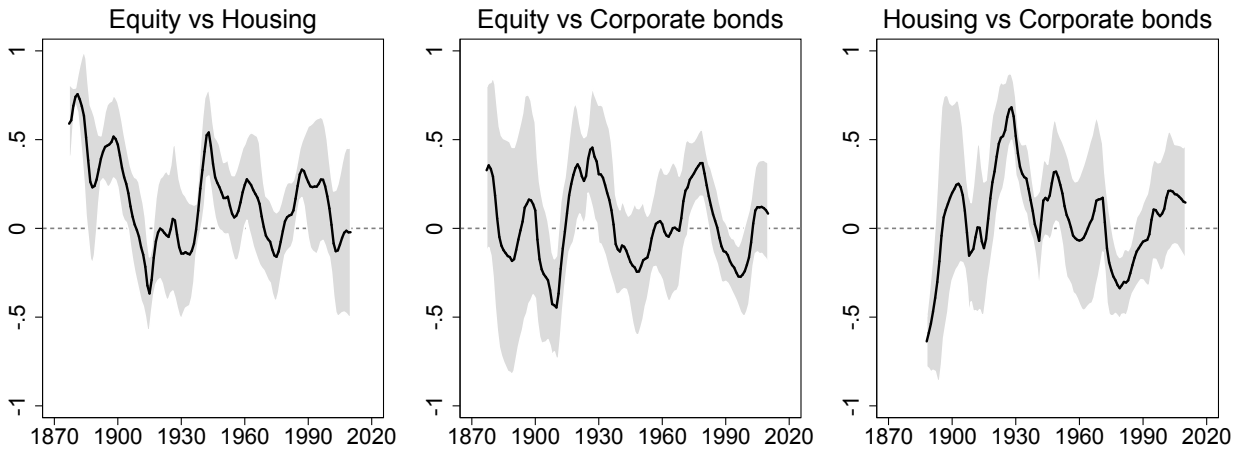
This paper re-examines the contribution of time varying discount rates to asset price fluctuations using a new historical dataset which covers three major risky asset classes – equity, housing and corporate bonds – in 17 advanced economies between 1870 and today. The importance of discount rate variation can be assessed by analysing the co-movement of expected returns – or "asset-specific discount rates" – across these three asset categories. Standard asset pricing theory stipulates that prices of all assets should be proportional to a single discount factor in order to rule out arbitrage. The time variation in this factor should, therefore, induce a positive co-movement in expected returns across all risky assets.

I show that this co-movement is absent in the data. Figure 1 displays the rolling decadal correlations between discount rate proxies for the three asset classes: the dividend-price ratio, rent-price ratio and the corporate bond spread. The correlation coefficients are roughly equal to zero and, for the most part, statistically insignificant.[1] For example, knowing that equity valuations are high tells us nothing about housing or corporate bond valuations.

This lack of co-movement presents a new "time varying risk puzzle" for the asset pricing literature. Variation in the discount rate – or the "price of risk" – is central to most standard asset pricing theories including time varying risk aversion (Campbell and Cochrane, 1999; Piazzesi, Schneider, and Tuzel, 2007), disaster risk (Barro, 2006; Gabaix, 2012), long-run risk (Bansal and Yaron, 2004) and intermediary risk appetite (He and Krishnamurthy, 2013). All these factors are simply different proxies for the aggregate price of risk (Cochrane, 2017). The low co-movement fact poses a challenge to such theories, and suggests that discount rate variation is ultimately not the key driver of asset price volatility. This fact does, however, favour another set of theories which rely on volatile expectations rather than discount rates. This expectation volatility can come about from behavioural biases relating to extrapolation of asset-specific outcomes such as past returns (Barberis, Greenwood, Jin, and Shleifer, 2015; Adam, Beutel, and Marcet, 2017), return surprises (Bordalo, Gennaioli, La Porta, and Shleifer, 2017), or relative performance of an asset class (Barberis and Shleifer, 2003). Since there is little reason for such expectation biases – and the associated asset price variation – to co-move across asset classes, these theories offer a potential resolution to the puzzle.

[1] The correlation becomes even weaker when I consider changes in discount rates, rather than levels (Appendix Figure A.1), and when using a cleaner discount rate measure (Section 6 Figure 5).

Figure 1: *Comovement of discount rate proxies across asset classes*



Note: Pairwise correlation coefficients between the dividend-price ratio, rent-price ratio and corporate bond spread over rolling decadal windows (e.g. the 1875 value covers the window 1870–1880). Shaded areas are 90% confidence intervals, using country-clustered standard errors. Underlying data are 3-year moving averages, to smooth over timing idiosyncracies across assets, demeaned at country level.

Much of the paper is spent documenting the time varying risk puzzle more rigorously and searching for potential explanations. Because the discount rate proxies in Figure 1 depend on expectations of fundamentals as well as returns, the lack of co-movement could simply be attributable to idiosyncratic cashflows. I test for the relative importance of expected returns and cashflows using the standard framework of return predictability regressions (see Cochrane, 2008). If asset valuations predict future returns, they are partly driven by non-fundamental factors such as discount rates or expectations.

Within a single asset class, however, variation in discount rates and expectations is observationally equivalent (Cochrane, 2011). But the same is not true for multiple classes of risky assets. For example, equity price could be low either because investors are risk averse, or because they are overly pessimistic. But if investors are risk averse, house prices should also be low, whereas excessive pessimism about future dividends does not imply pessimism about future rents. To test for such cross-asset co-dependence, I test for predictive power of asset valuations and other macro-financial risk factors such as consumption and bank leverage *across* asset classes. If a discount rate proxy for one asset class predicts returns across the risky asset spectrum, it measures an aggregate factor such as the discount rate. If it does not, it measures asset-specific factors such as expectations.

After establishing the facts, I explore various theoretical explanations that could rationalise the lack of co-movement. These include variation in asset-specific risk, investor heterogeneity, market segmentation and volatility of expectations. The final part of the paper assesses whether these asset-specific factors still matter for real economic outcomes, despite being unrelated to aggregate risk appetite. To do this, I estimate the effect of asset-specific sentiment variation on future GDP, and analyse the links between systematic shifts in sentiment and financial crises.

To study these questions, I introduce a new historical dataset of returns, cashflows and discount rates on all major risky asset classes – equity, housing and corporate bonds – in 17 advanced economies between 1870 and today. The comprehensive country and time dimension enables me to reliably distinguish variation in future cashflows from that in future discount rates or expectations, with these series observed over a horizon long enough to reliably approximate discounted present values, within a sample that is representative and covers less successful asset markets and disaster events.[2] The multi-asset nature of these data makes it possible to examine discount rate co-movement, and ultimately distinguish variation in discount rates from that in expectations. The dataset builds on the housing and equity data in the recent work of Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2017a), and adds to it a new series of returns and spreads on corporate bonds. The new corporate bond data capture a market which accounts for a sizeable proportion of risky wealth, and is seen as an important indicator of financial crises and macroeconomic fluctuations (Biais and Green, 2007; Gilchrist and Zakrajšek, 2012; Krishnamurthy and Muir, 2017). For most of the 17 countries in my sample, this paper presents the first historical database of corporate bond spreads and returns, with most series constructed from new hand-collected archival sources.

It turns out that the discount rate proxies in Figure 1 do reflect variation in expected returns as well as fundamentals. Each of the three valuation measures – the dividend-price ratio, rent-price ratio and the corporate bond spread – predicts the future return on the respective asset class. The relationship is both economically and statistically significant, with a 1 percentage point increase in the asset-specific discount rate predicting roughly 1.5 ppts p.a. lower returns one year ahead, and 5 ppts lower cumulative returns 5 years ahead. The fact that high asset valuations are associated with low future returns means that investors either knowingly accept lower future payoffs because of a low discount rate, or are overoptimistic about future cashflows whenever valuations are high, with these expectations subsequently corrected through a fall in prices. This non-fundamental volatility is modest for equities, and strongest for the relatively unexplored asset categories of housing and corporate bonds. My analysis shows that the seminal "excess volatility" puzzle of Shiller (1981) is a salient feature of risky asset markets across 17 advanced economies and three major asset classes, over the last century and a half.

This paper's central finding is that discount rates of different asset classes do not co-move. Put differently, what looks like discount rate variation for a single asset class cannot actually be interpreted as time-varying discount rates from the broader cross-asset perspective. To test for the extent of co-movement, I first construct a clean discount rate proxy for each asset class, equal to the discount rate news component of unexpected returns (Campbell, 1991).[3] I find that the correlation between discount rate news for different asset classes is near zero and not statistically significant, both in the full sample and across different countries, subsamples and data definitions. Cashflow

[2]See Stambaugh (1999) and Goyal and Welch (2008) for a further discussions on the need for representative long data samples in the return predictability regressions.

[3]Campbell (1991) uses a VAR to estimate the discount rate component for equities, and I extend the methodology by employing a similar technique for housing and corporate bonds.

news, on the contrary, show a significantly positive correlation. This turns the notion of idiosyncratic risk on its head. Asset pricing models typically assume that cashflows have a strong asset-specific component, while discount rates on all assets are driven by a single common factor. The reality is the opposite: it is asset-specific cashflows that co-move, and discount rates that do not. The benefits of diversification across different asset classes – a standard finding in finance – then also largely come about from hedging against asset-specific discount rate changes, rather than fundamentals.

The low co-movement finding holds within the more formal framework of cross-asset predictability regressions. The discount rate proxies for one asset class do not predict returns on other assets. For example, the dividend-price ratio does not predict future housing or corporate bond returns. The same is true for other macro-financial factors which have been used as proxies for the discount rate in the literature. I test the cross-asset predictive power of 8 macro-financial variables relating to consumption, such as surplus consumption (Campbell and Cochrane, 1999) and the consumption-wealth ratio (Lettau and Ludvigson, 2002); financial intermediary risk appetite, such as bank leverage and asset growth (Baron and Muir, 2018); and other empirical predictors of equity returns such as the term spread (Campbell, 1991). None of these variables predict returns across all three asset categories. The absence of cross-asset return predictability, and the low predictive power of macro-financial risk factors hold across different time periods, data definitions and empirical specifications. For example, they hold for five-year-ahead returns, nominal and real returns, when limiting the sample to recent decades, and both during economic recessions and expansions.

Taken together, the absence of co-movement in expected returns across asset classes is a robust and persistent feature of the data. This feature poses a challenge to discount rate based explanations of financial volatility, regardless of whether this discount rate variation is ultimately driven by time varying risk aversion, disaster risk or intermediary risk appetite. I consider several potential modifications which could improve the fit between the theory and these new data, relating to asset-specific frictions, investor heterogeneity and volatility of expectations.

Variation in asset-specific risk, or non-monetary payoffs not captured in my cashflow measure – such as liquidity services – can delink the movements in asset-specific expected returns from those in the aggregate discount factor. For example, if housing becomes more risky or less liquid relative to equities, expected returns on housing should increase relative to those of equities even in the presence of a common pricing kernel. To explain the puzzle, the time variation in these frictions needs to be asset-specific and quantitatively large. The data, however, only suggest a modest degree of such variation. For example, I show that a proxy for asset riskiness – the covariance between each risky return and the macro discount factor – is relatively stable over time and across asset classes.

If markets are segmented and investors in these markets are highly heterogeneous, the pricing kernel in each asset class will be asset-specific, offering another potential resolution to the puzzle. But the extent of both segmentation and heterogeneity in the data is relatively modest. While several studies have documented existence of segmentation and cross-asset arbitrage opportunities, their quantitative importance is typically an order of magnitude smaller than the expected return

differentials in my data.[4] The extent of investor discount rate heterogeneity also appears limited, with a large share of both bond equity securities held by institutional investors (Gompers and Metrick, 2001; Biais and Green, 2007), and discount rate proxies for housing and equity investors showing high co-movement.[5]

Expectation volatility can, on the other hand, not only generate the low co-movement in theory, but also match several other salient features of the data. To test for evidence of extrapolative and style investing behaviour, I construct a proxy for sentiment – or expected return – on each asset class following the methodology of López-Salido, Stein, and Zakrajšek (2017). The behaviour of this sentiment variable is consistent with return extrapolation: a high, or higher than expected return predicts an increase in sentiment for the specific asset class one year ahead. It is also consistent with investors switching between styles, with an increase in sentiment on one asset class predicting lower sentiment on other asset classes.

Despite not being driven by aggregate risk appetite, this asset-specific expectation volatility has real effects. Elevated sentiment in year t predicts low GDP growth in years $t+1$ to $t+5$, with the effect strongest and most persistent in the housing and corporate bond markets. Asset-specific sentiment also displays systematic variation around the onset of financial crises. An average crisis event is preceded by elevated sentiment – or "froth" – in equity or corporate bond markets, followed by sharp sentiment reversals when the crisis starts. Housing sentiment peaks after the crisis and slowly unwinds thereafter. But even during financial crises, sentiment fluctuations remain uncorrelated across asset classes, suggesting that they are, again, driven by expectations rather than a discount rate. The overall pattern in the data fits that of a Minsky (1977) financial instability cycle, with elevated sentiment accompanying an economic boom, followed by an eventual bust once the optimistic expectations are reversed and sentiment unwinds.

My findings complement the following three strands of existing literature. The first strand relates to the study of return predictability and price volatility for individual asset classes. A large literature, starting with Shiller (1981), has documented that US equity prices are excessively volatile, and returns – predictable (see Cochrane, 2008, for a summary). Knoll (2017) studies housing return predictability in a historical sample similar to this paper, and Greenwood and Hanson (2013) show that corporate bond returns in the US can be predicted by past issuance. I show that the evidence for predictability is both much more extensive, stretching to multiple countries and risky asset classes, and much more pervasive in the less studied markets of housing and corporate bonds.

The second strand relates to the study of return and discount rate co-movement across asset classes. Shiller (1982) proposed that the divergent patterns in US equity, housing and corporate

[4]For example, Fleckenstein, Longstaff, and Lustig (2010) document a 20 bps arbitrage between TIPS and government bonds plus an inflation hedge during normal times, whereas a one standard deviation higher dividend-price ratio in my data predicts 150 bps higher relative returns one year ahead and 500 bps higher returns five years ahead.

[5]More precisely, housing is primarily held by the middle class, while equities are held by the top of the income distribution (Kuhn, Schularick, and Steins, 2017) – but the income growth of these two income groups in the US data is strongly positively correlated.

bond prices pose a challenge to discount rate theories, but lacked the necessary data to formally test this hypothesis. Since then, several studies have reported a positive co-movement between or within expected returns on equities, corporate and government bonds in the post-1925 US data. Fama and French (1989) have documented this co-movement for corporate bonds and equities, Campbell and Ammer (1993) – for equities and government bonds, and Cochrane and Piazzesi (2005) – across different maturities of government bonds. A number of recent papers in the intermediary asset pricing literature find that proxies for intermediary risk appetite can predict returns on equities, bonds and foreign exchange (He, Kelly, and Manela, 2017; Baron and Muir, 2018; Haddad and Muir, 2018).

Despite the above evidence, the extent of bond and equity discount rate co-movement – even in the recent US data – remains subject to debate. In recent work, Giglio and Kelly (2018) and Haddad, Kozak, and Santosh (2017) show that the variation in expected returns across a wide range of financial securities cannot be explained by a single discount factor. Further to this, even though several papers have studied the co-movement of *realised* returns on equity and housing (Ibbotson and Siegel, 1984; Gyourko and Keim, 1992; Liu and Mei, 2003), there is, to the best of my knowledge, no evidence on the co-movement in *expected* returns across housing and other risky asset classes. My paper is the first study discount rate co-movement across all major risky asset categories, or in cross-country long-run data. The cross-asset discount rate correlation turns out to be very low – even lower than that in returns or cashflows – a puzzling new stylised fact which has deep implications for asset pricing theory.

The third strand of the literature relates to real effects of time varying sentiment. Most studies have focussed on the US corporate bond market, and find that increasing excess bond premiums or predictable reversals in bond sentiment forecast low GDP growth (Gilchrist and Zakrajšek, 2012; López-Salido, Stein, and Zakrajšek, 2017). Muir (2017) and Krishnamurthy and Muir (2017) find that equity and corporate bond premiums tend to spike around financial crises, using historical data for a number of advanced economies. There is little agreement, however, about whether these bond spread movements and the associated real effects can be attributed to changing credit supply or sentiment. My paper shows that these changes in spreads are best thought of as time-varying expectations or sentiment, that the real effects of this sentiment variation are present in the 150-year cross section of advanced economies and asset classes, and that housing sentiment matters at least as much as that in the corporate bond market.

Taken together, my findings have the following implication for existing literature. Asset price volatility does not, primarily, come about from volatile discount rates. Rather, it comes about from volatile expectations. It is the understanding of these volatile expectations which could form the central organising question of future asset pricing research.

2. Testing for volatile discount rates

The central question addressed by this paper is whether asset price volatility is driven by time varying discount rates or not. To delineate the different determinants of asset price variation, consider a risky asset i which yields a stream of stochastic payoffs or cashflows CF_t. These cashflows correspond to dividend payments for equity, rental payments for housing and coupon payments for bonds.[6] To make the marginal investor indifferent to owning the asset, the asset price should equal the present value of these payoffs:

$$P_{i,t} = \mathbb{E}_t \left(\sum_{s=1}^{\infty} m_{t+1}^{s} CF_{i,t+s} \right) \tag{1}$$

The stochastic discount factor m, inversely proportional to the discount *rate* DR, captures investor willingness to save in risky assets, and is a combination of the ex ante safe rate – measuring the general willingness to save – and the risk premium – measuring the willingness to accept uncertain payoffs on savings.[7] Most asset pricing theories work with a recursive version of equation (1), which takes the form of:

$$1 = \mathbb{E}_t \left(m_{t+1} R_{i,t+1} \right) \tag{2}$$

where R is period-ahead total return, $R_{i,t+1} = (P_{i,t+1} + CF_{i,t+1})/P_{i,t+1}$. This "fundamental asset pricing equation" allows to classify the drivers of asset price volatility into the following three categories:

1: Time-varying fundamentals or changes in future cashflows CF. The cashflows on each asset class in my study are by nature risky: dividends and rents can vary from year to year, and corporate bonds can default, ending the coupon payments. Fluctuations in future cashflows should be reflected in asset values. For example, if corporate profitability declines, dividends should fall and default risk should rise, reducing the value of equity and corporate bonds. Under this explanation, discount rates are constant, $m_{t+1} = M \; \forall \; t$, and hence so are expected returns:

$$1 = \mathbb{E}_t (M R_{i,t+1}) \tag{2F}$$

2: Time-varying discount rates or changes in m. The discount rate m_{t+1} reflects the desire to hold risky assets and accept uncertain future payoffs. Put differently, it measures the price of risk. When the desire to save in risky assets is low, prices of these assets will also be low to incentivise investors to hold them. To rule out arbitrage, the discount factor m has to be the same across all

[6] For owner-occupied housing, the payoff stream instead corresponds to "imputed rents", which capture the flow value of housing services, approximated by the hypothetical rental income the homeowner would have earned, had the house been placed on the rental market.

[7] Both in my data and in the existing literature on the US equity returns, changes in safe interest rates have a relatively limited effect on the cyclical variation in risky asset prices. Therefore, for the purposes of my analysis it is convenient to think of variations in m as being mainly driven by the risk premium.

risky assets (Ross, 1977). In the simple consumption asset pricing model, m is equal to the marginal rate of substitution between consuming today and tomorrow, $u'(c_{t+1})/u'(c_t)$. When consumption is high, investors are willing to save and take risks, and prices of risky assets are high.[8] Recent theories have proposed a number of modifications to define "good" and "bad" times – periods when the demand for risky savings is, respectively, low or high (see Cochrane, 2017, for a summary). These give m a more general formulation, such that it depends not only on consumption, but also on an another economic state variable Y_t, such as habit (Campbell and Cochrane, 1999), disaster risk (Barro, 2006; Gabaix, 2012) or financial intermediary risk appetite (He and Krishnamurthy, 2013):

$$1 = \mathbb{E}_t(\underbrace{Y_t * u'(c_{t+1})/u'(c_t)}_{m_{t+1}} R_{i,t+1}) \tag{2DR}$$

3: Time-varying sentiment or changes in $\mathbb{E}$. If agents form their expectations according to some statistical operator $\mathbb{E}^* \neq \mathbb{E}$, prices of risky assets can fluctuate even in the absence of shocks to future cashflows CF or the price of risk m. In line with the literature (Baker and Wurgler, 2000; Greenwood and Hanson, 2013), I label such deviations in expectations from their rational value as "investor sentiment". If sentiment is elevated, investors are overoptimistic and $\mathbb{E}_t^* > \mathbb{E}_t$, hence asset prices will be high.[9]

Differences in aggregate sentiment are indistinguishable from changes in discount rates in my data. If expected returns on all three risky asset classes are high, this could be either because m is high, or $\mathbb{E}^*$ is high. But in most theoretical models, sentiment is an asset-specific phenomenon, driven by extrapolation of past returns and fundamentals, or forecasts that overweigh certain asset-specific outcomes (Barberis and Shleifer, 2003; Greenwood and Hanson, 2013; Barberis et al., 2015; Adam et al., 2017; Bordalo et al., 2017). This means that there is no reason for expected returns across assets to co-move positively, or at all. Sentiment-based explanations imply the following reformulation of equation (2):

$$1 = \mathbb{E}_{i,t}^* \left(m_{t+1} R_{i,t+1}\right) \tag{2SENT}$$

Each of the three explanations above carries a testable hypothesis about the time variation in expected returns on different asset classes, $\mathbb{E}_t(R_{i,t+1})$, summarised below.

[8]This can be seen more clearly by reformulating equation (2) as $\mathbb{E}_t(R_{i,t+1}) = (1 - cov(R_{i,t+1}, m_{t+1})/\mathbb{E}_t(m_{t+1})$. Risky asset returns tend to be high during good times, when m is low, hence $cov(R_{i,t+1}, m_{t+1}) < 0$. Hence, periods of low m are associated with high expected risky asset returns $E(R)$.

[9]Note that the variation in sentiment includes "irrational" bubbles driven by biases in investor expectations. Strictly speaking, "rational" bubbles would appear as an extra term on the right-hand side of equation (1), equal to the discounted value of the terminal price of asset i, but given that the variation in terminal prices appears to be relatively limited in the data, and to ease the exposition, in this paper I interpret both irrational and rational bubbles as changes in sentiment.

Hypothesis 1. Fundamentals: Expected returns on all asset classes are constant.

Hypothesis 2. Discount rates: Expected returns on all asset classes vary over time, and exhibit high cross-asset co-movement.

Hypothesis 3. Sentiment: Expected returns vary over time, but expected returns on different asset classes can show zero or negative co-movement.

Within a single asset class, variation in discount rates and expectations is observationally equivalent. When it comes to multiple asset classes, discount rate variation induces co-movement in expected returns on different assets whereas expectation variation generally does not. To test for, first, the time variation in expected returns (hypothesis 2) and, second, for the co-movement in expected returns (hypothesis 3) in the data, I rely on the standard framework of return predictability regressions, extended somewhat to cover multiple classes of risky assets. Campbell and Shiller (1988) show that the discount rate $DR = 1/m$ can be approximated by the ratio of fundamentals CF to asset prices P. This "inverse" valuation ratio, dp, approximately equals the present value of expected returns and cashflows:

$$dp_{i,t} \approx \mathbb{E} \sum_{s=0}^{\infty} \rho^s r_{i,t+1+s} - \mathbb{E} \sum_{s=0}^{\infty} \rho^s dg_{i,t+1+s} \tag{3}$$

Here, dp are (inverted) asset valuations, such as the equity dividend-price ratio, r are holding period returns, and dg is the growth in cashflows for each asset class, all expressed in logs:

$$\begin{aligned} dp_{i,t} &= log\left(CF_{i,t}/P_{i,t}\right) \\ r_{i,t+1} &= log\left(\left(P_{i,t+1} + CF_{i,t+1}\right)/P_{i,t}\right) - log(1+\pi_{t+1}) \\ dg_{t+1} &= log\left(CF_{i,t+1}/CF_{i,t}\right) - log(1+\pi_{t+1}), \end{aligned}$$

Equation (3) holds, up to a small approximation, for equity and housing, with cashflows measured as dividends or rental income. It holds somewhat more approximately for bonds, with r the excess return over government bonds, dp the price premium compared to government bonds, and CF – the default-adjusted expected coupon payments (Nozawa, 2017).

If asset prices vary because of future cashflows, valuations dp should predict future cashflow growth dg. If they vary because of expected returns, dp should be predictive of future returns r. If time varying discount rats are important, this expected return variation should be common to all risky asset classes: i.e. valuations of one asset class should predict returns on all three risky assets. Both of these propositions can be tested by running return predictability regressions. To test for the importance of fundamentals and expected returns, I regress the return and cashflow growth of asset i at $t+1$ on the valuation of that asset at t:

$$r_{i,j,t+1} = \beta_{i,j,1} + \beta_{i,2} dp_{i,j,t} + u_{i,j,t} \tag{4}$$

$$dg_{i,j,t+1} = \gamma_{i,j,1} + \gamma_{i,2} dp_{i,j,t} + e_{i,j,t}, \tag{5}$$

where i is an index which denotes different asset classes. $j = \{1, 17\}$ is a country index, and $t = \{1870, 2015\}$ denotes the year of the observation. The return predictability regressions, with some straightforward modifications, also allow me to compute proxies for asset-specific expected returns $\mathbb{E} \sum_{j=0}^{\infty} \rho^j r_{i,t+1+j}$, or "discount rate news" in each year of the cross-country panel dataset, and estimate their contribution to the asset price volatility (i.e., variation in dp) and co-movement across asset classes.

To assess the importance of discount rates and expectations, I test whether valuations of asset class i predict not only returns on asset i, but also on the other two asset classes j and k:

$$r_{i,j,t+1} = \beta_{i,j,1} + \beta_{k1 \neq i} dp_{k1,j,t} + \beta_{k2 \neq i} dp_{k2,j,t} + u_{i,j,t} \quad i = \{eq, hous, bond\} \tag{6}$$

Finally, the absence of cross-asset predictability may arise because asset-specific valuations dp are a poor proxy for the aggregate discount rate. To check whether this is the case, I also test for predictive power of a broad range of macro-financial risk factors F, mostly related to consumption and financial intermediary balance sheets:

$$r_{i,j,t+1} = \beta_{i,1} + \sum_{f=1}^{F} \beta_{f,i} F_{j,t} + e_{i,t} \quad i = \{eq, hous, bond\} \tag{7}$$

The tests of hypotheses 1–3 can then be summarised as follows:

Test 1. Fundamentals vs expected returns: return predictability regressions with one risk factor. If $\beta_{i,2} > 0$ in regression (4), expected returns for asset i vary over time.

Test 2. Discount rates vs sentiment: return predictability regressions with cross-asset risk factors. If valuations on one asset i, or a macro-financial risk factor F, predict returns on all three risky asset classes, the variation in the aggregate price of risk contributes to time varying expected returns. If no single asset valuation or risk factor predicts returns on all three asset classes, the expected return variation is driven by asset-specific sentiment.

Testing these hypotheses requires data on the discount rate proxies, or asset valuations dp, risky returns r and cashflow growth dg. I describe the construction of the corresponding dataset in the following section.

3. New data on historical returns and discount rates

The dataset in this paper consists of valuations, cashflows and returns on the three major risky asset-classes: equity, housing and corporate bonds. The data are annual, and cover 17 advanced economies over the period 1870 to 2015. Table 1 summarises the data coverage by country and asset class. For most countries and series, the data go back to the late 19th century. The corporate bond data, by their nature, have slightly lower coverage, because in a number of countries, during some

Table 1: *Data coverage*

Country	Equity	Housing	Corporate Bonds
Australia	1870–2016	1901–2015	1915–2016
Belgium	1870–2015	1890–2015	1870–2016
Canada	1870–2015		1905–2015
Denmark	1872–2016	1875–2015	
Finland	1912–2012	1920–2015	1960–2015
France	1870–2016	1870–2015	1913–2016
Germany	1870–2016	1870–2015	1870–2016
Italy	1870–2015	1927–2015	1873–2016
Japan	1886–2015	1931–2015	1900–2016
Netherlands	1900–2015	1870–2015	1975–2003
Norway	1880–2016	1871–2015	1903–2004
Portugal	1870–2015	1948–2015	1905–1988
Spain	1899–2016	1900–2015	1913–2016
Sweden	1871–2012	1883–2015	1871–1990
Switzerland	1900–2015	1901–2015	1935–2002
UK	1871–2015	1895–2015	1870–2014
USA	1871–2015	1890–2015	1870–2015

historical periods the private unsecured corporate debt markets were more or less non-existent.[10] My study is the first to document the joint historical evolution of corporate bond spreads and returns for every country in the sample apart from the US.[11]

Because asset prices depend on the value of all future fundamentals, and predictability tests lack statistical power and representativeness over small time or country samples (Stambaugh, 1999; Goyal and Welch, 2008; Lettau and Van Nieuwerburgh, 2008), the long time and country dimension of the dataset is an essential prerequisite for the statistical analysis described in Section 2. The novel cross-asset dimension of the dataset also enables me to differentiate the time variation in discount rates from that in asset-specific expectations. I next describe the sources for each series.

Equity The data consist of total returns, dividends, and dividend-price ratios of listed equities, all taken from Jordà et al. (2017a), with the addition of a new data series covering Canada. The return, price and dividend data mostly consist of value-weighted all-share indices. The dividend-price ratio is computed as dividend income over the course of the year in proportion to the year-end share price. Returns are a sum of capital gain and dividend income, in proportion to previous year's price, net of inflation. Cashflows are measured as dividend growth in a given year, in excess of inflation.

[10] For example, in Denmark, all the private sector bonds on the market, until the recent decades, consisted of mortgage bonds, which were considered safe assets on par with government bonds, and were issued under a strict set of regulations.

[11] Greenwood and Hanson (2013) study the joint evolution of US corporate bond spreads and returns between 1926 and 2008. Compared to their study, my paper adds roughly another 60 years of data.

For more details on the sources and accuracy checks, see Jordà et al. (2017a).

Housing The data consist of total returns, rents, and rent-price ratios for residential real estate, all taken from Jordà et al. (2017a). The return, price and rent data are constructed to, wherever possible, cover both owner occupiers and renters, cover the national housing stock, and adjust for quality changes, maintenance costs, depreciation and other non-tax housing expenses. The rent-price ratio is calculated as net rent received over the course of the year in proportion to the house price. Total return is the sum of capital gain and rental income, and cashflows are measured as rental growth, both net of inflation. For more details on the sources and accuracy checks, see Jordà et al. (2017a).

Corporate bonds This paper introduces a dataset of yields, spreads, and holding period returns on bonds issued by private sector creditors, targeting 10-year maturity. Corporate bond valuations dp are proxied by the spread, which equals the yield to maturity differential between corporate and government bonds:

$$\text{spread}_t = YTM_{\text{corporate},t} - YTM_{\text{government},t} \tag{8}$$

The yield to maturity measures the implicit discount rate which would make the present value of future coupon payments equal the observed bond price, and the spread, therefore, measures the forward-looking risk premium embedded in the prices of corporate and government issued securities.

I construct two measures of the corporate bond return r. The first measure is the holding period return, which is the sum of capital appreciation ΔP and coupon payments C received during year t, in proportion to the previous year's bond price:

$$r^{holding}_{bond,t+1} = C_{bond,t+1}/P_{bond,t} + (P_{bond,t+1} - P_{bond,t})/P_{bond,t} \tag{9}$$

Because of a lack of secondary sources for corporate bond return data, I sometimes estimate the price change from the change in yields using duration approximation. Results are, however, robust to only using non-approximated bond returns. The second bond return measure does not rely on such approximation, and simply uses the change in spreads as a proxy for returns:

$$r^{implied}_{bond,t+1} = -(\text{spread}_{t+1} - \text{spread}_t) \tag{10}$$

The $r^{implied}_{bond,t+1}$ proxies both the direction and magnitude of the bond price change, and is commonly used in the literature (López-Salido et al., 2017). Comparing the current spread to future spread growth also allows to directly estimate the degree of predictable mean reversion in bond prices, with this mean reversion equivalent to expected return variation in the Campbell-Shiller decomposition equation (3). I use $r^{holding}_{bond,t+1}$ to summarise the moments of bond returns, and use $r^{implied}_{bond,t+1}$ as the main variable for the regression analysis. The use of either measure has no material bearing on the results.

Most of the corporate bond data were constructed from primary sources, by aggregating yields

and returns on individual bonds listed on the domestic stock exchange. The bulk of the data comes from domestic stock exchange listings, complemented with bonds listed on major foreign exchanges (e.g. London and New York) and over the counter transactions. I weight the average by the market capitalization of individual bonds – unless these data are missing or the sample size is small, in which case I use equal-weighted averages to avoid biasing the series towards any individual bond. The individual listings data are complemented by a rich selection of secondary sources from publications of statistical agencies, international organisations and central banks, as well as financial history books and research articles.

The corporate bond sample covers all private sector fixed-rate bonds traded on the secondary market of the respective country with a maturity close to 10 years. I exclude foreign company bonds, foreign currency bonds of domestic companies, bonds with explicit government guarantees, and mortgage bonds issued by credit institutions or special purpose vehicles.[12] For some historical periods, most listed bonds had very long maturities, or there were relatively few bonds listed and traded. In these cases I extend the maturity window, sometimes including all private sector listed bonds, in order to obtain a comprehensive sample coverage. For periods where secondary markets were thin but primary markets were active, I rely on issue yields instead of secondary market yields. Where maturity data are missing, I use current yields – the ratio of coupon to bond price – instead of yields to maturity. The government bond yield data are an extended and updated version of those in Jordà et al. (2017a). The government bond dataset also excludes foreign currency bonds and targets a maturity of 10 years.

The extensive use of these new and previously uncovered data sources allows me to guard against a number of biases in estimating a consistent corporate bond yield series. The potential biases and accuracy issues for the corporate bond series are discussed in Appendix A. The most pressing bias refers to the time variation in selection and credit quality of the corporate bond index, and is largely dealt with by using a large sample of bonds, comparing the bond yields on different bonds within the microdata, and tests for subperiod stability and robustness of results.

Comparison to existing datasets The data in this paper have a much broader cross-asset coverage compared to existing studies. They also significantly extend the return predictability and excess volatility analysis for individual asset classes. The notable exception is the PhD thesis of Knoll (2017) analyses excess volatility in housing markets within a historical dataset similar to this paper. For equities, Engsted and Pedersen (2010) assess return predictability using data for 5 countries' going back to the early 20th century. Muir (2017) documents dividend-price ratio movements around financial crises and deep recessions in a cross-country historical dataset sourced largely from *Global Financial Data*.

[12]For most of my sample, mortgage bonds were government guaranteed or strictly regulated, and generally considered safe assets on par with government debt. I do, however, include private non-financial company bonds backed by mortgages or property, which were generally not government-guaranteed, not strictly regulated, and considered risky.

Most of the excess volatility analysis for corporate bonds relies on historical or contemporary US data (Greenwood and Hanson, 2013; López-Salido et al., 2017). Muir (2017) and Krishnamurthy and Muir (2017) document corporate spread movements around financial crises in a broad historical cross-country dataset, and use these to shed light on the fundamental asset price determinants. The historical data in Krishnamurthy and Muir (2017) largely consist of foreign bonds listed on the London stock exchange over the period 1869 – 1929. The focus on domestic exchanges in my data allows for a considerably broader selection of bonds, and guards against a number of potential selection biases discussed above.[13] My data also have a broader time and country coverage, and provide estimates of corporate bond returns and yields, as well as the spread.

These new data mark a significant step forward in documenting the returns and riskiness of different classes of risky wealth. Going beyond US equities market reduces the selection bias of this relatively successful asset market. Adding housing and corporate bonds documents the returns and risks on the largest component of household wealth (residential real estate), and the most macro-informative asset (corporate bonds). The presence of both housing and corporate bond data also allows me to narrow down the range of potential explanations behind the low co-movement. For example, since corporate bonds and equities are traded on the same market while housing is traded over the counter, market segmentation could delink the expected returns on housing and equities, but not on equities and corporate bonds. The risky asset classes which are not included the analysis consist of commercial property, agricultural land, unlisted equity and business capital. Housing and equity return data provide rough proxies for these missing asset classes, but the more detailed analysis is left to future research.

4. Stylised facts

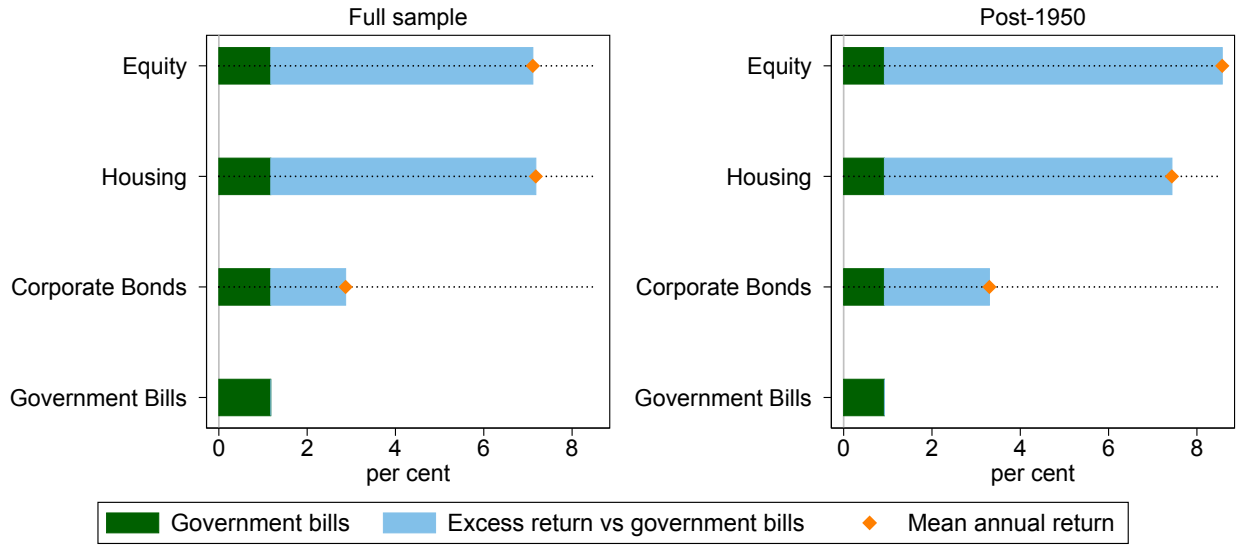
Before proceeding to the formal analysis of return predictability regressions, this section documents a number of facts relating to the volatility of asset prices in these new historical data, and its potential underlying drivers.

Fact 1: Each risky asset earns a positive excess return premium Risky assets should earn a positive return premium to compensate investors for the uncertain nature of the cashflows. This is, indeed, the case for each of the three asset classes in my dataset.

Figure 2 and Table 2 Panel 1 show the mean annual return for each asset class compared to a safe rate benchmark, taken to be the short-term government bill rate. Excess returns are positive for all three asset classes, in the full sample and after 1950. They are relatively high for housing and equity – around 6% p.a. – and moderate for corporate bonds, at around 2% p.a. Since all three risky assets have long durations, part of these excess returns actually consists of a term premium, which

[13] Foreign listings typically only include the largest companies in the country, with many of the international bond issues also guaranteed or backed by the domestic government. Bonds listed on foreign exchanges were also often denominated in foreign currency.

Figure 2: *Risky returns compared to a safe benchmark*



Note: Arithmetic average real total return on equity, housing and corporate bonds, compared to the real short-term government bill rate. Annual average of 17 countries, unweighted. Consistent coverage within countries: each country-year observation used to compute the average has data for all four asset returns.

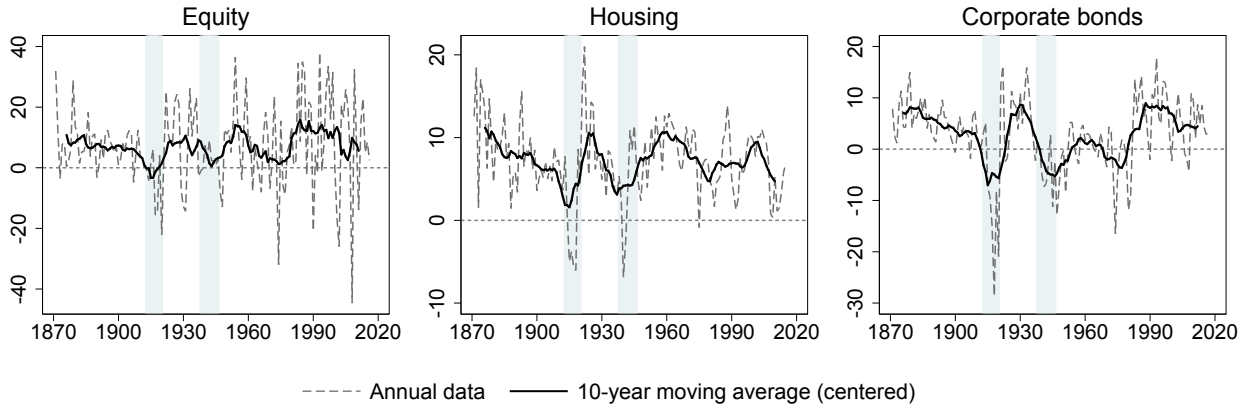
Table 2: *Risky asset returns, cashflows and discount rates*

Panel 1: *Real total returns*			
	Equity	Housing	Corporate bonds
Mean	7.19	7.04	2.38
Standard deviation	21.97	9.92	10.67
Geometric mean	4.98	6.61	1.71
Excess return over bills	6.52	6.51	1.79
Panel 2: *Cashflows*			
	Real dividend growth	Real rent growth	Corporate default rate
Mean	3.34	1.18	0.99
Standard deviation	29.08	8.02	1.51
Panel 3: *Discount rates*			
	Dividend-price ratio	Rent-price ratio	Corporate bond spread
Mean	3.92	5.31	0.90
Standard deviation	1.66	2.01	0.95
Observations	1381	1381	1381

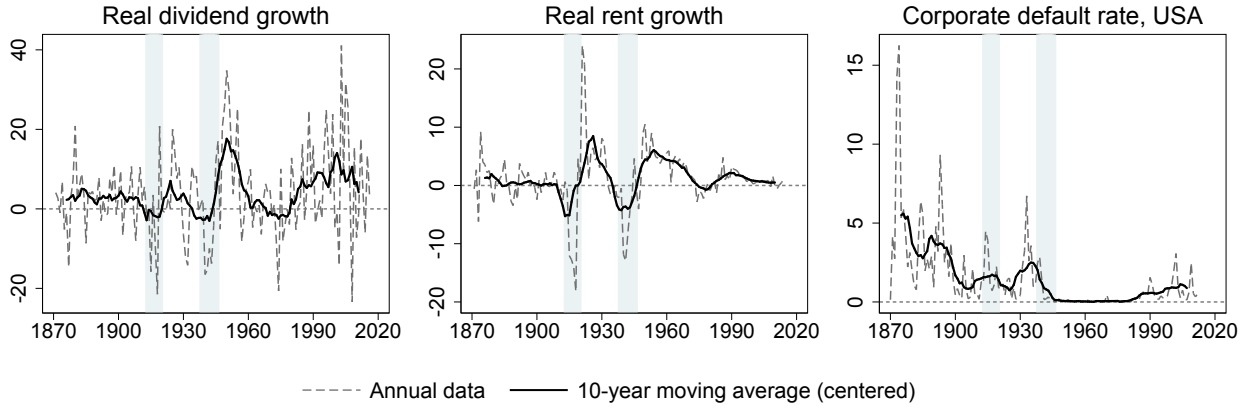
Note: Risky asset total returns, cashflows and discount rate proxies. Averages and standard deviations of pooled cross-country annual data, in percentage points. The corporate default rate measures the par value of bonds in default relative to total. Consistent sample: each country-year observation includes the data on all four asset classes.

Figure 3: *Risky asset returns, cashflows and discount rates over time*

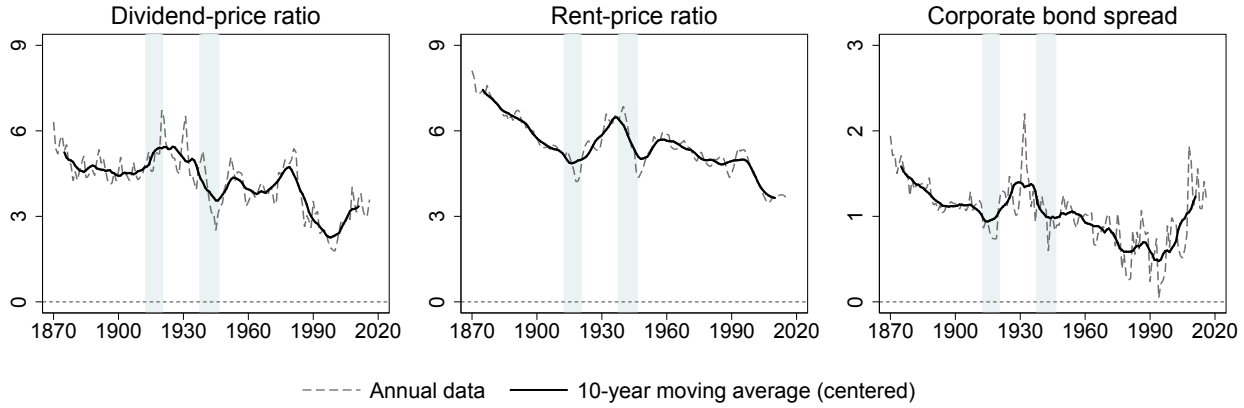
(a) *Real total returns*



(b) *Cashflows*



(c) *Discount rates*



Note: Unweighted averages of 17 countries. Shaded areas indicate world wars. Corporate default rate data are from Giesecke, Longstaff, Schaefer, and Strebulaev (2014).

amounts to around 1% p.a. in these historical data.[14] After 1950, risky returns on corporate sector assets – equity and corporate bonds – are somewhat higher than the full-sample averages, while housing returns are similar to the full sample (Figure 2, right-hand panel).

Fact 2: Returns on all three risky asset classes are volatile One reason why these assets command a risk premium is that their cashflows are uncertain, and returns – volatile. Table 2 Panel 1 shows that the annual standard deviation of real returns is 21 ppts p.a. for equities, and 10–11 ppts p.a. for housing and corporate bonds. A two-sigma return movement would, thus, lead to equity returns of -35%, housing returns of -13%, and corporate bond returns of -20%.

Figure 3a shows that risky asset returns are not only volatile in the sense of high annual standard deviation, but also show significant cyclical variability and tail risk. The figure displays the 17-country annual average return (grey dashed line), and its smoothed 10-year moving average time trend (solid black line) for each of the three asset categories.[15] The annual return series displays substantial volatility, as does the medium-term moving average trend. For example, the Global Financial Crisis saw a -40% return on equities in 2008, World War 1 saw real corporate bond returns of -30%, and both world wars saw below-zero total housing returns.

Fact 3: Risky cashflows are also volatile, but much less so than returns Some of the volatility in returns can be accounted for by the uncertain nature of the risky cashflows. Panel 2 of Table 2 shows that dividend growth has an annual standard deviation of 26 percentage points. As shown in Figure 3b, equity cashflows fell during world war 1 and the recent crisis, when equity returns were also low, and grew strongly during the dot-com boom of the 1990s when equity returns were high. Time variation in cashflows seems much less important when it comes to housing and corporate bonds. Rental growth shows almost no variation during peacetime, and corporate default rate – based on the data for US only – has varied little since the late 19th century. Housing and corporate bond returns have, however, shown substantial variability during these time periods.

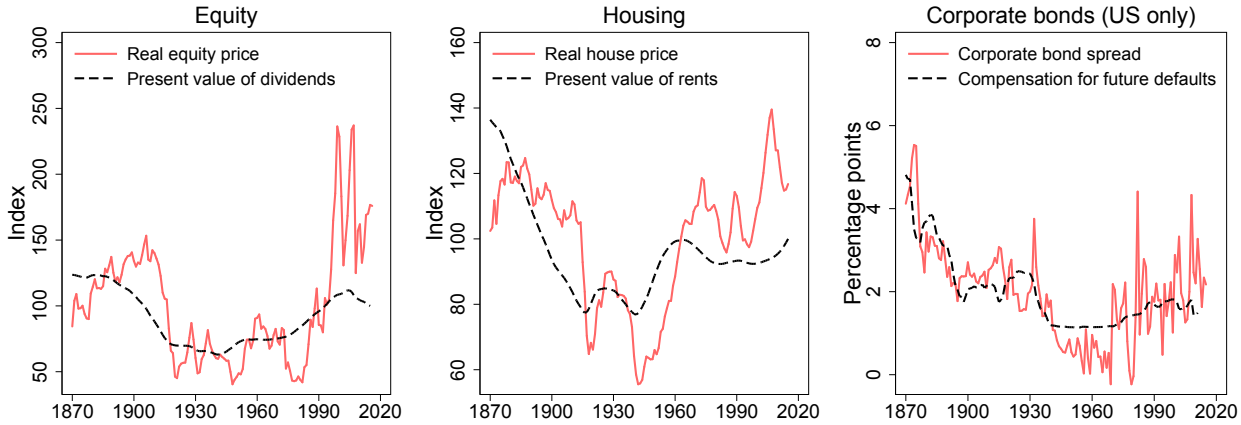
This fact suggest that at least some of the time variation in discount rate proxies – the inverted asset valuations dp shown in Figure 3c – corresponds to future returns rather than cashflows. For example, recent decades have seen a sharp increase in housing valuations while rental growth has slowed down. And bond spreads have varied substantially during the second half of the 20th century, while the default rate has remained flat.

Fact 4: Risky asset prices fluctuate more than future fundamentals To see whether asset values, indeed, vary more than cashflows, I next compute the present value of future fundamentals for each year and asset class. For equity and housing, this "fundamental price" $P^*_{i,t}$ simply equals

[14] The difference between returns on short and long dated government securities in this historical sample is, on average, 1% p.a..

[15] The time trend is centered, such that the 1875 data point corresponds to the 1871–1880 average.

Figure 4: *Risky asset prices and fundamentals*



Note: The equity and house price comparison follows Shiller (1981). Real equity and house prices are unweighted averages of the 17 countries in the sample, detrended using an exponential time trend. The present value of cashflows is the discounted sum of dividends or rents between year t and 2015, discounted at constant rate $1/(1+dp)$, where dp is the long-run average rent-price or dividend-price ratio. Terminal value of discounted cashflows is set to equal the long-run average between 1870 and 2015. The compensation for future defaults is constructed by regressing spreads on a constant and the 15-year ahead default rate, and using the predicted value of this regression.

the discounted sum of future dividends or rents, discounted at a constant rate:

$$P^*_{i,t} = \mathbb{E}_t \left(\sum_{s=1}^{T-t} \frac{CF_{i,t+s}}{DR_i^s} \right) \tag{11}$$

Above, the discount factor m is simply the average of the ex-post rate observed in the data, $\overline{m} = 1/(1+\overline{dp}_i)$, where dp_i is the dividend or rent to price ratio for equity and housing respectively. For corporate bonds, I compute the implicit default premium by regressing the bond spread on 15-year ahead defaults, and using the predicted spread value from that regression.[16]

Figure 4 show the corresponding observed asset price or spread (solid red line) and the present value of fundamentals (dashed black line). I follow Shiller (1981) for the details of the calculation: real prices are detrended using an exponential trend, and both observed prices and discounted cashflows equal 100 on average throughout the sample. The equity and housing data are an unweighted average of the 17 countries in my sample, whereas the corporate bond data cover the US – the only country for which historical default data are available (the default rate is sourced from Giesecke et al., 2014).

Figure 4 shows that prices of all three risky assets move a lot more than future fundamentals. Reassuringly, prices and fundamentals do track each other over the medium to long run. Both

[16]Specifically, I first regress spreads on 15-year ahead average default rate, $spread_t = \eta_1 + \eta_2 \overline{Defrate}_{t,t+15} + e_t$. The rational spread is the predicted value from this regression $spread^*_t = \hat{\eta}_2 \overline{Defrate}_{t,t+15}$, and proxies the spread that would have been demanded by a rational investor with a constant discount rate, had the investor known defaults 15 years ahead – the approximate maturity of the bond.

Table 3: *Correlations of discount rate proxies across asset classes*

	Equity	Housing	Corporate bonds
Equity	1		
Housing	0.17	1	
Corporate bonds	0.11**	0.09	1

Note: Pairwise correlation coefficients between the equity dividend-price ratio, housing rent-price ratio and the corporate bond spread. Underlying data are 3-year moving averages, to smooth over timing idiosyncracies across assets, and are demeaned at country level. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$

dividends and rents were relatively high in the late 19th and late 20th centuries and low in-between, and so were the real equity and housing prices. This U-shaped pattern mirrors the U-shaped evolution of wealth-to-income ratios documented by Piketty and Zucman (2014), and suggests that even at long horizons, fluctuations in national are affected by swings in asset prices and valuations.[17] The corporate bond spreads, and their rational counterpart also follow a U shape – but since prices are inversely proportional to spreads, this actually means that bond valuations were low (and default rates, high) in the 19th century, peaked in the mid-20th century and have been falling over the recent decades.

Despite this long-run correspondence, the price of each asset displays large cyclical deviations from it ex post rational value. Both in the early 1900s and 1990s, the rational equity price was close to its sample average, while the actual equity price was far above it. Detrended equity prices reached their all-time low in the 1980s, when discounted cashflows were a little subdued but not far from their long-run mean. The post-1960 surge in global house prices (Knoll, Schularick, and Steger, 2017) seems to have occurred without any discernible increase in real rental growth. And corporate bond spreads have fluctuated substantially since the end of World War 2, despite the fact that the default rate has remained roughly flat. The trends in Figure 4 fit a pattern of over-reaction to news about fundamentals. When discounted cashflows increase or fall, asset prices move in the same direction, but the magnitude of the price change is much larger than the movement in fundamentals.

Fact 5: Asset-specific discount rates do not co-move One reason why asset prices vary more than future cashflows is that the rate at which these cashflows are discounted changes over time. But this discount rate variation should induce co-movement in valuations of different asset classes. Consistent with Figure 1 in the introduction, Table 3 shows that this co-movement is absent in the data. It shows the pairwise sample average correlations between asset-specific discount rate proxies: the dividend-price ratio, rent-price ratio and the corporate bond spread. The correlation coefficients are all close to zero and mostly not statistically significant.

This low co-movement between asset valuations is puzzling and poses a challenge to discount

[17]Notably, the U-shaped real price pattern only becomes apparent when I detrend the real price series. Without adjusting for the exponential trend, the evolution of real equity and housing prices resembles a hockey stick, consistent with findings of Kuvshinov and Zimmermann (2018) and Knoll et al. (2017).

rate based explanations of excess volatility. Like the excess volatility finding of Figure 4, it echoes earlier work by Shiller (1982), who argued that prices of equity, housing and corporate bonds in the US follow highly distinct time series patterns, and hence the time variation in these prices is likely attributable to changing expectations rather than discount rates. But Shiller (1982) admitted that his data lacked accuracy and only included prices, not cashflows, which stopped him from drawing firm conclusions based on this low co-movement. The next two sections of this paper use my new historical dataset to test these propositions of excess volatility and low co-movement carefully withing the framework of return predictability regressions.

5. Return predictability within asset classes

Are swings in risky asset prices driven by time varying fundamentals, or non-fundamental factors such as discount rates or expectations? If financial volatility is purely fundamental driven, the lack of co-movement between asset valuations in Figure 1 simply corresponds to idiosyncratic cashflows, and is not, in itself, puzzling. As discussed in Section 2, I first test whether asset valuations dp help predict future returns and cashflows to gauge the relative importance of discount rate and cashflow variation.

Table 4 presents the results of predictability regressions in equations (4)–(5) for each risky asset class i. The first two columns show the outcomes of regressing, respectively, real equity returns r_{t+1} and real dividend growth dg_{t+1} on the dividend-price ratio dp_t. The numbers correspond to the predictive coefficients β_2 in equation (4) and δ_2 in equation (5) respectively. Columns 3 and 4 present the same results for housing. Column 5 tests for predictability of real corporate bond returns, while column 6 instead uses spread growth as the corporate bond return proxy, and effectively tests for mean reversion in spreads. Because spreads move in the opposite direction to returns, the coefficient in column 6 is equivalent to $-\beta_2$ in equation (4). In each regression, all the variables are demeaned at the country level.

The formal analysis in Table 4 confirms the pattern shown in Figure 4: returns on all three risky asset classes are predictable and hence, the prices of these assets are excessively volatile relative to fundamentals. Starting with equities, column 1 shows that high dividend-price ratios tend to be followed by high returns. This means that when the equity discount factor m is high, expected returns are also high, and hence either the price of risk is high, or market sentiment is depressed. A similar relationship is found for housing (column 3) and corporate bonds (column 5). The results are not only statistically, but also economically significant. A 1 percentage point increase in the dividend-price ratio forecasts 1.5 percentage points higher real equity returns 1 year ahead.[18] The magnitude of the effect is similar for housing, and somewhat smaller for corporate bonds – but returns on both of these assets are, in general, much less volatile than those on equities (Table

[18] A 1 percentage point increase in the dividend-to-price ratio means a 25% relative increase (4% to 5%), hence $0.25 * 0.055) \approx +1.4\%$ change in the gross real return. The expected return increases by $1.07 * 0.014 * 100 = 1.5$ percentage points, where 1.07 is the mean real equity return in the sample.

Table 4: *Predictability of real returns and cashflows within asset classes*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity		Housing		Corporate bonds	
	r_{t+1}	dg_{t+1}	r_{t+1}	dg_{t+1}	r_{t+1}	$\Delta spread_{t+1}$
Dividend-price ratio	0.055***	-0.120***				
	(0.014)	(0.030)				
Rent-price ratio			0.066***	-0.023**		
			(0.010)	(0.009)		
Bond spread					0.030***	-0.268***
					(0.007)	(0.038)
R^2	0.016	0.049	0.052	0.009	0.037	0.126
Observations	2203	2200	1818	1816	1594	1600

Note: OLS regressions with country fixed effects. Predictor (x) variables in rows. Dividend-price and rent-price ratios are in logs. Bond spread is the percentage point yield difference between corporate and government bonds. Dependent (y) variables in columns. r is the log real total return, dg is log real dividend or rental growth. $\Delta spread$ is the percentage point change in the bond spread. All variables are demeaned at the country level. Country-clustered standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

2). Finally, high corporate bond spreads not only predict high future returns, but a reduction, or mean reversion in the spread itself (column 6). The size of the mean reversion is substantial: a 1 percentage point higher spread in year t predicts 0.28 percentage point lower spreads at $t + 1$.

Asset valuations forecast not only future returns, but also future cashflows (Table 4, columns 2 and 4). Again, the impact is both significant and economically sizeable. A 1 percentage point higher dividend-price ratio implies 3 percentage points lower dividend growth 1 year ahead.[19] For housing, the importance of cashflows is somewhat smaller: 1 percentage point higher rent-price ratios forecast only 0.5 ppts lower rental growth 1 year ahead. For corporate bonds, Appendix Table A.3 shows that high spreads are significantly positively correlated with future defaults in the US data. Consistent with the broader time series pattern of Figure 4, financial booms and busts do partly reflect time-varying fundamentals, but that alone is insufficient to explain financial volatility, leaving an important role for time-varying discount rates or sentiment.

These findings hold under a wide range of alternative regression specifications, and across a variety of subsamples, presented in the Appendix Table A.4. The results for each risky asset class are robust to all standard tests undertaken in the literature. They hold under alternative variable definitions – for example, for nominal returns, excess returns and 5-year ahead returns. Consistent with the literature on US equities, predictability becomes more powerful at longer horizon: a 1 percentage point higher discount rate dp predicts 3–10 percentage point lower cumulative returns 5 years ahead, depending on the asset class (3 ppts for corporate bonds, 5 for equities and 10 for housing). Results remain the same if estimated using a VAR with present value moment constraints

[19]The sample mean real dividend growth is 1.003, so the calculation is $0.25 * (-0.12) * 1.003 * 100 \approx 3$ percentage points.

Table 5: *The relative importance of time varying discount rates and fundamentals*

	(1) Equity	(2) Housing	(3) Corporate bonds
The share of total variation in asset valuations explained by:			
Discount rate news	32	58	78
Cashflow news	68	42	22

Note: Ratios of discount rate and cashflow news variance to total dividend-price, rent-price and bond spread variance, per cent. Discount rate news capture both time-varying discount rates and expectation errors. Cashflow news capture changes in fundamentals. Equity and housing shares are derived from the long-run covariance matrix of the VAR in returns, dividend growth and valuations, estimated using present value moment constraints. Bond discount rate news share is the ratio of the variance in spreads to discounted 10-year ahead spread growth; cashflow share is the residual.

rather than OLS, or OLS with time fixed effects. Predictability becomes somewhat stronger if valuation ratios dp are adjusted for structural breaks. I find little difference in predictability across the full sample or after 1950. Unlike the findings for US equities, this long-run predictability is also stronger for cashflows, not just returns. Unlike much of the existing literature which argues that predictability is strongest in recessions, I find similar predictive power across economic recessions and expansions. Appendix Table A.5 also shows the predictability results for individual countries. Return predictability for housing and corporate bonds, and dividend growth predictability, is pretty much ubiquitous. For equity returns, predictive coefficients are generally of similar size to baseline but are not statistically significant in some countries due to the relatively lower precision of the within-country annual data.

Predictability regressions also allow me to calculate the relative importance of fundamental and expected return variation, by estimating the discount rate and cashflow news variance as discussed in Section 2, with estimation details provided in Appendix C.3. In brief, I estimate a VAR in returns, cashflow growth and valuations in order to calculate the infinite discounted sum of future expected returns $\mathbb{E}\sum_{j=0}^{\infty}\rho^j r_{t+1+j}$, and cashflow growth $\mathbb{E}\sum_{j=0}^{\infty}\rho^j dg_{t+1+j}$, and use their relative variance to assess the contribution of discount rates and cashflows to variation in the valuation ratios dp_t. For corporate bonds, I use 10-year ahead predictive OLS regressions instead of a VAR, because of the lack of corporate default (cashflow) data.

Table 5 summarises the relative importance of discount rate and cashflow news variation for each asset class. A discount rate share equal to 100 means that all of the variance in the valuation ratio dp is accounted for by changes in future returns – i.e. movements in discount rates or sentiment – and none by fundamentals. A share of 0 means all dp variation is fundamental driven. For equities, roughly one-third of the variation in the dividend-price ratios is accounted for by future returns, and two-thirds – by future cashflows. The discount rate news share is higher for housing, at 60%, and highest for corporate bonds. Roughly four-fifths of the corporate bond spread variation can be

attributed to future spread growth. The high excess volatility of corporate bonds mirrors the large R^2 and high mean reversion of the predictability regression in Table 4 column 6.

Appendix Section C.4 assesses how the excess volatility for each asset class has varied over time. It turns out that the importance of discount rate news has, if anything, increased throughout the 20th century, despite a number of fiscal and regulatory policy measures, such as the establishment of the welfare state, which should have reduced the time variation in risk aversion and financial intermediary risk appetite. The equity discount rate news share also showed a sharp spike during the Great Depression, pointing to the importance of non-fundamental asset price variation during this economic downturn, in line with views of a number of contemporaries (Keynes, 1936).

When it comes to analysing the drivers of excess volatility, going beyond the US equity market really does matter. The excess volatility in equity markets beyond recent US data is much lower, simply because the cashflow variation is much greater: extending the sample to the 19th century and to other advanced economies greatly increases the number of cashflow shocks and disaster events, as shown by the high variability of real dividend growth in Table 2 and Figure 3. But going beyond the relatively liquid, well-informed and centralised equity market to the markets for housing and corporate bonds, again, makes expected return variation central to the excess volatility analysis. Time-varying discount rates and sentiment explain more than half of movements in housing valuations, and almost all the variation in credit spreads.

The analysis of excess volatility paints a somewhat different picture to the "unconditional" volatility, or standard deviation of raw returns in Table 2. Unconditionally, equity returns are twice as volatile as those on housing and corporate bonds. But because dividends vary much more than rents and corporate defaults, the conditional or excess volatility in equity markets is, in fact, the lowest out of all three asset classes. Rents tend to be sticky and slow to adjust, and corporate defaults are rare and rather stable, at least in the 20th century US data. Cashflow volatility does little to explain the high variance of housing and corporate bond returns. Instead, this variation has to be driven by time-varying expected returns, i.e. discount rates or sentiment. Extending the analysis beyond US equities to include other countries and the two other risky asset classes is essential for correctly documenting the extent of this excess volatility, and understanding what it is that ultimately drives it.

As well as estimating the variance contribution of discount rates and cashflows, I can use the same empirical framework to construct an annual time series for the discount rate and cashflow news in unexpected returns following the methodology of Campbell (1991). These two time series allow me to disentangle the contribution of time-varying expected returns and cashflows to the discount rate proxy dp, with the discount rate news effectively providing a "clean" measure of the discount rate variation in the dp series. For equity and housing, discount rate news correspond to the change in the present value of future predicted returns, with the prediction constructed based on valuations, cashflow growth and returns in the current year. For corporate bonds, due to the lack of cashflow data and because most of the variation in spreads is attributable to discount rate news, I simply estimate discount rate news as the change in the spread. The estimation details are provided

in Appendix C.3.

The analysis in this section has two important implications for the co-movement tests in the Section 6. First, returns on each asset class are predictable, therefore expected returns do vary over time, and their co-movement can tell us something about the relative importance of volatile discount rates and expectations. Second, the predictability regressions allow me to construct a cleaned discount rate news series for each asset class, which is a proxy for the asset-specific discount factor m. Analysing the co-movement in this series thus allows for a more direct test of hypotheses 2 and 3 than that of the raw valuation ratios dp, since dp is driven by both discount rates and cashflows.

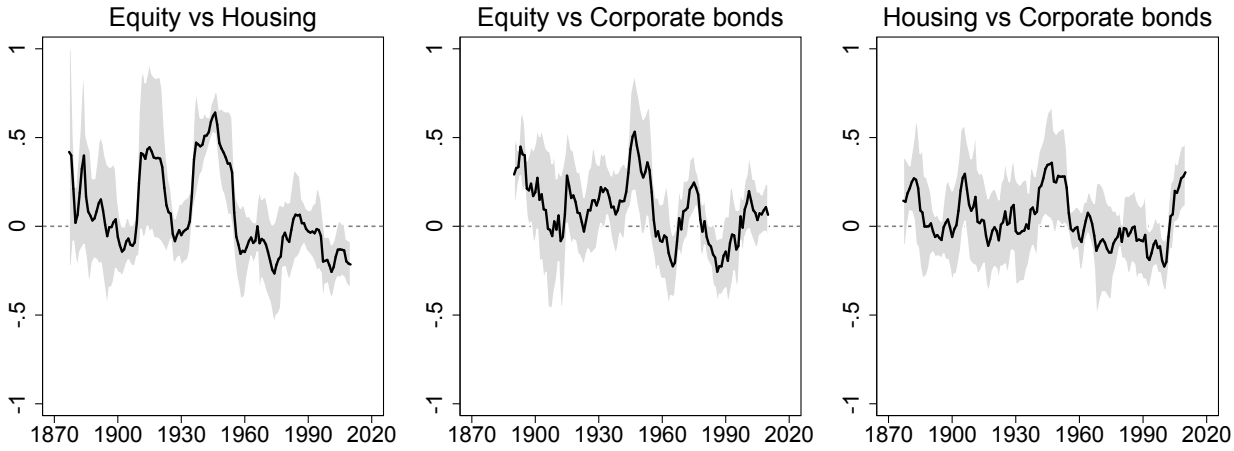
6. Comovement of discount rates across asset classes

Are expected returns driven by a single factor – the discount rate – or asset-specific factors? As discussed in Section 2, the new cross-asset dataset allows me to disentangle these two forces by testing for co-movement and co-dependence in discount rates of different asset classes. If discount rates are an important determinant of asset price volatility, all the asset-specific discount rates should be driven by a single common factor.

6.1. Discount rate correlations

I start by assessing the raw correlations between discount rate and cashflow news of different asset classes. Figure 1 and Table 3 show that risky asset valuations show low co-movement. But Section 5 shows that these valuations are affected by both future cashflows and expected returns. It could be

Figure 5: *Co-movement of discount rate news across asset classes*



Note: Pairwise correlation coefficients between the discount rate news on equity, bonds, and housing over rolling decadal windows (e.g. the value for 1875 if the correlation over the window 1870–1880). Shaded areas are 90% confidence intervals, using country-clustered standard errors. Underlying data are 3-year moving averages, to smooth over timing idiosyncracies across assets. Discount rate news correspond to changes in the present in future expected returns, for each asset class and year in the sample.

Table 6: *Correlations of discount rate and cashflow news across asset classes*

	Discount rate news			Cashflow news	
	Equity	Housing	Corporate bonds	Equity	Housing
Equity	1			1	
Housing	0.16	1		0.32***	1
Corporate bonds	0.03	0.06	1		

Note: Pairwise correlation coefficients. Underlying data are 3-year moving averages, to smooth over timing idiosyncracies across assets. Discount rate and cashflow news for equities and housing are estimated as the innovations to present value of, respectively, future returns and cashflows for each asset class, within a VAR in returns, cashflow growth and valuations, and present value moment constraints. Discount rate news for bonds equal the present value of 10-year ahead spread growth. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$

that idiosyncratic cashflow risk, rather than differences in expected returns are reponsible for the low co-movement between valuations of different asset classes.

Figure 5 shows the pairwise correlations of discount rate news on equity, housing and corporate bonds, with discount rate news on each asset i in year t estimated as the change in the present value of expected returns in that given year (see Section 5 and Appendix C.3). As in Figure 1, the correlations are computed over decadal rolling windows, with each underlying discount rate news series averaged over 3 years to make sure the results are not unduly affected by how quickly individual asset prices incorporate the changes in discount rates.

The correlations in Figure 5 paint an even starker picture than those for the raw valuation series in Figure 1. There is, give or take, no correlation between discount rates of different asset classes. The only robustly positive correlation appears during world war 2 – a unique historical episode when risk aversion and, hence, the price of risk is likely to have been high throughout the sample. If anything, the positive discount rate correlation during world war 2 suggests that the low co-movement during other periods is not a simple artefact of the data, and that periods when the price of risk varies substantially are rather rare.

Table 6 shows the pairwise correlation coefficients between discount rate news of different asset classes, computed over the full sample panel, with each underlying series demeaned at country level and averaged over 3 years. The results echo those of Figure 5: the discount rate correlations are close to zero and not statistically significant. Equity and housing cashflow news, on the contrary, do show a robustly positive correlation.[20] This stylised fact speaks against the fundamental based explanations for the low co-movement puzzle. These explanations would require cashflow news on different asset classes to show zero or negative co-movement which offsets the positive co-movement in discount rates. But the reality is the opposite: it is cashflow news that correlate strongly across asset classes, perhaps driven by general macroeconomic risk, and discount rates which are an asset-specific phenomenon.

[20]Because of the lack of data on corporate bond default rates, I restrict the cashflow news analysis to the housing and equity asset classes.

Table 7: *Discount rate and cashflow news correlations, alternative samples and definitions*

	(1)	(2)	(3)	(4)	(5)
	Baseline	Housing 1 year ahead	10-year averages	Post 1950	Post 1980
Discount rate news:					
Equity, housing	0.16	0.13**	0.18*	−0.05	−0.11**
Equity, corporate bonds	0.03	0.03	−0.04	−0.04	0.00
Housing, corporate bonds	0.06	0.04	−0.03	−0.03	−0.11
Cashflow news:					
Equity, housing	0.32***	0.23***	0.40***	0.21***	0.26***

Note: Pairwise correlations, three-year moving averages of risky asset discount rate news and cashflow news. All series are demeaned at country level. Housing 1 year ahead correlates the housing data at $t+1$ and other asset data at t. 10-year averages smoothes each series using a 10-year rolling average. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$

Table 7 shows that the low discount rate and high cashflow correlations hold across a variety of different variable definitions and subsamples. Column 1 shows the baseline correlations in Table 6, whereas each of the columns 2–5 changes the sample or variable definitions. The correlations are low and mostly insignificant when I forward housing returns by 1 year to account for delayed price transmission in this market (column 2), when looking over medium-term correlations using 10-year moving averages of the series (column 3), or when restricting the sample to the more recent decades (columns 4 and 5). After 1980, the correlation between equity and housing discount rate news is negative. Appendix Table A.2 shows that the low discount rate correlation and high cashflow correlation are also the predominant feature of the data within individual countries, including the US. Taken together, these findings confirm that the low co-movement of asset-specific discount rates is, indeed, a robust feature of the data.

6.2. Cross-asset return predictability

The statistical power of cross-asset co-movement in expected returns can be tested more formally using the framework of return predictability regressions described in Section 2. For example, it could be the case that the dividend-price ratio helps predict housing or corporate bond returns, even if it is uncorrelated with the rent-price ratio or the bond spread. In this case, changes in the dividend-price ratio would correspond to the time-varying price of risk, with rent-price ratios and bond spreads measuring the asset-specific factors affecting housing and corporate bond return expectations.

Table 8 shows the results of cross-asset return predictability regressions. As in Table 4, each column corresponds to a different asset class, and each row – to a different predictor. Panel 1 tests for unconditional predictability across asset classes, and Panel 2 additionally includes the own-asset

Table 8: *Predictability of real returns across asset classes*

	(1)	(2)	(3)
	Equity r_{t+1}	Housing r_{t+1}	Corporate bond $\Delta spread_{t+1}$
Panel 1: Unconditional predictability			
Dividend-price ratio		-0.002	0.002
		(0.011)	(0.047)
Rent-price ratio	0.030		-0.083
	(0.023)		(0.058)
Bond spread	0.010	0.001	
	(0.009)	(0.003)	
R^2	0.004	0.000	0.001
Observations	1263	1227	1217
Panel 2: Conditional predictability			
Dividend-price ratio	0.089***	-0.009	0.034
	(0.024)	(0.011)	(0.045)
Rent-price ratio	0.006	0.073***	-0.016
	(0.022)	(0.014)	(0.097)
Bond spread	0.008	-0.002	-0.307***
	(0.008)	(0.002)	(0.057)
R^2	0.036	0.053	0.148
Observations	1226	1220	1217

Note: OLS regressions with country fixed effects. Dependent (y) variables in columns. Dividend-price and rent-price ratios are in logs. Bond spread is the percentage point yield difference between corporate and government bonds. Predictor (x) variables are the log real total return on each asset class. Country clustered standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

predictor (for example, the dividend-price ratio for equities), and tests whether the discount rates on asset classes carry predictive power for future returns that goes above and beyond that of the own-asset predictor.

Consistent with the discount rate correlation evidence in Figure 5 and Table 6, the estimates in Table 8 show that there is, essentially no cross-asset return predictability in the data. Asset-specific valuations do not help predict returns on other asset classes, either conditionally or unconditionally. Knowing that the rent-price ratios are low, and housing valuations are high, tells us nothing about the expected returns on equity or corporate bonds.

Table 9 shows that the lack of cross-asset return predictability continues to hold under a variety of alternative return definitions, and across different time periods. Each row shows the predictive coefficient on the asset-specific return, when regressed on valuations of the other two risky assets. Column 1 corresponds to the unconditional predictability results in Table 8 Panel 1. Columns 2-6 look, respectively, at longer-horizon predictability, nominal returns, and restricting the sample to the post-1950 period, recessions or expansions (identified by applying the Bry and Boschan (1971) algorithm to real GDP per capita). There is no consistent evidence for cross-asset return predictability under any of these alternative specifications. When it comes to nominal returns,

Table 9: *Predictability of real returns across asset classes: alternative specifications*

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	5-year returns	Nominal returns	Post 1950	Recessions	Expansions
Equity r_{t+1}:						
Rent-price ratio	0.030	-0.016	0.024	0.044	-0.005	0.039
	(0.023)	(0.022)	(0.026)	(0.036)	(0.038)	(0.025)
Bond spread	0.010	0.001	0.004	0.012	0.054***	-0.001
	(0.009)	(0.005)	(0.007)	(0.012)	(0.020)	(0.009)
Housing r_{t+1}:						
Dividend-price ratio	-0.002	0.001	-0.019	-0.005	0.015	-0.006
	(0.011)	(0.008)	(0.016)	(0.018)	(0.020)	(0.011)
Bond spread	0.001	0.002	-0.006	0.003	0.004	0.002
	(0.003)	(0.004)	(0.006)	(0.004)	(0.012)	(0.004)
Corporate bond $\Delta spread_{t+1}$:						
Dividend-price ratio	0.002	-0.029		0.048	0.231**	-0.027
	(0.047)	(0.037)		(0.073)	(0.111)	(0.046)
Rent-price ratio	-0.083	-0.024		-0.126**	-0.221	-0.088
	(0.058)	(0.028)		(0.053)	(0.288)	(0.060)

Note: Predictive coefficents of returns on one asset class at $t+1$ regressed on the discount rate proxies of other asset classes at t. Dividend-price and rent-price ratios are in logs, bond spread is in percentage points. Predictors (x variables) in rows. Specifications in columns. r_{t+1} is log real total return; $\Delta spread$ is the percentage point change in the corporate bond spread. 5-year returns uses 5-year ahead average returns or spread growth as the dependent (y) variable. Expansions and recessions are dated using the Bry-Boschan algorithm. OLS regressions with country fixed effects. Country clustered standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

high dividend-price ratios predict low, rather than high future returns on housing. Similarly, high dividend-price ratios forecast high spreads – and hence low, rather than high corporate bond returns – during recessions. During expansions, dividend-price ratios do help forecast bond spread growth in the right direction, but they do not forecast housing returns.

6.3. Predictive power of macro-financial risk factors

I now turn to examine the predictive power of various macro-financial risk factors. The factor selection mirrors existing theoretical and empirical asset pricing literature, subject to historical data availability constraints. Broadly speaking, I include those macroeconomic and financial variables which serve as proxies for the price of risk in theoretical asset pricing models, or have been shown to predict equity returns in the empirical literature. The list of factors can be broadly divided into the following three categories:

Consumpton-based factors The notion of the price of risk is strongly linked to household consumption. When consumption is low, households should be unwilling to save or take risks, and

hence demand high compensation for holding risky assets. Campbell and Cochrane (1999) show that rather than looking at raw consumption growth, the deviation of consumption from a slow-moving trend – or "habit" – does a better job in explaining the time variation in equity valuations. Lettau and Ludvigson (2002) show that rather than consumption itself, the "consumption-wealth ratio" *cay* – measured as the deviation of consumption relative to wealth from its long-run trend – has strong predictive power for stock returns in the US.

To proxy the consumption and habit factors, I use, respectively, the 3-year consumption growth, and the deviation from consumption from its 10-year moving average trend. For the consumption-wealth ratio, I proxy total financial wealth as the sum of stock market capitalization and housing wealth, and use real wages as a proxy for real income.[21] I then follow Lettau and Ludvigson (2002) and estimate the cointegrating relationship between consumption, financial wealth and labour income, and compute the consumption-wealth ratio as the deviation of consumption from this long-run cointegrating relationship. The consumption and wage data are sourced from the latest vintage of the Jordà-Schularick-Taylor macrohistory database (Jordà, Schularick, and Taylor, 2016), stock market capitalization data come from Kuvshinov and Zimmermann (2018), and housing wealth data are from Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2017a).

Financial intermediary factors A series of recent papers suggest that high risk appetite by financial intermediaries affects prices of risky assets, both in theory and in the data (He and Krishnamurthy, 2013; Baron and Muir, 2018). Most measures of risk appetite either correspond to balance sheet strength, or balance sheet growth of financial intermediaries. Growing leverage or bank assets are, therefore, signs of high intermediary risk appetite. To this end, I add the 3-year growth in bank leverage, real bank assets and real credit to the predictor set. The leverage data are from Jordà, Richter, Schularick, and Taylor (2017b), while bank asset and credit data come from (Jordà, Schularick, and Taylor, 2016).

Other factors I add the stock market capitalization relative to GDP and term spread – two variables which have been shown to have considerable forecasting power for equity returns. Kuvshinov and Zimmermann (2018) show that the stock market cap to GDP ratio outperforms the dividend-price ratio as an equity return predictor, because it incorporates changes in quantities, or issuance, as well as prices. Campbell (1991), among others, finds that the term spread reliably forecasts US stock returns.

Table 10 reports the outcomes of forecasting regressions in equation (7). As before, each column corresponds to a different asset class, while each row corresponds to a different predictor. For each predictor, the table includes the expected sign of the coefficient on equity and housing returns. Because I use spread growth to proxy bond returns, the expected coefficient sign in Table 10 column

[21] Because of the lack of data on other classes of wealth, or total income for my historical sample, I restrict the analysis to stock market and housing wealth, and use wages rather than total labour income to proxy the flow of human wealth.

Table 10: *Return predictability using macro-financial risk factors*

	(1)	(2)	(3)
	Equity r_{t+1}	Housing r_{t+1}	Corporate bond $\Delta spread_{t+1}$
Consumption-based factors:			
$\Delta_3 Real\ Consumption_t(-)$	-0.271**	0.172*	0.325
	(0.136)	(0.088)	(0.376)
$Surplus\ Consumption_t(-)$	0.021	-0.040	-0.730
	(0.154)	(0.094)	(0.590)
$cay_t(+)$	0.018	0.037	0.162
	(0.041)	(0.027)	(0.106)
Financial intermediary factors:			
$\Delta_3 Bank\ Leverage_t(-)$	-0.060	-0.033**	-0.003
	(0.039)	(0.016)	(0.117)
$\Delta_3 Real\ Bank\ Assets_t(-)$	-0.029	0.019	0.220
	(0.055)	(0.024)	(0.263)
$\Delta_3 Real\ Credit_t(-)$	0.007	0.046***	0.270
	(0.043)	(0.016)	(0.170)
Other factors:			
$log(MCAP_t/GDP_t)(-)$	-0.045***	0.000	-0.023
	(0.008)	(0.004)	(0.033)
$Term\ Spread_t(+)$	0.012**	0.006***	0.043
	(0.006)	(0.002)	(0.034)
R^2	0.039	0.053	0.012
Observations	1471	1391	1103

Note: OLS regressions with country fixed effects. Dependent (y) variables in columns. $\Delta_3 Real\ Consumption_t$ is the log change in real consumption per capita from $t-3$ to t. $Surplus\ Consumption_t$ is the real consumption per capita at t relative to a backward-looking 10-year moving average trend, from t-10 to t. cay_t is a proxy for the consumption-wealth ratio, estimated as the deviations from the cointegrating relationship between real consumption, a proxy for financial wealth (the combined capitalization of the equity, housing and government bond markets) and real wages. $\Delta_3 Bank\ Leverage_t$ is the change in the log of bank leverage from $t-3$ to t. $\Delta_3 Real\ Bank\ Assets_t$ is the change in the log of real bank assets from $t-3$ to t. $\Delta_3 Real\ Credit_t$ is the change in the log of real credit to non-financials from $t-3$ to t. $log(MCAP_t/GDP_t)$ is the log of the market capitalization to GDP ratio. $Term\ Spread_t$ is the percentage point yield spread between the long and short term government debt. Predictor (x) variables are the log real total return on equity and housing, and the percentage point change in the corporate bond spread. Country clustered standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

3 is the opposite of that in columns 1 and 2, e.g. positive for real consumption growth. Because most of my indicators are high when the price of risk is low, the expected coefficient sign is mostly negative. Expected returns should be low when consumption growth or surplus consumption is high (and hence, desire to save in risky assets – high, and price of risk – low), or when intermediary risk appetite is high. Expected returns should be high when consumption relative to wealth is high (and hence, the high quantity of wealth is suggestive of a low desire to save more in risky assets). Turning to other factors, high market capitalization is a sign of high equity valuations, a low price of

risk and low expected returns, while high term spreads indicate that the price of term, or duration, risk is high, and hence expected returns should be high.

The results in Table 10 confirm those in the preceding sections. The cross-asset predictive power of macro-financial risk factors is limited. Some of these factors are important for individual asset classes. For example, high consumption growth or high stock market capitalization predict low subsequent equity returns. Growing bank leverage – and hence, high intermediary risk appetite forecasts low housing returns. But this predictive power is highly asset specific. No single factor predicts returns on all three asset classes, and some factors predict returns in the wrong direction. For example, high credit growth predicts high, rather than low housing returns, which suggests that these higher housing returns and prices are simply a result of increased credit availability, rather than intermediary-based asset pricing factors.

The only factor that predicts returns on more than one asset class in the right direction is the term spread, which measures time-varying term premia, rather than the time-varying price of risk. Indeed, similarly to the high cashflow news correlation (Table 6) or high equity and housing discount rate co-movement during wars (Figure 5), the predictive power of the term premium works against discount rate based explanations for excess asset price volatility. Because both equities and housing are long duration assets, we would expect their returns to be predictable by a factor that reflects the price of duration risk, and indeed this is what we find. Because corporate bond spreads are taken over those of government bonds of similar maturity, the term premium has no explanatory power for corporate bond spreads. This shows that when there is a common risk factor which affects multiple asset classes, this factor shows up with significant predictive coefficients for the respective returns, with the right sign. The fact that other factors do not show up in such a manner speaks against single-factor explanations of excess asset price volatility.

The low cross-asset power of macro-financial factors holds under a variety of return definitions and sample specifications, with the results reported in the Appendix Table A.9. Conditioning on own valuations, looking at 5-year ahead returns or limiting the sample to after 1950 does not materially change the results.

Figure 6 compares the cross-asset predictive power of own asset valuations, valuations of other assets, and those of macro and financial risk factors. More precisely, it contrasts the R^2 from return predictability regressions using only the own asset valuation (as in Table 4), to those using only the valuations of other asset classes (as in Table 8 panel 1), and those using only the consumption-related, or only the financial factors in Table 10. Own valuations are the most informative predictor of expected returns. Valuations of other assets have almost no predictive power. Macro-financial factors do have some predictive power for equity and housing returns, but as discussed above, this power corresponds to asset-specific rather than cross-asset factors. Consistent with the comparison of excess volatility across asset classes in Section 5 Table 5, the relative forecasting power as measured by the R^2 is highest for corporate bonds, moderate for housing and relatively low for equities.

Taken together, the analysis in this section makes clear that discount rates – or expected returns – on different assets do not co-move. Therefore, discount rate variation is not an important driver of

Figure 6: *Explanatory power of different sets of predictors*

Note: Comparison of R2 statistics from return predictability regressions. The dependent (y) variables are the log real total return on equity or housing, and the spread growth for corporate bonds, at $t+1$. Predictor (x) variables change depending on the specification. The "own valuation" specification uses the asset-specific valuation ration dp_t only, "valuations of other assets" uses only the valuations of the other two asset classes. The macro factors are consumption growth, surplus consumption, and the consumption-wealth ratio. The financial factors are growth in bank leverage, real bank assets and real credit. All macro-financial growth rates are from year $t-3$ to t. OLS regressions using country fixed effects. Consistent sample used across all specifications within an asset class: i.e. all the bars in the equity specification use the same sample, but a different sample may be used for housing.

asset price volatility. But as the analysis in Section 5 has shown, asset prices do move excessively relative to fundamentals. If not discount rates, what is it, then, that drives this excess financial volatility? The next section explores a range of potential theoretical explanation behind the asset-specific variation in expected returns.

7. The time varying risk puzzle

Sections 5 and 6 have documented the following stylised feature of the new cross-asset risk and return dataset: asset-specific discount rates vary over time, but do not correlate across asset classes. This stylised fact poses a challenge to most of the prominent models in macro-finance. Cochrane (2017) argues that most modern macro-finance theories rely on the time variation in the discount rate, or the price of risk, to generate excess volatility, and only differ in the specific ways in which this time variation in the price of risk is generated. But even though such models can match asset price volatility within an asset class, they are not able to generate a lack of co-movement in expected returns across asset classes, because the discount factor variation is common to all risky assets. The lack of co-movement in asset-specific discount rates, therefore, constitutes a new "time varying risk" puzzle for the asset pricing literature.

In this section, I evaluate in more detail whether standard asset pricing models are able to match this low co-movement fact, and discuss several modifications or classes of models – including investor heterogeneity and volatile expectations – that may be able to account for the low co-movement in discount rates observed in the data. Asset pricing theories which rely on time variation in the price of risk can be divided into five broad categories. Each of these classes of models relies on time variation in the discount rate m to explain excess volatility, but gives a different reason as to why m should vary over time.

Representative agent consumption CAPM The simplest macro asset pricing model simply attributes time variation in the price of risk to changes in the marginal utility of consumption:

$$m_t = u'(c_{t+1})/u'(c_t)$$

It is generally accepted that this formulation of the pricing kernel does not generate sufficient volatility in m, hence a number of modifications have been proposed to make the discount factor and hence asset prices more volatile.

Time-varying risk aversion These theories stipulate that the price of risk is determined by some additional parameter H, which affects investors' marginal utility and thus makes their "effective" risk aversion volatile, such that the marginal utility of consumption varies by more than consumption itself:

$$m_t = f(H_{t+1}/H_t)$$

The most most popular candidate for H is time variation in the consumption habit or surplus consumption proposed by Campbell and Cochrane (1999). Piazzesi et al. (2007) argue that time variation in the housing consumption share can also drive such movements in risk preferences.

Long-run risk models, such as Bansal and Yaron (2004), rely on time variation in consumption volatility to generate movements in the discount factor:

$$m_t = f(\sigma_{C,t})$$

Rare disasters In this class of models, time variation in m reflects the time-varying disaster risk, determined by the probability of disasters p, disaster consumption losses B and disaster-specific asset returns R^{dis}_{t+1} (Barro, 2006; Barro and Ursua, 2008; Gabaix, 2012):

$$m_t = p_t f(B_{t+1} R^{dis}_{i,t+1})$$

A high disaster risk would elicit high expected returns on on all risky asset classes, particularly for those assets which experience low disaster returns.

Intermediary asset pricing This set of theories argues that instead of being priced by a representative households, assets are priced by financial intermediaries or market makers, with the pricing kernel m corresponding to financial intermediary risk appetite, usually tied to their balance sheet characteristics bs (He and Krishnamurthy, 2013):

$$m_t = f(bs_t)$$

The measures bs_t include intermediary leverage, balance sheet strength and asset growth, which act as proxies for the ability and willingness to bear financial risk.

Every single one of these models relies on time variation in the price of risk to generate the volatility in m necessary to explain the variation in expected returns documented in Section 5. This discount rate variation, however, induces a strong co-movement in expected returns on different asset classes, which is something that we do not observe in the data, as documented in Section 6. This lack of co-movement is directly stipulated by the time-varying risk aversion, long-run risk and financial intermediary theories. It is somewhat more subtle in the case of disaster risk models: if returns and risk premiums during disasters differ markedly across the risky asset classes, time-varying disaster risk loadings may generate some heterogeneity in cross-asset expected returns. But in the data, all three assets show low returns during consumption disaster period, and expected returns across the three asset classes show high co-movement during consumption disasters as illustrated, for example, by the high equity and housing discount rate correlations during the two world wars in Figure 5. Therefore, the heterogeneity in disaster returns is unlikely to be important in explaining the low co-movement puzzle.

There are three different ways to reconcile asset pricing models with the low co-movement and resolve the time varying risk puzzle. The first approach introduces additional pricing factors or frictions which delink asset-specific returns from the discount factor. The second approach seeks to generate asset-specific m_is which are rationalised via some form of market and investor heterogeneity. The third approach uses an altogether different source of variation in expected returns, namely volatile expectations, to generate excess financial volatility without a need for high cross-asset expected return co-movement. I consider each of these solutions in turn.

7.1. Asset-specific risk and non-monetary payoffs

Expected return on asset class i does not depend on the discount factor m alone. It also depends on the riskiness of the asset class and any non-cash utility payoffs accruing to the asset holder, such as liquidity services. Asset-specific variation in these risks or payoffs could therefore delink expected returns from discount rate variation, and generate the low co-movement observed in the data.

Asset-specific risk Expected returns should be higher if an asset is riskier. In the CAPM, the excess return premium is captured by the asset "beta": the higher the comovement of an asset with

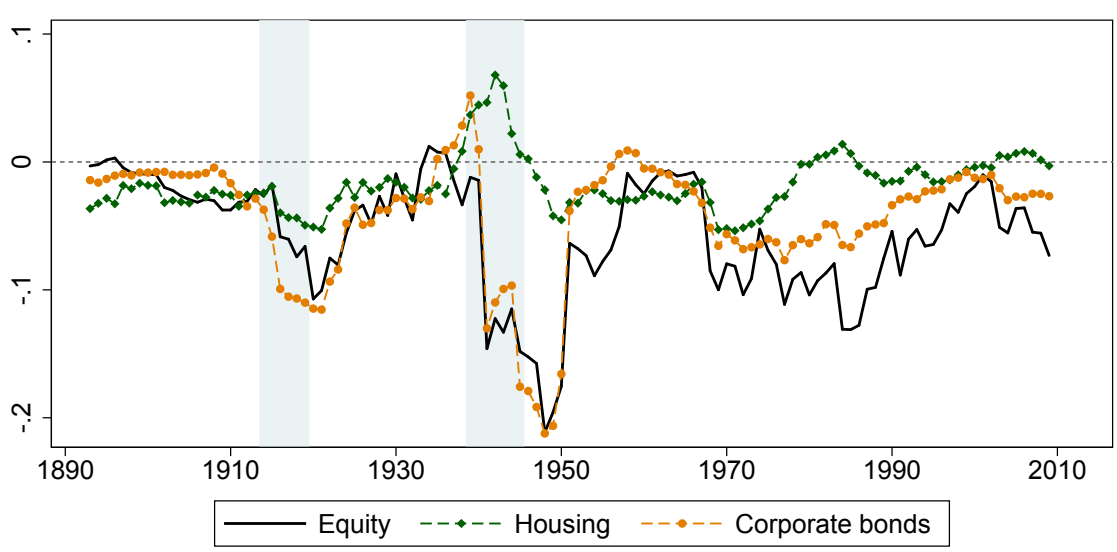
the market return, the higher the required compensation for that extra risk. In macro asset pricing models, asset "beta" equals the covariance of the return with the discount factor: the lower the asset's payoffs in bad states, the higher the expected return. Decomposing the joint expectation $\mathbb{E}(mR)$ into variation in expected return $\mathbb{E}(R)$ and risk $cov_t(R_{i,t+1}, m_{t+1})$ yields:

$$\mathbb{E}_t(R_{i,t+1}) = \frac{1 - cov_t(R_{i,t+1}, m_{t+1})}{\mathbb{E}_t(m_{t+1})} \tag{12}$$

Most asset pricing models implicitly assume that the beta, or asset risk, stays constant over time. But this need not be so. For example, Lettau, Maggiori, and Weber (2014) augment the standard CAPM with an additional downside-risk beta, with the asset riskiness at time t effectively an average of the exposure to downside risk and the riskiness during normal times. An increase in downside risk would then increase the riskiness of those asset classes which are sensitive to this factor, such as fixed-income securities.

The question, then, becomes: how much does asset-specific risk or beta fluctuate in practice? This is inherently difficult to assess because the discount factor m, which affects asset riskiness through covariance $cov_t(R_{i,t+1}, m_{t+1})$ is itself not directly measurable, and I argue that the asset-specific discount rate proxies are a poor measure of the aggregate pricing kernel. But we can proxy the aggregate m as the simple average of the asset-specific ms: the dividend-price ratio, rent-price ratio, and the corporate bond yield (after normalising each series to mean zero and standard deviation of 1). Figure 7 then plots a proxy for the time-varying asset-specific beta: the covariance between the realised return and the proxy for m computed over rolling 10-year windows.

Figure 7: *Time variation in asset-specific risk, or "beta"*



Note: Covariance between equity, housing and corporate bond returns, and a simple proxy for the discount factor m. Centered 10-year rolling windows. The m proxy equals the average of three asset-specific discount factors (the log inverse dividend-price ratio, rent-price ratio and corporate bond spread, each normalised to mean 0 and standard deviation of 1 over the full sample).

Figure 7 suggests that asset-specific riskiness or beta does vary over time: for example, asset risk increased during the two world wars, and fell during the Great Moderation. But the time variation in betas is both small – with a covariance of around -0.1 during most of the peacetime – and similar across the different risky asset classes. The only instance where the risk of each asset class diverges is World War 2, when housing returns exhibited substantally lower risk than those on equity and corporate bonds. Notably, world war 2 happens to be the only time period during which the discount rates on different asset classes actually do co-move (Figure 5).[22] Appendix Figure A.5 uses a more sophisticated proxy for m which utilises data on all cross-asset expected returns and macro-financial risk factors, but finds that the time variation in riskiness becomes smaller and more homogenous across asset classes.

This suggests that time-variation in betas is small and similar across the three risky asset classes, and hence not capable of accounting for the zero expected return correlation in the data. The low importance of asset-specific risk is a direct consequence of the dataset used in this paper: all the assets included in this study are risky and exclude safe securities such as bills or government bonds and furthermore, each of these assets is actually a major asset class and a sizeable component of the return on risky wealth. This assures that the asset classes remain risky throughout the sample, and their returns do not deviate markedly from those on the market portfolio.

Non-monetary payoffs The monetary cashflows in the data may not capture the full value of utility services provided by an asset class. It the expected value of these services varies over time and across asset classes, it could make specific asset classes relatively more or less attractive, and reduce the co-movement in expected returns. For example, housing is relatively illiquid, and if liquidity premia rise, expected returns on housing should fall relative to the other two asset classes.

The two primary candidates for these non-monetary services are housing utility and liquidity services. Housing utility variation should, however, be captured in my rental cashflow measure, which includes imputed rents of owner occupiers. Still, the imputed rent measure is noisy and may not fully capture the time variation in preferences. As further evidence, Appendix Figure A.6 shows that the share of rents in GDP – a proxy for housing consumption share, which in turn drives the marginal utility of housing services (Piazzesi et al., 2007) – displays little cyclical variation, especially during peacetime. Finally, the variation in housing preference would be unable to explain the low co-movement between equities and corporate bonds.

Turning to liquidity, because housing transactions are costly and take time to execute, a high liquidity preference should reduce housing valuations relative to those of the other two asset classes. But corporate bond markets are also illiquid (Bao, Pan, and Wang, 2011). This means that time variation in liquidity premiums should induce some co-movement between housing and corporate

[22] In addition to this, the riskiness of housing investments during world war 2 is likely to be understated in the data, for two reasons. First, may countries introduced rent or price controls which means that returns do not necessarily reflect true market prices. Second, my measure of housing return does not account for destruction of buildings during the war (see Jordà et al., 2017a).

bond discount rates. In the data however, the co-movement between housing and corporate bond discount rates is even lower than that between equities and housing. Further to this, liquidity tends to be pro-cyclical and co-move strongly with risk appetite measures such as intermediary leverage (Brunnermeier and Pedersen, 2009; Adrian and Shin, 2010).

Taken together, the time varying risk puzzle cannot be fully attributed to time-varying betas or asset-specific frictions which generate heterogeneity in asset-specific returns even in the presence of an aggregate discount factor m. But asset-specific discount factors could themselves be heterogeneous because of differences among investors and market segmentation – a set of explanations for the puzzle that I consider next.

7.2. Heterogenous investors and segmented markets

Investor heterogeneity or market segmentation alone cannot account for the time varying risk puzzle. If investors are heterogenous but markets are not segmented, there will be a common discount factor which drives expected returns on all risky asset classes, with the time variation in that discount factor driven by some average of individual investor discount rates (Constantinides and Duffie, 1996; Gârleanu and Panageas, 2015).[23] If markets are segmented but investors in each market are the same, the discount factors across different asset classes will also be equal. Put differently, heterogeneity and segmentation need to be large enough to, effectively, allow for arbitrage across expected returns on different asset classes. Investor heterogeneity allows these return differentials to arise in the first place, and market segmentation ensures that they are not arbitraged away. Existing evidence, however, suggests that neither of these two heterogeneities is sufficiently large to generate the observed absence of discount rate co-movement.

Starting with market segmentation and limits to arbitrage, several recent studies have documented an existence of arbitrage opportunities across different assets. But outside of crises, the size of return differentials generated by these arbitrage strategies is an order of magnitude smaller than those implied by the cross-asset discount rate differentials in my data. For example, Fleckenstein, Longstaff, and Lustig (2010) document a return differential of around 20 bps between inflation-linked bonds and a combination of a nominal bond and an inflation swap outside of crisis years, and Hu, Pan, and Wang (2013) document differentials of around 6 bps between different government securities. In my data, a one standard deviation higher rent-price ratio is not informative of future equity or corporate bond returns, but implies a 150 bps higher return on housing 1 year ahead (Table 4), and 800 bps higher returns over 5 years (Table A.4).

These return differentials remain large if we narrow the focus to equity and corporate bond securities, which have low transaction costs and are typically traded on the same stock exchange by the same investors. A 1 standard deviation higher dividend-price ratio is not informative

[23] In Constantinides and Duffie (1996), this discount factor can be linked to the cross-sectional variance of consumption growth, and in Gârleanu and Panageas (2015) – to a weighted average of individual investors' risk aversion.

Table 11: *Correlations of real post-tax income growth across the income distribution*

	Average growth	Income growth correlations		
		Bottom 50%	Middle 40%	Top 10%
Bottom 50%	1.23	1		
Middle 40%	1.34	0.76	1	
Top 10%	1.95	0.43	0.76	1

Note: Mean real post-tax income growth, and pairwise correlation coefficients of mean real post-tax income growth among the bottom 50%, percentiles 50–90, and the top 10% of the income distribution. Data are from Piketty et al. (2018), and cover US 1962–2014 only. All correlations are significant at the 1% level.

about future bond returns, but signals 150 bps higher equity returns 1 year ahead, and 500 bps higher cumulative return 5 years ahead. All these results hold in normal times or during economic expansions, as well as during recessions or financial crisis.

Arbitrage opportunities aside, the degree of market segmentation and investor heterogeneity across the three risky asset classes also does not appear to be quantitatively large. A large share of the equity and corporate bond market is held by large institutional investors, especially over recent decades (Gompers and Metrick, 2001; Biais and Green, 2007). Even though housing is primarily held by the middle class, and equity – by high-income individuals, there is a large degree of cross-asset holdings even among these groups: high income earners still own their house, and middle income earners have an exposure to the equity market through their pensions (Kuhn, Schularick, and Steins, 2017; Garbinti, Goupille-Lebret, and Piketty, 2017; Martínez-Toledano, 2018). The income shocks – and hence discount factors – of these two groups are also highly positively correlated.

Table 11 reports the average income growth, and income growth correlation of the bottom of the income distribution – who can be thought of as holding no risky assets – the middle – the representative housing owner – and the top, the representative equity owner, using the post-1962 US data from Piketty, Saez, and Zucman (2018). While these income groups have experienced substantially different trend income growth (Table 11, column 1), the year-to-year growth variation which drives the stochastic discount factor is strongly positively correlated. The correlation in income growth between a representative housing and equity owner – the middle 40% and the top 10% – is around 0.76.

These facts suggest that while investor heterogeneity and market segmentation may reduce the co-movement in expected returns, they are unlikely to explain the zero correlation observed in the data – either alone or in combination with asset-specific risk or non-monetary payoffs (Section 7.1). To reconcile the low co-movement fact with theory, it may be more fruitful to focus on a different source of time variation in expected returns altogether: that of volatile expectations.

7.3. Volatile expectations

Volatility in expectations means that investors form their forecasts of future cashflows using an operator $\mathbb{E}_i^*$ that differs from the ex-post rational forecast $\mathbb{E}$. These differences can vary over time and across asset classes, generating the patterns of asset-specific excess asset price volatility documented in Sections 5 and 6.

Behavioural theories provide a number of possible forms for such variation in expectations. Most of these rely on some form of extrapolation – of past returns, cashflows, or other features of observable data. The simplest form of extrapolation simply makes return forecasts on the basis of past realised returns on the specific asset class i:

$$\mathbb{E}_{i,t}^*(R_{i,t+1}) = f(R_{i,t-1}) \tag{13}$$

For example, if returns are high during one period, investors expect them to also be high in the future, even if these expectations are not justified from a rational ex post perspective. Barberis, Greenwood, Jin, and Shleifer (2015) argue that a model where some investors form beliefs from extrapolating past price changes, and other investors hold rational beliefs provides a good match for asset price data and survey evidence. Adam and Merkel (2018) show that a general equilibrium model with extrapolative expectations can reconcile the variation in equity prices with that in macroeconomic aggregates.

A somewhat more sophisticated form of extrapolation builds on the representativeness heuristic through "diagnostic expectations" (Bordalo, Gennaioli, La Porta, and Shleifer, 2017). It assumes that investor expectations overweight surprising return outcomes, and expect assets which have shown higher than expected returns in the past to also do so in the future:

$$\mathbb{E}_{i,t}^* = f(R_{i,t-1} - \mathbb{E}_{t-1}R_{i,t-1}) \tag{14}$$

Another class of models helps explain why expected return co-movement across asset classes may be negative, rather than positive. The "style investing" model of Barberis and Shleifer (2003) assumes that if one asset class performs relatively well to others, investors expect continuied overperformance:

$$\mathbb{E}_{i,t}^* = f(R_{i,t-1} - R_{k\neq i,t-1}) \tag{15}$$

For example, if housing returns outperform those of equities over a certain time period, investors would expect this to be the case in the future, which means that the housing investment class will become popular and housing sentiment – elevated.

All of these theories are consistent with a low or negative co-movement in expected returns across asset classes. Expected returns are simply a function of past asset-specific factors, and there is no reason for them to co-move positively across asset classes. Extrapolation of non-fundamental factors – such as return surprises – or style investing can also generate a correlation in expected

returns that is lower that that of realised returns or fundamentals, consistent with the stylised fact in Table 6.

Extrapolative expectation formation can not only match the low co-movement fact in theory, but also matches a number of other salient features of the new cross-asset data. To test for this, I first construct a refined expected return measure for each asset class – in line with the literature, labelled as "sentiment" – and then test how this measure co-moves with past returns, return surprises and across asset classes.

A measure of asset-specific sentiment I follow López-Salido, Stein, and Zakrajšek (2017) and measure asset-specific sentiment as the inverse of the expected return on asset class i. To do this, I first estimate the expected return on each asset class i using the familiar toolkit of return predictability regressions. I predict returns on each asset class using their own valuation and the macro-financial risk factors F, which all have considerable predictive power for returns on individual asset classes (Figure 6). The predictive regression takes the following form:

$$r_{i,j,t+1} = \beta_i dp_{i,j,t} + \sum_{f=1}^{F} \beta_{f,i} F_{j,t} + u_{i,j,t} \tag{16}$$

As in López-Salido et al. (2017), the corporate bond return is approximated as negative spread growth, $\hat{r}_{bond,j,t+1} \approx -\Delta \widehat{spread}_{j,t+1}$. Expected return is the year-ahead prediction from regression (16):

$$\hat{r}_{i,j,t+1} = \hat{\beta}_i dp_{i,j,t} + \sum_{f=1}^{F} \hat{\beta}_{f,i} F_{j,t} \tag{17}$$

When expected returns are high, risk premiums are also high, and hence sentiment – low or depressed. Sentiment is then simply the negative expected return from equation (17):

$$\widehat{sent}_{i,j,t} = -\hat{r}_{i,j,t+1} \tag{18}$$

Reformulated in terms of sentiment, the empirical predictions of the different extrapolation theories above can be summarised as follows.

Prediction 1. Extrapolation of returns: High returns at t increase investor demand for asset class i, and hence predict high sentiment at $t+1$.

Prediction 2. Diagnostic expectations: Higher than expected returns at t increase investor demand for asset class i, and hence predict high sentiment at $t+1$.

Prediction 3. Style investing: elevated sentiment on asset i is a sign of high expected returns relative to other asset classes, and hence predicts depressed sentiment on asset j.

Evidence for return extrapolation Figure 8a tests prediction 1 by documenting the correlation between past returns and future sentiment. Importantly, I look at correlation with changes rather

than levels of sentiment (results do, however, also hold in levels). High past returns at t would mechanically lower the asset valuation at t, and because valuations are highly autocorrelated, also the valuation at $t+1$, which would mechanically lead to elevated levels of sentiment at $t+1$. To avoid this from biasing my results, I instead assess the correlation between the return from $t-1$ to t, and the change in sentiment from t to $t+1$. If there is no extrapolative behaviour, these two variables should be uncorrelated. But Figure 8a shows that they, in fact, do show a strong positive co-movement in the data.

Figure 8a shows the binned scatter plot of returns at t and changes in sentiment at $t+1$, for each of the three asset classes. To ease exposition, data are grouped into 100 bins and each series is normalised such that +1 on the x or y axis corresponds to a 1 standard deviation increase in returns or sentiment. As predicted by equation (13), higher returns at t forecast elevated sentiment at $t+1$. The relationship is both statistically and economically significant for each asset class. A one standard deviation increase in the asset-specific return increases sentiment by 0.3 standard deviations for equities or housing, and by 1 standard deviation for corporate bonds. Echoing the results of Table 5 in Section 5 , the degree of extrapolation is highest for corporate bonds. This suggests that high excess volatility and mean reversion in corporate bond spreads are largely driven by extrapolative behaviour – a finding consistent with models and US data on investor sentiment in the bond market (Greenwood and Hanson, 2013; López-Salido et al., 2017).

Evidence for diagnostic expectations Figure 8b shows the correlation between past return surprises and sentiment for each asset i. The "surprise" return is simply the residual from the predictive regression in (16):

$$\hat{r}^{surprise}_{i,j,t+1} = r_{i,j,t+1} - \hat{\beta}_i dp_{i,j,t} - \sum_{f=1}^{F} \hat{\beta}_{f,i} F_{j,t} \tag{19}$$

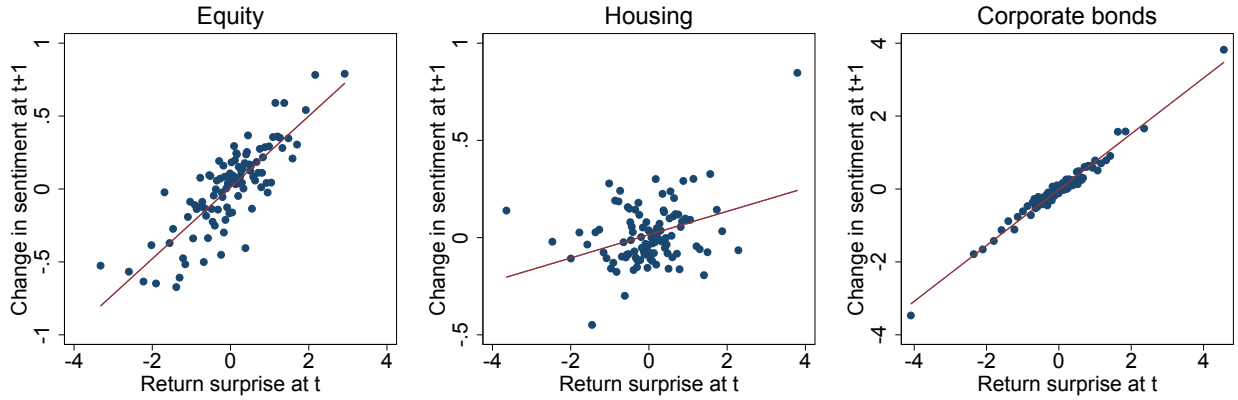
Figure 8b shows that these unexpected returns are positively correlated with future changes in sentiment, again using scatter plots of normalised data divided into 100 bins. A one standard deviation increase in surprise return at t is associated with 0.3 standard deviations elevated equity sentiment, 0.2 standard deviations elevated housing sentiment and 1 standard deviation elevated corporate bond sentiment. with all the relationships statistically significant. This strong positive correlation is in line with prediction 2. The size and significance of the relationship suggests that diagnostic expectation formation can explain a large part of the excess asset price volatility in my data.

Evidence for style investing Figure 8c considers evidence for style investing by correlating changes in sentiment across asset classes. It compares the changes in sentiment on equity and housing (left panel), equity and corporate bonds (middle panel), and housing and corporate bonds (right-hand panel), again using normalised data divided into 100 bins. Consistent with prediction 3,

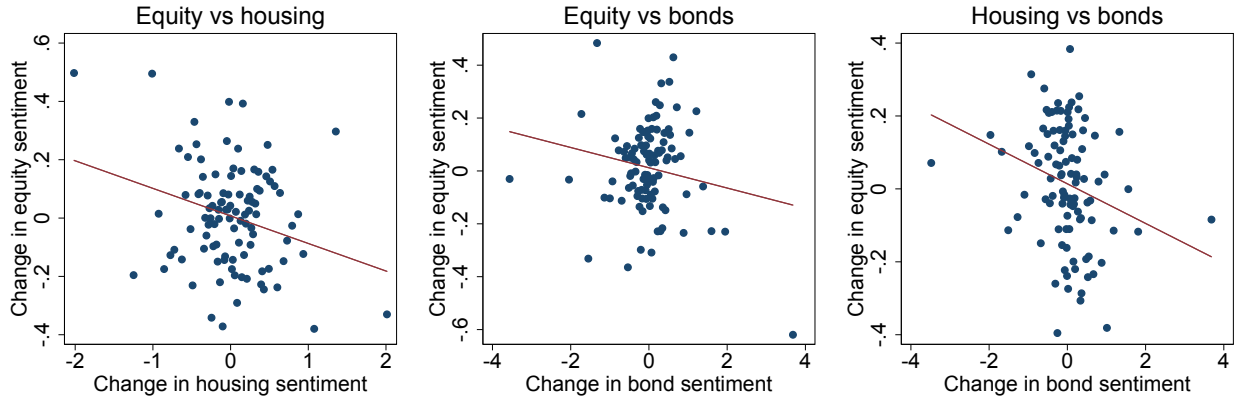
Figure 8: *Behavioural drivers of asset-specific sentiment*

(a) *Changes in sentiment and past returns (extrapolation)*

(b) *Changes in sentiment and past return surprises (diagnostic expectations)*



(c) *Co-movement of sentiment across asset classes (style investing)*



Note: Binned scatter plots, number of bins equals 100. High asset-specific sentiment at t means a low expected return on asset i at $t+1$, estimated by regressing returns at $t+1$ on asset-specific valuations, macro-financial and other risk factors at t.

the contemporaneous correlation in sentiment across asset classes is negative: for example, a one standard deviation increase in housing sentiment predicts a one-quarter standard deviation fall in equity market sentiment, with each negative correlation, again, statistically significant. This negative co-movement in sentiment speaks against discount rate based theories of excess volatility, which would, instead, predict a strongly positive co-movement in expected returns across asset classes. The strength of the correlation between sentiment of different asset classes is, however, weaker than that between past realised or surprise returns in Figures 8a and 8b. Moreover, low past returns on one asset class do not, generally, predict high future sentiment on other asset classes, which is one feature of the style investing model in Barberis and Shleifer (2003).[24] This leads me to conclude that the evidence for style investing is somewhat weaker than that for extrapolative and diagnostic expectations – but these types of cross-asset linkages are also more difficult to test for in my broad macro-historical data.

Taken together, the analysis in this section suggests that time variation in expected returns is not driven by volatile discount rates. The prominent asset pricing theories that rely on such discount rate variation will struggle to match the low co-movement of discount rates, even allowing for some variation in asset-specific riskiness and liquidity premiums. Models with investor heterogeneity and segmented markets also only play a limited role in explaining the puzzle. Instead, the explanation lies in embracing volatile expectations, not volatile discount rates, as the primary driver of financial volatility. I next consider whether these volatile expectations have an effect not only on asset prices, but also on real activity.

8. Real effects of time-varying sentiment

Volatile expectations – or time-varying sentiment – is an important driver of asset price volatility. These swings in asset prices, by themselves, directly affect the structure and distribution of wealth (Piketty, 2014; Benhabib and Bisin, 2016; Garbinti et al., 2017; Kuhn et al., 2017), and carry implications for financial market efficiency (Shiller, 2000). The work of Minsky (1977), however, puts these changes in expectations and sentiment not only at the center of asset price fluctuations, but also those in real activity. Under Minsky's financial instability hypothesis, elevated sentiment and optimistic expectations are accompanied by booming economic activity, but when these expectations are eventually reversed, the economy enters a crisis phase, with both real activity and health of the financial system deteriorating markedly. To test whether Minsky's hypothesis is supported by the new macro-financial data in this paper, I test whether elevated levels of sentiment are, indeed, associated with future recessions and financial crises.

[24] Results available upon request.

8.1. Sentiment and GDP growth

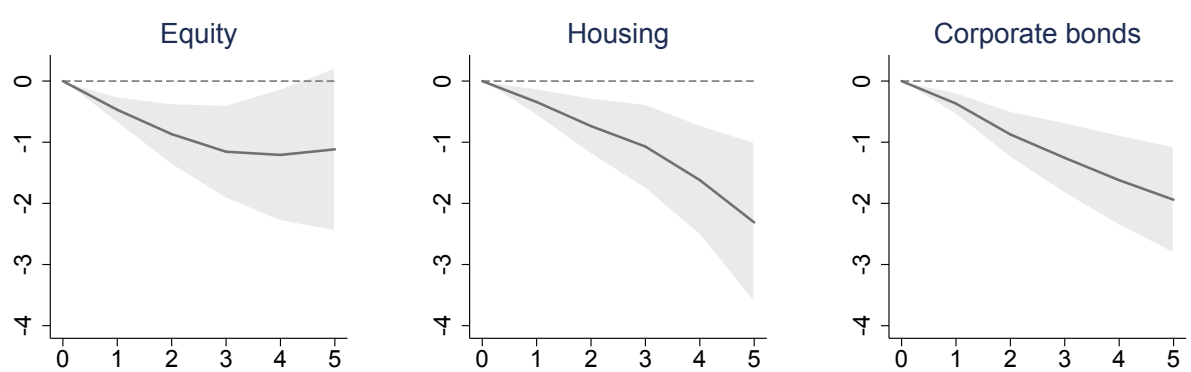
To assess how the influence of sentiment on future real activity, I follow López-Salido et al. (2017) and regress GDP growth on the past level of asset-specific sentiment for each of the three risky asset classes. Unlike López-Salido et al. (2017), I estimate the full dynamic path of future GDP 1 to 5 years ahead to enable a more parsimonious assessment of the effects. To do this, I estimate a Jordà (2005) local projection response of cumulative GDP growth for years $t+1$ to $t+5$ as a function of sentiment at t:

$$\Delta \text{GDP}_{j,t+h} = \beta_1^h + \beta_{gdp}^h \Delta \text{GDP}_t + \sum_{i=eq,hous,bond} \beta_i^h \widehat{sent}_{i,j,t} + \epsilon_{j,t}$$

Figure 9 shows the response of real GDP to a one standard deviation increase in sentiment $\widehat{sent}_{i,j,t}$ on each of the three risky asset classes, over a horizon of up to five years. Elevated sentiment – or low risk premiums – in each asset market tends to be followed by low, rather than high real GDP growth. The effect of time-varying equity sentiment on future GDP is small and relatively short-lived, peaking at less than 1% GDP. Effects of time varying housing and corporate bond market sentiment are, however, much larger and more persistent. A one standard deviation increase in housing or corporate bond market sentiment forecasts around two percentage points lower real GDP over the horizon of 5 years.

The impulse responses in Figure 9 suggest that low risk premiums and elevated market sentiment forecast poor, rather than favourable economic performance. My results cannot be interpreted causally but again, this evidence is consistent with behavioural explanations for the time varying risk puzzle: low risk premiums are precursors of falling asset prices and GDP, rather than precursors of favourable economic and financial fundamentals It turns out that the two markets for which excess volatility has, up to this point, been relatively sparsely documented and less well explored – those of corporate bonds and housing – are also the ones that matter most for the macroeconomy.

Figure 9: *GDP response to elevated asset-specific sentiment*



Note: Response of cumulative real GDP growth to a one standard deviation increase in asset-specific sentiment at $t = 1$. Estimated using local projections. Shaded areas are 90% confidence intervals. High sentiment at $t = 1$ means a low asset-specific discount rate at $t = 0$.

8.2. Sentiment and financial crises

Muir (2017) documents that equity risk premia tend to increase sharply around financial crises, and Krishnamurthy and Muir (2017) document a similar pattern for corporate bond spreads. Muir (2017) also shows that risk premia do not show similar spikes during consumption disasters, and interprets the high financial-crisis premia as evidence for intermediary asset pricing theories, and a fact difficult to reconcile with behavioural theories. Here I re-examine these findings using the new dataset in this paper, which offers a more extensive cross-country coverage, and a more refined measure of risk premiums – asset-specific sentiment described in Section 7.3, which covers housing as well as equities and corporate bonds. I show that while sentiment does tend to fall around financial crises – or, in other words, risk premiums tend to increase – it is volatile expectations rather than intermediary balance sheets that are likely to underly these trends.

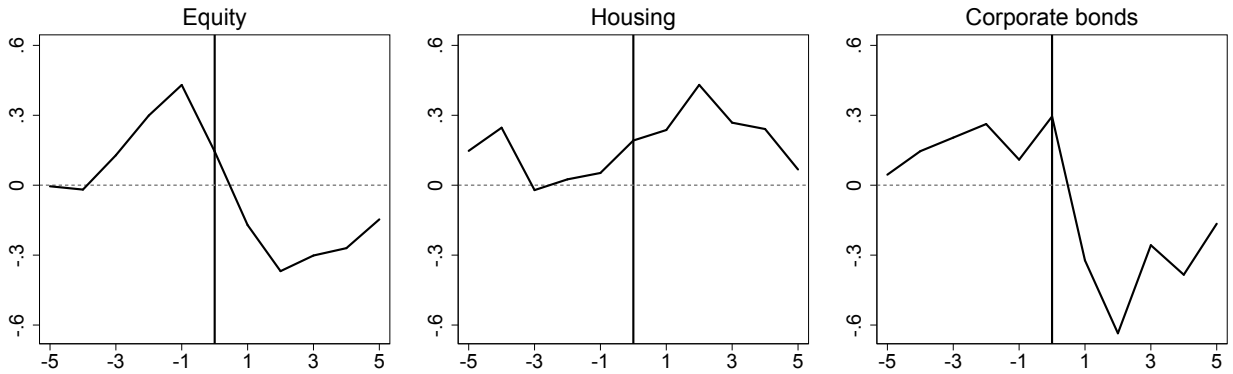
Figure 10a plots the evolution of sentiment around financial crises. It depicts the average level of sentiment for each asset class over the time window of 5 years before to 5 years after the crisis ($t = 0$), with crisis dates taken from Jordà et al. (2016). As described in Section 7.3, sentiment measures the expected return on each asset class, predicted using own valuation and a broad range of macro-financial factors. High levels of sentiment correspond to low expected returns and low discount rates or risk premia, with the sentiment measure standardised to mean 0 and standard deviation of 1 across the full sample.

The behaviour of sentiment across all three risky asset classes shares a number of characteristics with a Minsky (1977) boom-bust cycle. There is "froth" in the build-up, with sentiment elevated above the sample average, followed by a sharp reversal in expectations and depressed levels of sentiment over subsequent years. The froth is most strongly manifested in equity markets, while the expectation reversal is strongest for corporate bonds. This is consistent with the notion of equity markets as best incorporating forward-looking expectations, and corporate bonds being most responsive to extreme macroeconomic events. The delayed slow rise and gradual reversal in housing sentiment indicates a build-up of vulnerabilities during the early crisis phase, which are then slow to adjust during the crash. The findings are consistent with those of Muir (2017) and Krishnamurthy and Muir (2017), who find that equity and corporate bond risk premiums spike around the crisis using simpler dividend-price ratio measures. Appendix F shows that the simpler valuation and discount rate news measures behave in a similar ways to the sentiment measure in Figure 10 around crisis events.

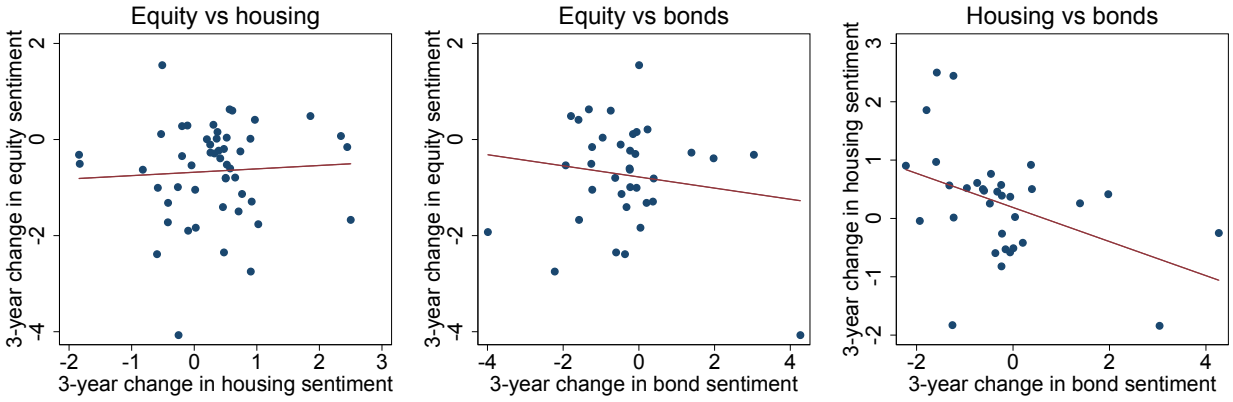
But are these changes in sentiment best interpreted as effects of financial frictions, or time-varying expectations. In his analysis, Muir (2017) favours the financial-friction based interpretation of these events, while this paper argues that most of such asset price swings can be traced back to expectation volatility. To distinguish between these two hypotheses, Figure 10b plots the correlation in changes in sentiment during the 3 years surrounding the start of the crisis. This correlation, just like the broader cross-asset discount rate correlations in the full sample, turns out to be roughly zero, and sometimes negative. The lack of correlation carries over to simpler measures of asset-specific

Figure 10: *Sentiment and financial crises*

(a) *Average level of sentiment around financial crisis events*



(b) *Co-movement of sentiment during financial crises*



Note: Financial crisis at $t = 0$. All sentiment variables are standardised to mean 0 and standard deviation of 1 in the full sample. Correlations are for the 3-year change around the crisis year (from $t = -1$ to $t = +1$). Each point on the scatter is an individual crisis event. High asset-specific sentiment at t means a low expected return on asset i at $t + 1$, estimated by regressing returns at $t + 1$ on asset-specific valuations, macro-financial and other risk factors at t.

discount rates such as valuation ratios and discount rate news, presented in Appendix F. Some of this low correlation can be attributed to the slightly different timing in sentiment reversals across asset classes. But especially when it comes to corporate bonds and equities, the lack of co-movement during financial crisis largely reflects the fact that crisis-related build-ups in sentiment tend to be asset-specific phenomena, with some crises resulting in high equity or corporate bond risk premiums, but relatively few displaying high risk premiums on all three risky asset classes.

The zero sentiment correlation strongly hints that financial crises, and the associated asset price booms and busts can be traced back to time variation in expectations, rather than financial frictions. The fact that this variation is especially large is then a factor contributing to the crisis, rather than a crisis outcome. The reversal in expectations during the crisis is so large that it generates distress

and bankruptcies in the banking system, and carries a large economic cost. It is highly likely that financial frictions play an important role in generating this cost (Eggertsson and Krugman, 2012; Mian and Sufi, 2014). This paper merely argues that these frictions are relatively unimportant for the asset price swings around the crisis, which are driven largely by agents' expectations.

Taken together, the real consequences of sentiment variation tend to be persistent and sizeable, and manifest themselves both during general business cycle fluctuations and more severe crisis events. Elevated sentiment does not entail the anticipation of an economic boom, but is instead a forebearer of asset price declines, financial crises and economic downturns. The associated boom-bust cycle echoes Minsky (1977)'s financial instability hypothesis, with elevated sentiment fostering an economic boom while sowing the seeds of a future financial crisis, which materialises when once the overoptimistic expectations are reversed. This shows that volatile expectations on all three risky asset classes not only affect the prices of these assets, but also broader economic outcomes. Incorporating this expectation volatility into business cycle models could, therefore, foster a deeper understanding of the underlying drivers behind macroeconomic fluctuations and their links with financial market outcomes.

9. Conclusion

This paper has introduced a new historical cross-country dataset of returns, cashflows and valuations of three major risky asset classes: equity, housing and corporate bonds, and used it to study the determinants of booms and busts in prices of these assets. These data have both cast an old puzzle in new light, and put forward a novel asset pricing anomaly.

The old excess volatility puzzle of Shiller (1981) stands firm in these new data. In some ways, excess volatility is not as bad as previously thought: time-varying discount rates only explain one-third of the variation in equity dividend-price ratios, rather than all of it. In other ways, it is worse than previously thought: the relatively unexplored housing and corporate bond markets display far higher excess volatility than equities, with valuations determined by expectations of returns much more than fundamentals.

The new puzzle that emerges from these data is that discount rates on different asset classes do not co-move. This lack of co-movement cannot be explained by idiosyncratic fundamentals, and does not disappear once conditioned on a broad range of macro-financial risk factors. It is at odds with most asset pricing theories, which tend to rely on the discount rate – or time variation in the price of risk – to explain why excess volatility arises. Model modifications which increase asset-specific heterogeneity but do not modify agents expectations are unlikely to fully resolve the puzzle.

Instead, my analysis suggests that behavioural theories, centered around extrapolative biases in investor expectations, provide an explanation for both the old volatility puzzle and the new time varying risk puzzle. Extrapolation of asset-specific returns or return surprises can generate the low co-movement in theory, and is consistent with a number of stylised features of the data. Such time

variation in asset-specific sentiment contributes to volatility not only in financial markets, but also the real economy. A better understanding of the underlying drivers of these sentiment swings, much of which is left to future research, should therefore help shed light on the underlying determinants of macroeconomic, as well as financial, booms and busts.

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Appendix

A. Accuracy of corporate bond data

Constructing a data series that captures the evolution of corporate bond credit risk premiums over time and across countries faces three main challenges. First, corporate bond data are subject to sample selection issues. Not all companies have access to the corporate bond market, and the type of company that has access may vary over time. Much of the early corporate bond market was dominated by railway companies. Later, railway bonds became less and bank bonds – more important. A second, related, bias is that outside of the US and the recent sample period, I do not have data on bond credit ratings. Therefore, the credit quality of the representative bond in the sample may change over time and across countries.

I guard against these biases in several ways. First, I utilise a wide array of new and previously unused sources that document bond prices and yields on domestic stock exchanges, in over the counter transactions, and for primary market issuance, complemented by data from international or foreign exchange listings. This gives me a comprehensively broad coverage of historical corporate bond transactions. Within this broad coverage, the scope for selection bias is less apparent. For example, the series that were constructed from microdata include non-financial non-railway bonds for every country and data period, and in general, the trends in the yields of non-railway bonds are very similar to the overall index. By excluding mortgage bonds and government-guaranteed bonds, I ensure that my sample always measures the credit risk faced by private sector bond issuers, regardless of selection. Additionally, the corporate bond risk premium shows no clear time trend – in fact, the long-run risk premium on this asset class is more stable than those for equities and housing.

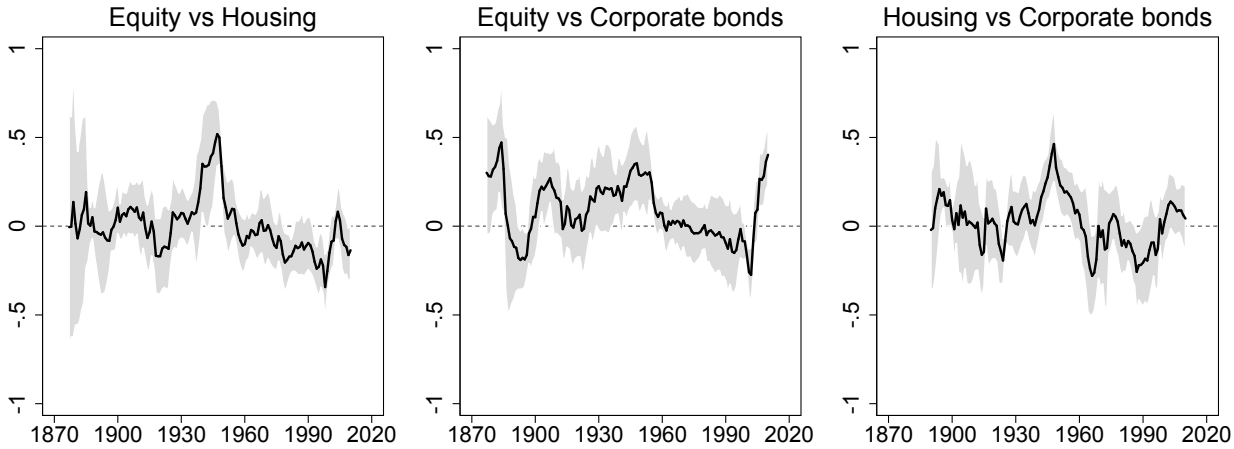
To the extent that selection biases do exist, they seem to mainly affect cross-country rather than cross-time differences. Some countries, such as UK, US and Germany, have had active and diverse corporate bond markets throughout most of the sample. In other countries, such as Sweden and Australia, market participation was generally tilted towards larger, safer companies. Several countries, such as Portugal and Spain, had comparatively small but diverse corporate bond markets, which included a wide variety of credit risks. To guard against remaining selection biases, I always demean the series within country, and as a robustness check, also across country-specific time periods, using the algorithm of Bai and Perron (2003) to detect structural breaks. I also test the validity of my results across a variety of subsamples and historical time periods. The focus throughout the paper is on variation across time rather than across countries: most statistics shown are cross-country averages, and regressions include country fixed effects, with various robustness checks for stability across time periods. Even though it is not possible to eliminate selection bias completely, the impact of this bias on my findings is likely to be small.

A third potential difficulty relates to calculating yields to maturity. Accurate maturity data are difficult to come by for some historical sources, and often do not account for embedded options and bond conversions. In one sense, the long time dimension of my data helps guard against such biases. For countries where I have the microdata, I can observe the first and last trade for each bond, and hence when the bonds were effectively matured or a redemption option exercised. These allow me to obtain additional, and improve existing bond maturity proxies. Some data series also contain information on options, in which case I follow the usual practice of taking the option date as the maturity date if the bond is trading above par (as in, for example, Klovland, 2004). A number of publications also include option-adjusted effective yield estimates, even for historical data, and even for individual bonds (see, for example Mediobanca, Various years). For the early historical period, relatively few bonds had embedded conversion options. That being said, I do sometimes

have to rely on current yields, and some of the secondary sources do not specify whether the yield is calculated as a yield to maturity, or a simple current yield. Over the whole historical sample, the biases arising from uncertainty around maturity dates, and the use of current yield data, are likely to be small.

B. Discount rate co-movement: additional results

Figure A.1: *Co-movement of asset-specific discount rate proxies, first differences*



Note: Pairwise correlation coefficients between 3-year changes in the dividend-price ratio, rent-price ratio and corporate bond spread over rolling decadal windows (e.g. the value for 1875 if the correlation over the window 1870–1880). Shaded areas are 90% confidence intervals, using country-clustered standard errors.

Table A.1: *Discount rate and cashflow news correlations within each country*

	Discount rate news			Cashflow news
	Equity and housing	Equity and corporate bonds	Housing and corporate bonds	Equity and housing
Australia	0.14	0.22**	0.08	0.15
Belgium	0.61***	0.10	0.15	0.57***
Canada		0.21***		
Denmark	−0.01			0.09
Finland	0.16	−0.23	−0.48***	0.29***
France	0.22*	0.06	−0.16	0.40***
Germany	0.09	0.08	−0.09	−0.01
Italy	0.43**	0.28**	0.34**	0.29*
Japan	0.28***	−0.06	−0.02	0.19*
Netherlands	−0.11	0.30	−0.26	0.35***
Norway	−0.05	0.13	−0.18	0.19*
Portugal	−0.34**	−0.04	−0.14	0.47***
Spain	−0.06	−0.24*	0.28***	0.28***
Sweden	0.05	0.15	0.24**	0.16
Switzerland	−0.14	−0.20	0.28**	0.16
UK	0.17	0.00	−0.07	0.40***
USA	0.07	0.04	0.23***	0.31***
Sig. > 0 / Total	4/16	3/16	5/15	11/16
Sig. < 0 / Total	1/16	1/16	1/15	0/16
Not sig. / Total	11/16	12/16	9/15	5/16

Note: Pairwise correlation coefficients. Underlying data are 3-year moving averages, to smooth over timing idiosyncracies across assets. Discount rate and cashflow news for equities and housing are estimated as the innovations to present value of future returns and cashflows, respectively, for each asset, using a VAR in returns, cashflow growth and valuations, and present value moment constraints. Discount rate news for bonds is the change in the spread. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$

Table A.2: *Discount rate and cashflow news correlations within each country, after 1950*

	Discount rate news			Cashflow news
	Equity and housing	Equity and corporate bonds	Housing and corporate bonds	Equity and housing
Australia	0.14	0.22**	0.08	0.15
Belgium	0.61***	0.10	0.15	0.57***
Canada		0.21***		
Denmark	−0.01			0.09
Finland	0.16	−0.23	−0.48***	0.29***
France	0.22*	0.06	−0.16	0.40***
Germany	0.09	0.08	−0.09	−0.01
Italy	0.43**	0.28**	0.34**	0.29*
Japan	0.28***	−0.06	−0.02	0.19*
Netherlands	−0.11	0.30	−0.26	0.35***
Norway	−0.05	0.13	−0.18	0.19*
Portugal	−0.34**	−0.04	−0.14	0.47***
Spain	−0.06	−0.24*	0.28***	0.28***
Sweden	0.05	0.15	0.24**	0.16
Switzerland	−0.14	−0.20	0.28**	0.16
UK	0.17	0.00	−0.07	0.40***
USA	0.07	0.04	0.23***	0.31***
Sig. > 0 / Total	4/16	3/16	5/15	11/16
Sig. < 0 / Total	1/16	1/16	1/15	0/16
Not sig. / Total	11/16	12/16	9/15	5/16

Note: Pairwise correlation coefficients. Underlying data are 3-year moving averages, to smooth over timing idiosyncracies across assets. Discount rate and cashflow news for equities and housing are estimated as the innovations to present value of future returns and cashflows, respectively, for each asset, using a VAR in returns, cashflow growth and valuations, and present value moment constraints. Discount rate news for bonds is the change in the spread. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$

C. Return predictability: additional results

C.1 Corporate bond cashflow predictability

Table A.3: *Predicting corporate default rates with yield spreads, US data*

	(1)	(2)
	Default rate, t+1	Δ Default rate, t+1
spread$_t$	1.262***	
	(0.248)	
Δ spread$_t$		0.226***
		(0.221)
R^2	0.378	0.005
Observations	142	141

Note: Dependent (y) variables are the one-year ahead level and absolute change in the corporate bond default rate. The default rate is calculate as the par value of bonds in default relative to total outstanding. Data are for US only. Predictor (x) variables are the level and the change in the corporate bond spread. OLS regressions with heteroskedasticity-robust standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

C.2 Robustness to alternative specifications

Table A.4 assess whether the baseline predictability result holds under different regression specifications. Column 1 shows the baseline estimates in Table 4, and each of the columns 2-10 changes the regression specification or variable definition to assess whether the baseline results still hold. Table A.4 column 2 tests for predictability in nominal, rather than real returns and cashflows, and finds that regression coefficients are essentially unchanged. A similar result comes out of using excess returns over government bills, rather than returns in excess of inflation, as a dependent variable (Table A.4 column 3). This suggests that changes in expected returns are best interpreted as movements in asset-specific risk premiums, rather than shifts in the safe interest rate.[25]

Column 4 of Table A.4 shows that risky asset valuations also predict returns and cashflows at longer horizons. It regresses 5-year ahead average real return, cashflow growth or spread growth on the valuation dp_t. Over the longer horizon, the variation in excess returns and cashflows becomes even more powerful. A 1 percentage point higher dividend-price ratio forecasts 5 percentage points higher cumulative returns, and 10 percentage points lower cumulative real dividend growth 5 years ahead. 1 percentage point higher rent-price ratios forecast 8 percentage point higher cumulative returns, and 5 percentage point lower real rental growth. Elevated corporate bond spreads more or less mean revert within 5 years: a 1 percentage point higher bond spread at t forecasts 0.7 percentage points lower spreads at $t+5$. Finally, Table A.4 column 5 assesses the equity and housing return predictability using a VAR in dp, r and dg, which respects the present value moment constraints implied by equation (3). The details of the VAR estimation are provided in Appendix C.3. The VAR

[25] In the present value equation (1), the discount rate DR is the sum of the safe rate R^S and a risk premium RP_i.

Table A.4: *Return and cashflow predictability: alternative specifications*

	Panel 1: Different definitions and specifications				
	(1)	(2)	(3)	(4)	(5)
	Baseline	Nominal returns and cashflows	Excess returns	5-year ahead average growth	Constrained VAR
Equity:					
r_{t+1}	0.055***	0.037***	0.038***	0.039***	0.058***
	(0.014)	(0.013)	(0.011)	(0.012)	(0.012)
dg_{t+1}	-0.120***	-0.138***		-0.081***	-0.133***
	(0.030)	(0.029)		(0.015)	(0.020)
Housing:					
r_{t+1}	0.066***	0.067***	0.068***	0.064***	0.062***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.007)
dg_{t+1}	-0.023**	-0.022***		-0.042***	-0.029***
	(0.009)	(0.008)		(0.011)	(0.008)
Corporate bonds:					
r_{t+1}	0.030***	0.016***	0.022***	0.022***	
	(0.007)	(0.003)	(0.004)	(0.007)	
$\Delta spread_{t+1}$	-0.268***			-0.139***	
	(0.038)			(0.011)	
	Panel 2: Different time periods				
	(6)	(7)	(8)	(9)	(10)
	Year fixed effects	Structural breaks	Post-1950	Expansions	Recessions
Equity:					
r_{t+1}	0.061***	0.110***	0.077***	0.057***	0.031
	(0.016)	(0.021)	(0.013)	(0.015)	(0.034)
dg_{t+1}	-0.153***	-0.221***	-0.111***	-0.125***	-0.094*
	(0.043)	(0.038)	(0.042)	(0.031)	(0.052)
Housing:					
r_{t+1}	0.069***	0.118***	0.066***	0.061***	0.083***
	(0.013)	(0.025)	(0.010)	(0.010)	(0.022)
dg_{t+1}	-0.023***	-0.024	-0.022	-0.027***	-0.017
	(0.007)	(0.028)	(0.015)	(0.009)	(0.014)
Corporate bonds:					
r_{t+1}	0.023***	0.030***	0.022***	0.025***	0.039***
	(0.006)	(0.008)	(0.007)	(0.007)	(0.013)
$\Delta spread_{t+1}$	-0.272***	-0.307***	-0.340***	-0.240***	-0.361***
	(0.040)	(0.040)	(0.062)	(0.045)	(0.066)

Note: Predictive coefficents on the log dividend-price ratio for equity, log rent-price ratio for housing, and percentage point spread for corporate bonds. Dependent variables in rows. Specifications in columns. r_{t+1} is log real total return; dg_{t+1} is log real dividend or rent growth, Δspread_t is the change in corporate bond credit spread. Baseline is OLS with fixed effects. Excess returns are net of short-term government bill rates. Constrained VAR estimates the VAR in three variables – r, dg and dp, using GMM subject to present value moment constraints. Structural breaks adjust not only for country-specific, but also time-specific movements in the mean of each variable, with break dates identified using the Bai-Perron procedure. Expansions and recessions are dated using the Bry-Boschan algorithm. Country clustered standard errors in parentheses. VAR estimation also allows for clustering across time. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

allows for a richer dependence structure across variables (dp, r and dg for each asset class) and over time, but the resulting coefficient estimates are the same as the OLS in Column 1.

Panel 2 of Table A.4 tests for coefficient stability across different time periods. Column 6 starts by taking out the common cross-country time variation through year fixed effects, and finds the results unchanged. Column 7 adjusts each series for structural breaks in the valuation ratio dp_t, following the methodology established by Lettau and Van Nieuwerburgh (2008) for the US equity market. To do this, I first identify the break dates for each country using the Bai and Perron (2003) procedure, allowing for a maximum of 3 country-specific breaks. I then demean the variables dp_t, r_t and dg_t within each country and structural break specific time period, before running the usual regressions (4) and (5) on the adjusted data.[26] The results for adjusted data are similar to baseline, and if anything find somewhat stronger return predictability, with a 1 percentage point increase in the dividend-price or rent-price ratio forecasting 3 percentage point lower returns, and a 1 percentage point elevated bond spread forecasting a 0.33 percentage point spread decline in the following year.

Table A.4 columns 8–10 test for the stability of results across different time periods, to check whether the baseline results are applicable to the more recent data, and across the different stages of the business cycle. This is generally the case, with return predictability somewhat stronger after 1950, and relatively stable across expansions and recessions.[27] If anything, predictability is somewhat more robust during expansions than recessions, which favours sentiment and expectation-based explanations of excess financial volatility: whereas we would expect discount rate effects to be strongest in recessions when consumption is hit hard, the overoptimism and irrational expectations are likely to be more prevalent during expansions.

Table A.5 tests the predictability of returns on each asset class within individual countries. The coefficients on all return, dividend growth and spread growth variables in columns 1–6 are of similar magnitude to the baseline panel regression in Table 4. Because of the annual data frequency and the lower number of observations, the statistical power of the estimates is somewhat smaller than that in the panel regression. Equity cashflows, housing returns, and bond return and spread growth are all robustly predictable. The coefficients in Table A.5 columns 2, 3, 5 and 6 are significant in almost every country, with signs and magnitudes consistent with the panel. The same pattern holds if we limit the sample to the post 1950 period, with results shown in Table A.6.

The evidence for within-country predictability of equity returns and housing cashflows is somewhat more mixed. The equity return coefficients in column 1 display the right sign and magnitude, but are only significant in one in every 3 countries. The coefficient on equity returns for the US is not significant, in contrast to the findings of Cochrane (2008). This difference mainly comes about from the data sample. Return predictability in the US becomes much stronger, and cashflow predictability – much weaker in the later parts of the sample. Most studies of the US data use the CRSP dataset which starts in 1925, and find strong evidence of return predictability, and only weak evidence for predictable dividend growth. My data are sourced from the S and P 500 index in Shiller (2000) which goes back to 1870. If I limit the estimation to the post-1925 sample, the β coefficient on US equity returns becomes significant, although it does not change much in size. For the longer post-1870 sample, the evidence for the US equity return predictability is weaker, and for dividend growth predictability – stronger, consistent with the findings of Golez and Koudijs (2018). Housing cashflows are only significantly predictable for one in every 4 countries.

[26] For example, similarly to the findings of Lettau and Van Nieuwerburgh (2008), the US dividend-price ratio displays two structural breaks, in 1954 and 1995. The structural break adjusted regression demeans the dp_t variable in the 1870–1954 period using the 1870–1954 mean, the 1955–1995 dp_t using the 1955-1995 series mean, and the remainder using the post-1995 mean.

[27] The recession and expansion periods are identified by applying the Bry and Boschan (1971) algorithm to real GDP per capita (see Jordà et al., 2013, for further details on the application to this dataset).

Table A.5: *Return and cashflow predictability in individual countries*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity		Housing		Corporate bonds	
	r_{t+1}	dg_{t+1}	r_{t+1}	dg_{t+1}	r_{t+1}	$\Delta spread_{t+1}$
Australia	0.202***	-0.012	0.035	-0.030	0.023**	-0.328***
	(0.061)	(0.065)	(0.027)	(0.027)	(0.011)	(0.082)
Belgium	0.068	-0.123	-0.045	-0.152***	-0.015	-0.356***
	(0.056)	(0.142)	(0.043)	(0.054)	(0.058)	(0.088)
Canada	0.054	-0.220***			0.042***	-0.187
	(0.038)	(0.047)			(0.013)	(0.134)
Denmark	0.002	-0.132***	0.062***	-0.002		
	(0.031)	(0.046)	(0.015)	(0.007)		
Finland	0.066	-0.218**	0.104***	-0.034	0.003	-0.259
	(0.068)	(0.110)	(0.028)	(0.029)	(0.010)	(0.260)
France	0.210***	0.063	0.157***	0.085***	-0.002	-0.129**
	(0.042)	(0.066)	(0.036)	(0.027)	(0.020)	(0.050)
Germany	-0.048	-0.350***	0.095***	0.008	0.038***	-0.166**
	(0.052)	(0.077)	(0.022)	(0.009)	(0.012)	(0.075)
Italy	0.053	-0.158	0.043***	-0.031	0.058***	-0.566***
	(0.087)	(0.115)	(0.011)	(0.024)	(0.017)	(0.115)
Japan	0.049**	-0.046*	0.072***	-0.026	0.024	-0.139*
	(0.024)	(0.025)	(0.027)	(0.017)	(0.016)	(0.073)
Netherlands	0.043	-0.348***	0.073***	-0.024		
	(0.057)	(0.070)	(0.021)	(0.017)		
Norway	0.027	-0.131**	0.119***	0.019	0.087***	-0.317***
	(0.053)	(0.058)	(0.038)	(0.027)	(0.017)	(0.081)
Portugal	0.039	0.003	0.010	-0.080**	0.045***	-0.307***
	(0.051)	(0.111)	(0.037)	(0.032)	(0.017)	(0.106)
Spain	0.116***	-0.112*	0.067**	-0.015	-0.015	-0.032
	(0.044)	(0.065)	(0.028)	(0.015)	(0.013)	(0.118)
Sweden	0.005	-0.299***	0.055**	-0.015	0.041***	-0.125*
	(0.057)	(0.052)	(0.027)	(0.015)	(0.014)	(0.071)
Switzerland	0.003	-0.105	0.041	-0.042*	0.026***	-0.283***
	(0.058)	(0.075)	(0.029)	(0.022)	(0.007)	(0.103)
UK	0.210***	-0.202***	0.099***	-0.001	0.013	-0.357***
	(0.067)	(0.055)	(0.029)	(0.024)	(0.018)	(0.119)
USA	0.051	-0.090***	0.158***	-0.044	0.038***	-0.233***
	(0.035)	(0.028)	(0.059)	(0.032)	(0.005)	(0.067)
Significant/Total	5/17	11/17	12/16	4/16	9/15	12/15

Note: OLS regressions at country level. Predictor (x) variables are the log dividend-price ratio, log rent-price ratio and percentage point corporate bond spread. Dependent (y) variables in columns. r is the log real total return, dg is log real dividend or rental growth. Δ spread is the percentage point change in the bond spread. Heteroskedasticity-robust standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

Table A.6: *Return and cashflow predictability in individual countries, post-1950*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity		Housing		Corporate bonds	
	r_{t+1}	dg_{t+1}	r_{t+1}	dg_{t+1}	r_{t+1}	$\Delta spread_{t+1}$
Australia	0.374***	-0.002	0.023	-0.032	0.017	-0.269***
	(0.130)	(0.144)	(0.022)	(0.025)	(0.012)	(0.090)
Belgium	0.079	-0.036	0.064***	0.019**	0.036**	-0.361***
	(0.068)	(0.061)	(0.019)	(0.009)	(0.016)	(0.126)
Canada	0.069	-0.234***			0.050**	-0.156**
	(0.058)	(0.079)			(0.024)	(0.076)
Denmark	0.029	-0.156**	0.092***	0.003		
	(0.040)	(0.062)	(0.024)	(0.008)		
Finland	0.018	-0.300**	0.028	-0.139***	0.003	-0.259
	(0.084)	(0.141)	(0.065)	(0.050)	(0.010)	(0.260)
France	0.134**	-0.048	0.138***	0.073***	-0.009	-0.123**
	(0.066)	(0.044)	(0.029)	(0.025)	(0.009)	(0.052)
Germany	-0.049	-0.420***	0.046	-0.023*	0.030**	-0.136*
	(0.102)	(0.125)	(0.029)	(0.013)	(0.013)	(0.082)
Italy	0.119	-0.143*	0.087**	-0.114*	0.030**	-0.722***
	(0.081)	(0.074)	(0.037)	(0.061)	(0.014)	(0.142)
Japan	0.095***	0.025	0.121***	0.047*	0.003	-0.099
	(0.031)	(0.023)	(0.040)	(0.024)	(0.013)	(0.095)
Netherlands	0.074	-0.376***	0.111***	0.023**		
	(0.068)	(0.078)	(0.025)	(0.010)		
Norway	0.112	-0.097	0.068*	-0.002	0.101***	-0.278**
	(0.099)	(0.077)	(0.035)	(0.011)	(0.017)	(0.120)
Portugal	0.063	0.039	0.012	-0.077**	0.039***	-0.392***
	(0.082)	(0.185)	(0.038)	(0.033)	(0.012)	(0.144)
Spain	0.090*	-0.111***	0.055*	-0.016	-0.028***	-0.107
	(0.054)	(0.042)	(0.029)	(0.025)	(0.010)	(0.098)
Sweden	0.066	-0.279***	0.044	-0.008	-0.003	-0.395**
	(0.093)	(0.065)	(0.033)	(0.013)	(0.044)	(0.191)
Switzerland	0.072	-0.064	0.042	-0.040***	0.024***	-0.259**
	(0.090)	(0.146)	(0.029)	(0.009)	(0.007)	(0.109)
UK	0.284***	-0.031	0.073**	0.003	0.008	-0.379***
	(0.093)	(0.027)	(0.029)	(0.023)	(0.019)	(0.137)
USA	0.098**	-0.041**	0.096*	-0.030	0.054***	-0.496***
	(0.045)	(0.019)	(0.057)	(0.026)	(0.008)	(0.120)
Significant/Total	6/17	9/17	10/16	9/16	9/15	12/15

Note: OLS regressions at country level, post-1950 period. Predictor (x) variables are the log dividend-price ratio, log rent-price ratio and percentage point corporate bond spread. Dependent (y) variables in columns. r is the log real total return, dg is log real dividend or rental growth. Δ spread is the percentage point change in the bond spread. Heteroskedasticity-robust standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

The extent of excess volatility can be roughly approximated by comparing the size of the r and dg coefficients for housing and equities, or by looking at the degree of mean reversion for bonds (column 6). For stocks, French and Australian equity returns seem to vary most in excess of fundamentals, with coefficients on r_{t+1} 3 times the size of the panel estimate, and roughly zero dg coefficients. Denmark, Norway and Sweden, on the contrary, show strong cashflow predictability, but only a very weak correlation between equity valuations and year-ahead returns. Jordà et al. (2017a) show that risky returns in Scandinavian countries have been relatively high and stable throughout history, which goes in line with the low levels of excess volatility for these countries. The US market has displayed the largest excess volatility when it comes to housing, with the booms and busts of the 1920s, 1990s and 2000s all occurring without substantial changes in future rental growth. The Italian corporate bond spreads are more excessively volatile than those in other countries, with more than half of any elevated spread level, on average, expected to mean revert during the following year. The Italian bond market has been dominated by relatively mature companies and banks throughout my data sample. Since this type of company is relatively unlikely to default, most of the variation in Italian bond spreads bears little relation to the underlying riskiness of the bond portfolio.

C.3 Discount rate and cashflow news, VAR estimation

Equation (3) decomposes risky asset valuation into a discount rate and cashflow component. Similarly, the variance in valuation ratios dp can be attributed to discount rate and cashflow news, as shown below:

$$\mathrm{Var}(dp_{i,t}) = \underbrace{\mathrm{Var}(\mathbb{E}\sum_{s=0}^{\infty}\rho^s r_{t+1+s})}_{\text{DR news}} + \underbrace{\mathrm{Var}(\mathbb{E}\sum_{s=0}^{\infty}\rho^s dg_{t+1+s})}_{\text{CF news}} - 2\mathrm{Cov}(\mathbb{E}\sum_{s=0}^{\infty}\rho^s r_{t+1+s}, \mathbb{E}\sum_{j=0}^{\infty}\rho^s dg_{t+1+s}) \tag{A.1}$$

To estimate the discount rate and cashflow news components of equity and housing valuations, I follow Golez and Koudijs (2018) and estimate a VAR in three variables $[r_{i,t}, dg_{i,t}, dp_{i,t}] \equiv z_{i,t}$:

$$z_{i,t} = Az_{i,t-1} + u_{i,t} \tag{A.2}$$

$$z_{i,t} = [r_{i,t}, dg_{i,t}, dp_{i,t}]' \tag{A.3}$$

$$\mathbb{E}(zz') = \Gamma; \quad \mathbb{E}(uu') = \Sigma; I = (e1, e2, e3) \tag{A.4}$$

The VAR is estimated using GMM, with the following 9 moment conditions:

$$E[(z_{i,t+1} - z_{i,t}) \otimes z_{i,t}] = 0 \tag{A.5}$$

The present value relation in (3) imposes three additional moment restrictions:

$$(e1' - e2' + \rho e3')A = e3' \tag{A.6}$$

I estimate the VAR using 6-equation GMM subject to the constraints in (A.6), and accounting for time and cross-sectional dependence in standard errors. The resulting estimates allow me to do two things. First, I can estimate the relative contribution of discount rate and cashflow news to the variance of the dividend or rent to price ratios in (**??**):

$$\mathrm{Var}(dp_{i,t}) = e3\Gamma e3 = \underbrace{e1'A(I-\rho A)^{-1}\Gamma e3}_{\text{DR news}} - \underbrace{e2'A(I-\rho A)^{-1}\Gamma e3}_{\text{CF news}} \tag{A.7}$$

Here, A is the VAR coefficient matrix, and Γ is the covariance matrix of the regressors in (A.4).

Second, following Campbell (1991), I can derive a "clean" series of the time-varying risk premium and fundamental component of returns on each asset – more precisely, the discount rate and cashflow news in the unexpected asset returns $r_{i,t+1} - \mathbb{E}r_{i,t+1}$:

$$r_{i,t+1} - \mathbb{E}r_{i,t+1} = \underbrace{-e1'\rho A(I-\rho A)^{-1}u_{i,t+1}}_{\text{DR news}} + \underbrace{(e1 + e1'\rho A(I-\rho A)^{-1})u_{i,t+1}}_{\text{CF news}} \tag{A.8}$$

As a robustness check, I also use an excess return VAR specification $z_t = [r_t^e, r_t^f dg_t, dp_t]'$ to check if changes in discount rates are driven by the risk-free rate r_t^f, rather than risk premiums. Here, r_t^e is the excess return over the risk-free bill rate, $r_t^e = log(1 + R_t - R_t^{\text{bill}})$, and r_t^f is the the real short-term risk free rate $r_t^f = log[R_t^{\text{bill}} - \pi_t]$. It turns out that the risk-free rate is not forecastable by the valuation ratios, which means that we can think of the "discount rate news" term above as risk premium news. Results are available upon request.

For corporate bonds, Nozawa (2017) shows that the credit spread can be expressed as a sum of expected returns, and expected default risk over the remaining maturity of the bond – taken to be 10 years, the maturity I target in the data. Since I do not observe default risk, I simply compare the variance of the corporate bond spread with the variance of future spread growth, discounted at factor ρ, and take the residual to be attributable to cashflow news:

$$\text{Var}(\text{spread}_t) = \text{Var}(\sum_{s=1}^{s=9} \rho^s \Delta\text{spread}_{t+s}) + \text{Cashflow news} \tag{A.9}$$

Since spread changes should be proportional to log price growth, I use the same linearisation constant $\rho = 0.96$ as for housing and equities, but results are not sensitive to this. An alternative way of assessing the importance of expected returns is simply to regress the ten-year ahead credit spread growth on the current credit spread – an exercise that, similarly to the long-horizon regressions in Table A.4, show that almost all of the variation in credit spreads can be accounted for by expected returns over the lifetime of the bond. Due to the lack of corporate default data outside of the US, and the fact that most spread variation reflects future expected returns, I simply use the change in the bond spread as a proxy for the discount rate news on this asset class.

Table A.7 shows the estimated VAR for housing and equity, using GMM specified in equations (A.5) and (A.6), and the corresponding variance decomposition rations in equation (A.7). Dependent variables z_{t+1} are in columns, and predictor variables z_t are in rows. As in Table 4, the first two columns present the predictive coefficients on next period's real equity returns r_{t+1} and real dividend growth dg_{t+1}. The bottom row uses the dividend-to-price ratio dp_t as a predictor, so the estimates in the first two columns row 3 correspond directly to the OLS estimates in the first two columns row 1 in Table 4.

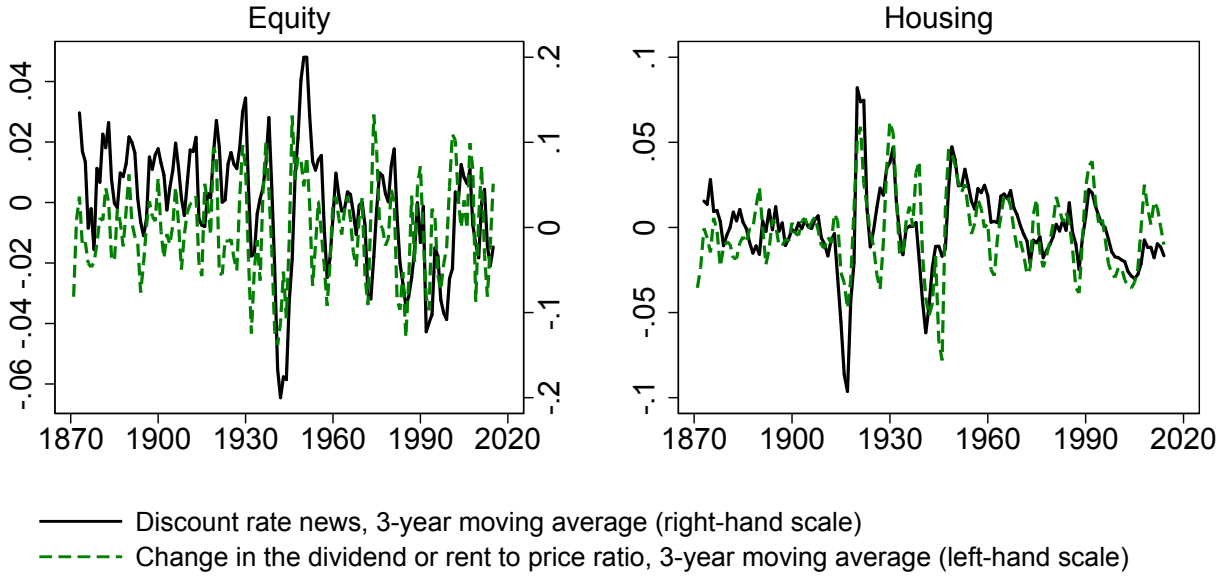
The coefficients on returns and dividend growth in row 3 are more or less unchanged when compared to the OLS estimation in Table 4. Compared to OLS, the VAR estimates a richer dynamic structure, also allowing current returns and dividend growth r_t and dg_t to predict future dividend and rental growth. The corresponding coefficients are in the top two rows of the table. Unlike the results in the literature on the US, current returns actually help predict future returns with a positive sign, even conditional on current valuation ratios. This is suggestive of the existence of aggregate momentum in the housing and equity markets. The coefficients are small – on average only one-tenth of high equity returns, and one-fifth of high housing returns is sustained into next period, but they do paint a more nuanced picture of the expected return variation. Even though high returns this year mean that the return is likely to be somewhat above mean next year, a prolonged

Table A.7: *Return predictability in a VAR*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity			Housing		
	r_{t+1}	dg_{t+1}	dp_{t+1}	r_{t+1}	dg_{t+1}	dp_{t+1}
Estimated coefficients:						
r_t	0.094***	0.034	-0.063*	0.217***	-0.009	-0.236***
	(0.034)	(0.044)	(0.036)	(0.047)	(0.033)	(0.047)
dg_t	0.039	-0.049	-0.091**	0.155***	0.446***	0.306***
	(0.027)	(0.048)	(0.044)	(0.042)	(0.049)	(0.045)
dp_t	0.058***	-0.133***	0.840***	0.062***	-0.029***	0.954***
	(0.012)	(0.020)	(0.019)	(0.007)	(0.008)	(0.008)
Variance decomposition of dp_t:						
DR share			32			58
CF share			68			42
Observations			2177			1793

Note: VAR subject to present value moment constraints. Estimated using GMM, accounting for cross-sectional and time dependence in standard errors. Variables are log real total return r, log real dividend or rent growth dg, and log of dividend-price or rent-price ratio dp. DR share is the proportion of variation in dp_t that is due to discount rate news. CF share is the proportion of variation in dp_t that is due to expected cashflow movements. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

Figure A.2: *Discount rate news and raw valuation measures*



Note: Discount rate news are the change in the present value of expected future returns in any given year.

period of high returns raises valuations dp, and eventually is followed by low returns, and mean reversion, which persists for several years. The estimates in the bottom row also show that valuation ratios are very persistent, with autocorrelation coefficients of 0.84 for equities and 0.95 for housing. The variance decomposition shares show that most variance in equity valuations comes about from future cashflows, and in housing valuations – from expected returns.

The annual time series for discount rate news on equity and housing, estimated using equation (A.8) are shown in Figure A.2, alongside changes in the "raw" valuation metric dp. Consistent with Figure 1, both series are plotted as three-year moving averages. Changes in asset valuations dp closely follow those in discount rate news, and hence serve as useful proxies for variation in discount rates or systematic expectation errors.

C.4 The importance of discount rate news through time

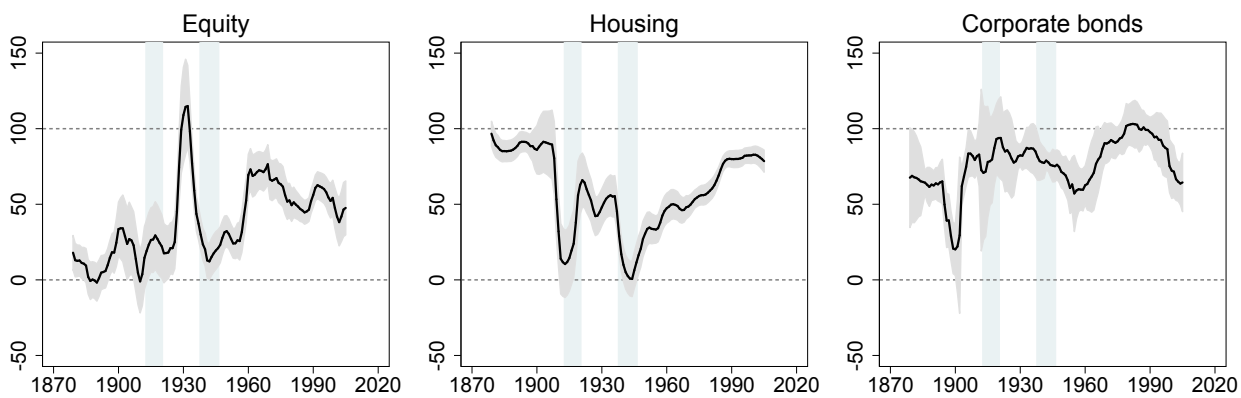
Figure A.3 assesses how the excess volatility for each asset class has varied over time. It plots the relative importance of discount rate news over centered 20-year rolling time windows. For each time window, the discount rate news share is computed as the ratio of the predictive coefficient β in the return regression (4) to the sum of β and the coefficient γ from the cashflow growth regression (5):

$$\text{DR share}_t = \beta_{i,2,t-9,t+10} / (\beta_{i,2,t-9,t+10} + \gamma_{i,2,t-9,t+10}) \tag{A.10}$$

For corporate bonds, the discount rate share is computed by comparing the variance of 10-year ahead spread growth (discount rates), and the spread (bond valuations), within the 20-year window. As in Table 5, the value of 100 indicates that all the variance is accounted for by discount rate news, and none – by fundamentals.

Starting with the left-hand panel of Figure A.3, the time trend suggests that if anything, equity markets have become more excessively volatile over time. This is consistent with the fact that the

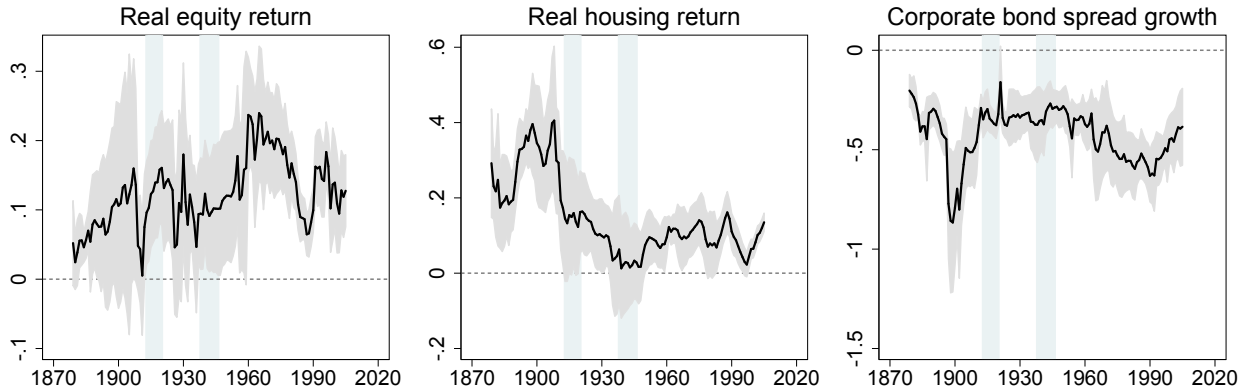
Figure A.3: *The importance of time varying discount rates through time*



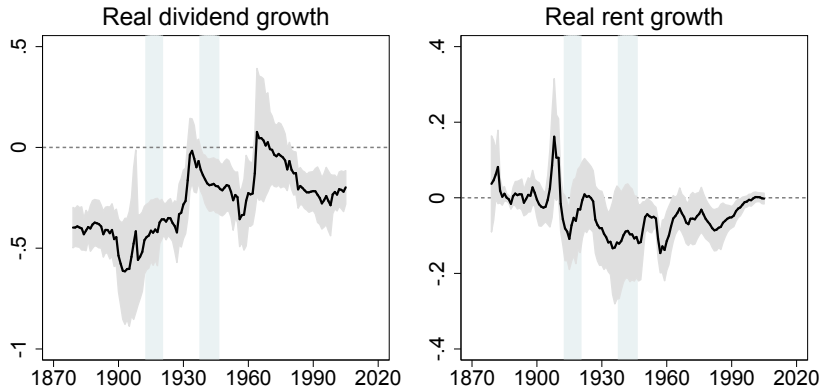
Note: The share of variation in valuation ratios dp that is accounted for by discount rate news, for each asset class, centered 20-year moving windows. Share equal to 100 means all of the variation in valuations is accounted for by discount rate news. Calculated using rolling 20-year window predictability regressions of 10-year ahead discounted returns. For housing and equity, the share equals the ratio of the predictive coefficient on the return to the sum of the return and dividend growth coefficients, $\text{DR share}_t = \beta_{i,2,t-9,t+10} / (\beta_{i,2,t-9,t+10} + \gamma_{i,2,t-9,t+10})$. For bonds, it is the proportion of spread variance that is explained by the co-variation with future spread growth, within the 20-year rolling window. Horizontal shaded grey areas are 90% confidence intervals. Vertical shaded blue areas are the two world wars.

Figure A.4: *Return and cashflow predictability through time*

(a) *Predictability of real returns:*



(b) *Predictability of real dividend and rent growth*



Note: Return and cashflow predictability regression coefficients, calculated using regressions over 20-year rolling windows. Panel (a) shows the $t+1$ return coefficient $\beta_{i,2,t-9,t+10}$ in the predictive regression (4), calculated over the window $t-9$ to $t+10$ years, for each year t. Estimates use OLS with fixed effects and country-clustered standard errors. Horizontal shaded grey areas are 90% confidence intervals. Vertical shaded blue areas are the two world wars.

underlying equity returns have become somewhat more volatile, while cashflows have not (Figure 3). The Figure also highlights the Great Depression of the 1930s as the period when discount rates, rather than fundamentals were particularly important. This suggests that risk tolerance and risk perception played an important role in the financial crises of the 1930s – a fact highlighted by a number of contemporaries, including Keynes (1936). Turning to housing, the world wars stand out as the two large shocks to fundamentals. During these periods, almost all of the housing market volatility was attributable to cashflows. Excess volatility in housing was high in the late 19th century, low in the mid-20th century, and steadily increased from the low post-war level in the six decades following 1950. Throughout the sample, the variation in corporate bond spreads is largely attributable to future returns.

Figure A.4 also separates out the importance of discount rate news relative to cashflows into

standalone discount rate and cashflow news importance. Put differently, it plots the rolling-window β (Figure A.4a) and γ (Figure A.4b) coefficients over time. The predictability for equity returns is strongest over the recent time period, while that of housing returns – during the late 19th century. Dividend growth predictability largely stems from the period before the 1930s, which helps explain the lack of dividend growth predictability found in the post-1925 US data (Cochrane, 2008).

D. Cross-asset predictability: additional results

Table A.8: *Predictability of cashflows across asset classes*

	(1)	(2)	(3)	(4)
	Unconditional		Conditional	
	Equity dg_{t+1}	Housing dg_{t+1}	Equity dg_{t+1}	Housing dg_{t+1}
Dividend-price ratio		0.004	-0.090***	0.007
		(0.008)	(0.033)	(0.007)
Rent-price ratio	-0.055**		-0.028	-0.025*
	(0.027)		(0.038)	(0.013)
Bond spread	-0.009	0.006	-0.006	0.007
	(0.008)	(0.004)	(0.007)	(0.004)
R^2	0.006	0.005	0.032	0.013
Observations	1225	1220	1225	1220

Note: OLS regressions of cashflows on one asset class on discount rates of other asset classes. All specifications use country fixed effects. Predictor (y) variables in rows. Dividend-price and rent-price ratios are in logs. Corporate bond spread is in percentage points dg is log real dividend or rental growth. Country-clustered standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

Table A.9: *Return predictability using macro-financial risk factors: alternative specifications*

	(1)	(2)	(3)
	Equity r_{t+1}	Housing r_{t+1}	Corporate bond $\Delta spread_{t+1}$
Panel 1: Conditional predictability			
Dividend-price ratio	0.042***		
	(0.014)		
Rent-price ratio		0.072***	
		(0.011)	
Bond spread			-0.315***
			(0.064)
$\Delta_3 Real\ Consumption_t$	-0.224	0.233***	-0.235
	(0.144)	(0.073)	(0.446)
$Surplus\ Consumption_t$	-0.006	-0.107	-0.341
	(0.151)	(0.081)	(0.685)
cay_t	0.009	0.014	0.441
	(0.043)	(0.015)	(0.307)
$\Delta_3 Bank\ Leverage_t$	-0.073*	-0.018	-0.095
	(0.038)	(0.015)	(0.158)
$\Delta_3 Real\ Bank\ Assets_t$	-0.018	0.006	0.420
	(0.056)	(0.024)	(0.268)
$\Delta_3 Real\ Credit_t$	-0.009	0.062***	0.162
	(0.041)	(0.019)	(0.202)
$log(MCAP_t/GDP_t)$	-0.034***	0.003	-0.002
	(0.008)	(0.003)	(0.035)
$Term\ Spread_t$	0.014**	0.006***	-0.013
	(0.006)	(0.001)	(0.031)
R^2	0.044	0.123	0.141
Observations	1430	1385	1103
Panel 2: 5-year ahead average returns			
$\Delta_3 Real\ Consumption_t$	-0.110**	0.012	-0.064
	(0.055)	(0.059)	(0.203)
$Surplus\ Consumption_t$	-0.027	0.082	-0.163
	(0.087)	(0.061)	(0.214)
cay_t	-0.007	0.020	0.018
	(0.039)	(0.023)	(0.061)
$\Delta_3 Bank\ Leverage_t$	-0.096***	-0.020*	0.103
	(0.020)	(0.011)	(0.092)
$\Delta_3 Real\ Bank\ Assets_t$	-0.073**	-0.030	0.049
	(0.032)	(0.028)	(0.064)
$\Delta_3 Real\ Credit_t$	0.045	0.023	0.029
	(0.030)	(0.025)	(0.090)
$log(MCAP_t/GDP_t)$	-0.044***	-0.002	-0.021
	(0.007)	(0.004)	(0.037)
$Term\ Spread_t$	0.004	0.005**	0.026***
	(0.003)	(0.002)	(0.010)
R^2	0.141	0.048	0.043
Observations	1439	1357	1055

Table A.9: *Return predictability using macro-financial risk factors: alternative specifications, continued*

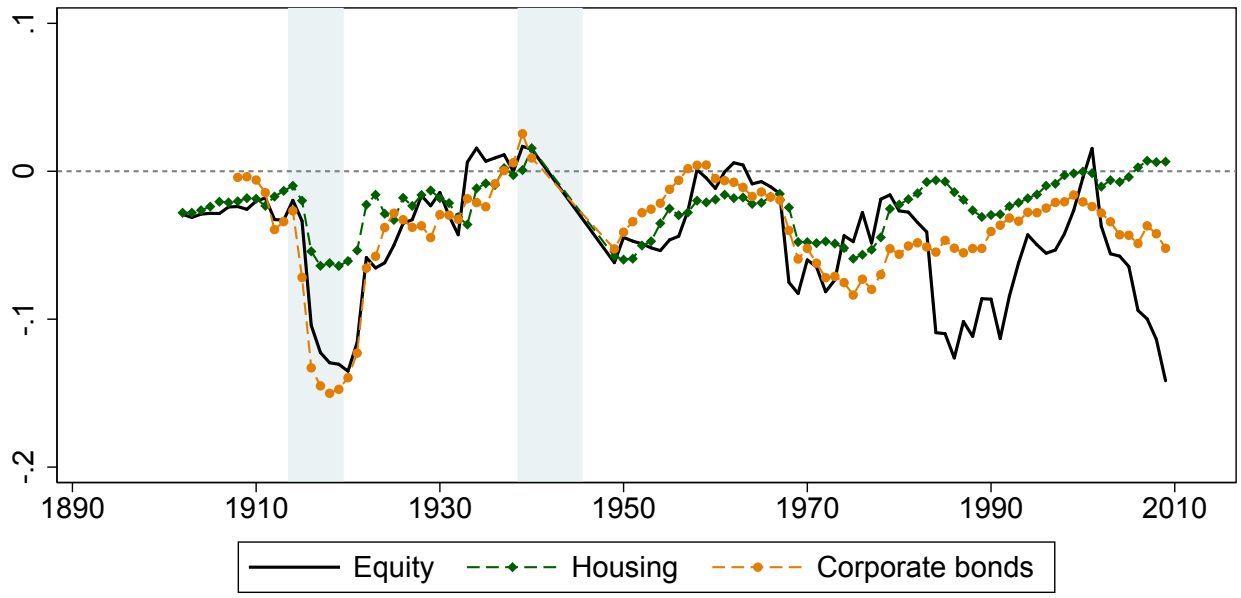
	(1)	(2)	(3)
	Equity r_{t+1}	Housing r_{t+1}	Corporate bond $\Delta spread_{t+1}$
	Panel 3: Post 1950		
$\Delta_3 Real\ Consumption_t$	-0.564*	0.482***	1.175
	(0.307)	(0.130)	(1.043)
$Surplus\ Consumption_t$	-0.050	-0.036	-1.354
	(0.352)	(0.137)	(1.071)
cay_t	-0.008	-0.004	0.263
	(0.062)	(0.023)	(0.333)
$\Delta_3 Bank\ Leverage_t$	0.012	-0.033*	0.065
	(0.048)	(0.020)	(0.115)
$\Delta_3 Real\ Bank\ Assets_t$	-0.063	-0.017	0.350
	(0.073)	(0.027)	(0.368)
$\Delta_3 Real\ Credit_t$	-0.051	-0.001	0.214
	(0.076)	(0.033)	(0.261)
$log(MCAP_t/GDP_t)$	-0.045***	0.007	-0.034
	(0.014)	(0.005)	(0.037)
$Term\ Spread_t$	0.009	0.006***	0.041
	(0.009)	(0.001)	(0.041)
R^2	0.060	0.111	0.014
Observations	931	911	755

Note: OLS regressions with country fixed effects. Predictor (x) variables in rows. $\Delta_i Real\ Consumption_t$ is the log change in real consumption per capita from $t-i$ to t. $Surplus\ Consumption_t$ is the real consumption per capita at t relative to a backward-looking 10-year moving average trend, from t-10 to t. cay_t is a proxy for the consumption-wealth ratio, estimated as the deviations from the cointegrating relationship between real consumption, a proxy for financial wealth (the combined capitalization of the equity, housing and government bond markets) and real wages. $\Delta_i Bank\ Leverage_t$ is the change in the log of bank leverage from $t-i$ to t. $\Delta_i Real\ Bank\ Assets_t$ is the change in the log of real bank assets from $t-i$ to t. $\Delta_i Real\ Credit_t$ is the change in the log of real credit to non-financials from $t-i$ to t. $log(MCAP_t/GDP_t)$ is the log of the market capitalization to GDP ratio. $Term\ Spread_t$ is the percentage point yield spread between the long and short term government debt. Dependent (y) variables in columns. r is the log real total return, and Δ spread is the percentage point change in the bond spread. Country clustered standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

E. Explanations for the time varying risk puzzle: additional results

E.1 Asset-specific risk

Figure A.5: *Time variation in asset-specific risk: alternative discount rate measure*

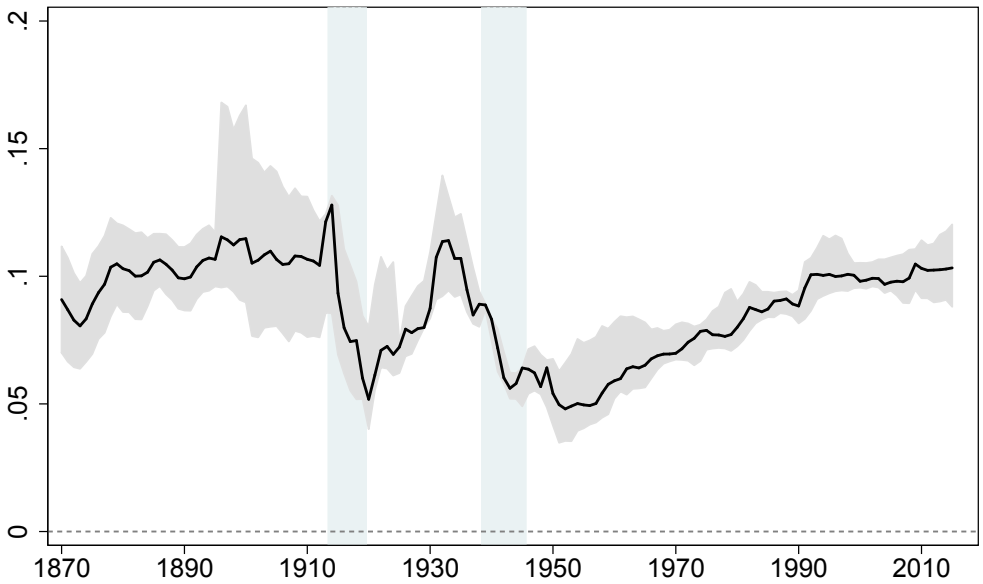


Note: Covariance between the return on equity, housing and corporate bonds, and a proxy for the aggregate discount factor, constructed as the average of asset-specific sentiment on each asset class, normalised to mean 0 and standard deviation of 1 over the full sample. Centered 10-year rolling windows.

Section 7 compared the time variation in riskiness of different asset classes using the covariance with a simple proxy of the discount factor m – the average of standardised asset-specific valuations. Figure A.5 plots the same m, R covariance using a more sophisticated proxy for m which utilises the information on other macro-financial predictors such as the surplus consumption ratio and bank leverage. I construct this proxy as the average of asset-specific sentiment – the inverse of the expected return on each asset class, with expected returns calculated using a regression on the own valuation ratio and a broad range of the macro-financial risk factors (see Section 7.3 for details on the estimation). Similarly to Figure 7, this measures suggests that each of the three asset classes is risky, and that this riskiness varies little over time or across asset classes.

E.2 Non-monetary payoffs

Figure A.6: *The share of rental expenditure in GDP*



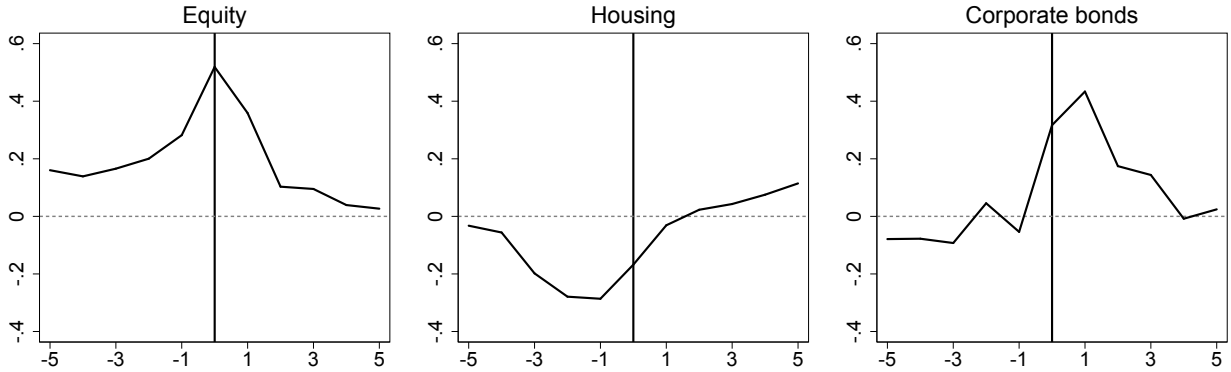
Note: Ratio of total rental expenditure to GDP, which acts a proxy for the marginal utility of housing services. Data for Australia, France, Germany, Sweden, UK and USA. Sweden and USA data start in the 1930, Australia and France around 1900, Germany and UK in 1870.

Figure A.6 provides further evidence on whether the utility of housing services is likely to vary much from year to year. It shows how the rental income to GDP ratio has evolved over the long run in 6 of the countries in my sample. The solid black line shows an unweighted average, while the shaded areas mark the interquartile range. The rent to GDP ratio is a proxy for the housing share in consumption, which in turn is a measure of the marginal utility of housing services. This ratio is relatively stable over time and displays little movement at business cycle frequency. The only sizeable variation occurs around the two world wars – the periods when asset-specific expected returns do actually show some positive co-movement (Figure 5).

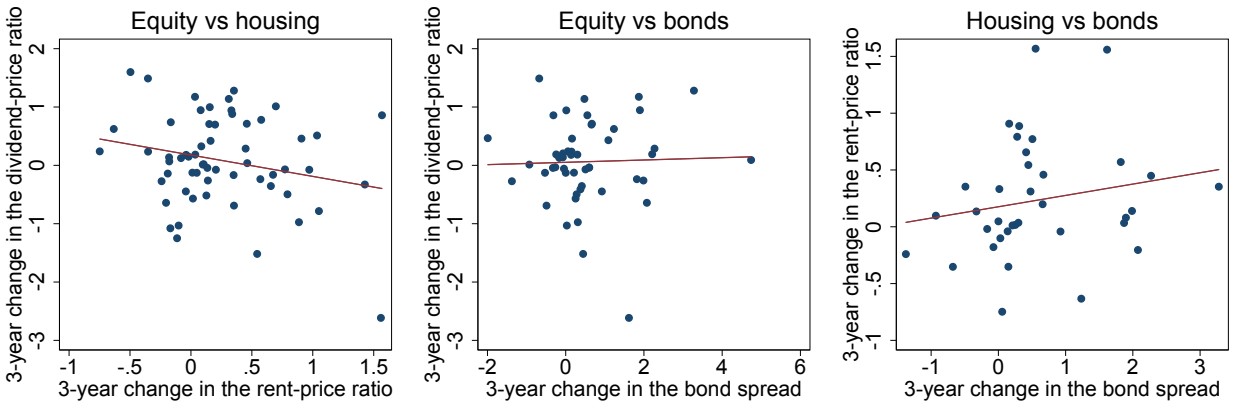
F. Real effects of time-varying sentiment: additional details

Figure A.7: *Risky asset valuations around financial crises*

(a) *Discount rate proxies during the crisis*



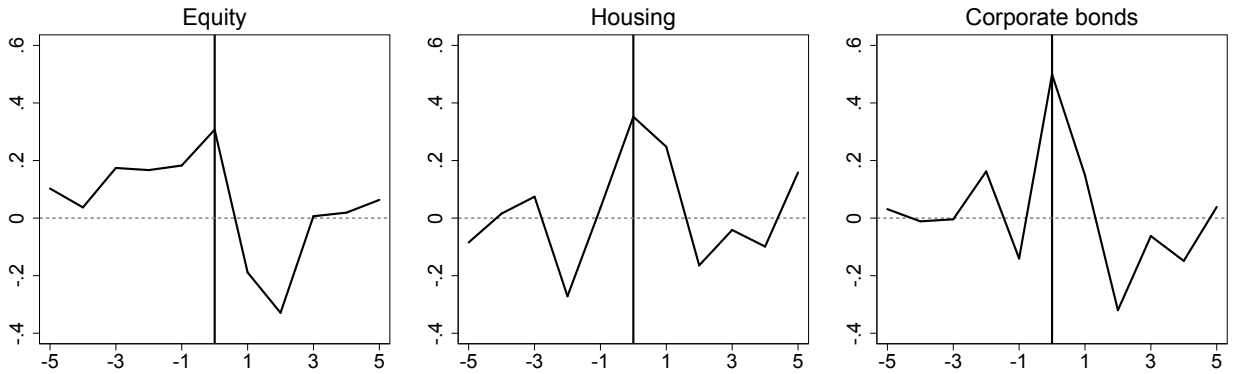
(b) *Co-movement of asset-specific discount rate proxies around the crisis*



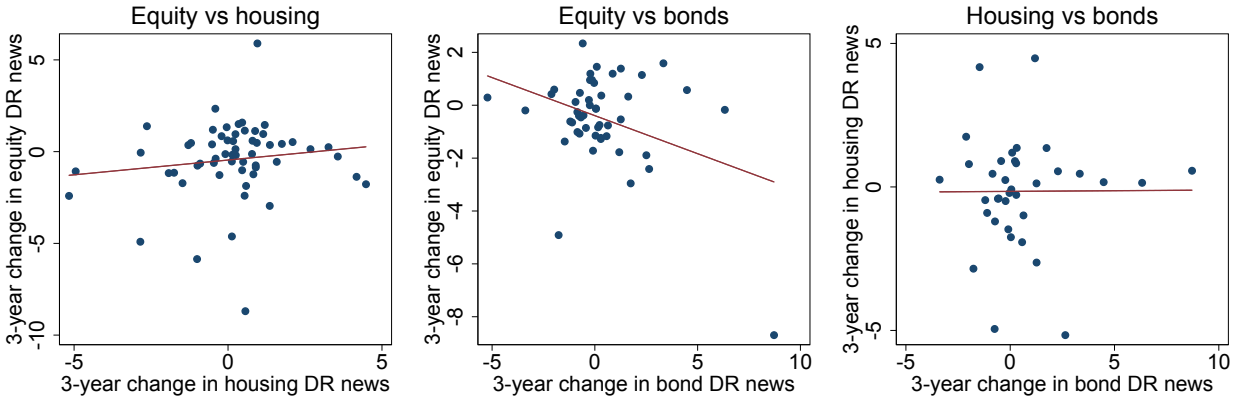
Note: Financial crisis at $t = 0$. All data are standardised to mean 0 and standard deviation of 1 in the full sample. Correlations are for the 3-year changes around the crisis year (from $t - 1$ to $t + 1$). Each point on the scatter plot is an individual financial crisis event.

Figure A.8: *Discount rate news around financial crises*

(a) *Discount rate news during the crisis*



(b) *Co-movement of asset-specific discount rate news around the crisis*



Note: Financial crisis at $t = 0$. All data are standardised to mean 0 and standard deviation of 1 in the full sample. Correlations are for the 3-year averages around the crisis year (from $t - 1$ to $t + 1$). Each point on the scatter plot is an individual financial crisis event. Discount rate news correspond to changes in the present in future expected returns.