Title: The Co-Movement Puzzle

Authors: Dmitry
Kuvshinov

Date: April 2021

RTG 2281 – Discussion Papers

No. 2021-6

Abstract

This paper shows that the discount rates on three major risky asset classes – equity, housing and corporate bonds – do not co-move. Using new long-run data for 17 advanced economies, I show that asset-specific discount rates are uncorrelated, and that asset valuations and macro-financial risk factors predict returns on individual asset classes, but not across asset classes. This lack of co-movement presents a new asset pricing puzzle with important implications. Most theories in macro-finance assume a joint pricing kernel and attribute excess volatility across all asset classes to time variation in this common discount factor. My findings show that most excess volatility is, in fact, asset-specific and is therefore not driven by cross-asset risk factors such as risk aversion, long-run risk, disaster risk and intermediary risk appetite.

Funded by
Deutsche Forschungsgemeinschaft
German Research Foundation

The Co-Movement Puzzle *

Dmitry Kuvshinov §

April 2021

Abstract

This paper shows that the discount rates on three major risky asset classes – equity, housing and corporate bonds – do not co-move. Using new long-run data for 17 advanced economies, I show that asset-specific discount rates are uncorrelated, and that asset valuations and macro-financial risk factors predict returns on individual asset classes, but not across asset classes. This lack of co-movement presents a new asset pricing puzzle with important implications. Most theories in macro-finance assume a joint pricing kernel and attribute excess volatility across all asset classes to time variation in this common discount factor. My findings show that most excess volatility is, in fact, asset-specific and is therefore not driven by cross-asset risk factors such as risk aversion, long-run risk, disaster risk and intermediary risk appetite.

Keywords: discount rates, risk premia, return predictability, excess volatility, discount rate co-movement

JEL classification codes: G12, G15, G17, E44, N20

*An earlier version of this paper was circulated as "The Time Varying Risk Puzzle". This work is part of a larger project kindly supported by a research grant from the Bundesministerium für Bildung und Forschung (BMBF). I am grateful to Christian Bayer, Johannes Beutel, John Cochrane, Barry Eichengreen, Òscar Jordà, Moritz Kuhn, Yueran Ma, Gernot Müller, Björn Richter, Moritz Schularick, Alan Taylor, Kaspar Zimmermann, seminar participants at BI Business School, Bocconi, Bonn, Cologne, Copenhagen Business School, Copenhagen University, Glasgow Adam Smith Business School, Hanken School of Economics, IESE, Sauder School of Business, Sveriges Riksbank, Swedish House of Finance, Toulouse School of Economics and Universitat Pompeu Fabra, as well as conference participants at the Bundesbank conference on Financial Cycles and Regulation, CEPR Economic History Symposium, EAYE Workshop on Housing and Macroeconomy, EHES Congress, ESWM, and the Frankfurt Workshop on Financial History for valuable comments. I would like to thank the researchers who helped with data for individual countries, Katharina Knoll who shared her code, and Francisco Amaral for helpful comments and help collecting the data. Felix Rhiel, Thomas Schwarz, Maira Talha and Yevhenii Usenko have provided invaluable research assistance.

§Department of Economics and Business, Universitat Pompeu Fabra; Barcelona Graduate School of Economics; and CEPR (dmitry.kuvshinov@upf.edu).

1. Introduction

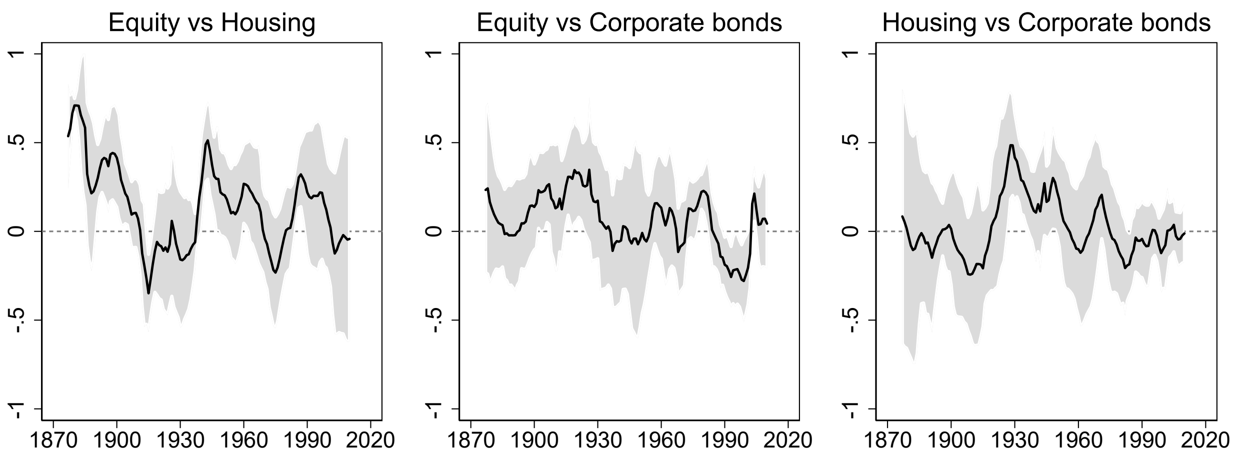
Prices of risky assets fluctuate substantially over time. Much of this variation is difficult to square with changes in fundamentals such as dividends, rents, and corporate default rates (Shiller, 1981; Plazzi, Torous, and Valkanov, 2010; Greenwood and Hanson, 2013). Instead, the dominant explanation for asset price volatility is time variation in the discount rate – the idea that investors are sometimes less willing to save or bear risk, eliciting a low asset price. 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 by studying the co-movement of expected returns across three major asset classes – equity, housing and corporate bonds – in long-run cross-country data. A time varying discount rate should result in asset price variation that is different from fundamentals but common across the different classes of risky assets. For example, if stock prices are high not because of high future dividends but because of a low discount rate, then, other things being equal, house prices should also be high. The importance of discount rate co-movement can be tested by running return predictability regressions within and across asset classes (Campbell and Shiller, 1988; Fama and French, 1989). If discount rate variation is important, high equity valuations should be followed by mean reversion and predict low future returns – not only for stocks, but also for housing and corporate bonds.

The main contribution of this paper is to show that even though expected returns on different asset classes vary over time, they do not co-move. Put differently, asset prices are excessively volatile but this excess volatility is highly asset-specific, with non-fundamental asset price variation for one asset class largely disconnected from that for the other asset classes. Figure 1 shows a preview of this finding. It displays rolling decadal correlations between asset-price-to-fundamentals ratios for equity, housing and corporate bonds for a broad cross-country sample covering years 1870 to 2016. The correlation coefficients are close to zero and mostly statistically insignificant: on average, high dividend-price ratios are not accompanied by high rent-price ratios or corporate bond spreads. In the paper, I show that between one-half and two-thirds of the variation in these valuation ratios is non-fundamental: i.e. attributable to predictable movements in future returns rather than cashflows. But this non-fundamental variation is highly asset-specific, with, for example, high dividend-price ratios predicting low future returns on equity, but not on housing or corporate bonds. Across all the different tests and specifications, cross-asset discount rate co-movement is very much the exception rather than the norm.

The near-absence of discount rate co-movement posits a new asset pricing puzzle with far-reaching implications. Existing literature has focussed on explaining why the common cross-asset discount factor – the price of risk – varies over time, putting forward a number of alternative explanations including time-varying risk aversion (Campbell and Cochrane, 1999), disaster risk (Barro, 2006), long-run risk (Bansal and Yaron, 2004) and intermediary risk appetite (He and Krishnamurthy, 2013). My findings show that, to an extent, this focus on cross-asset risk factors

Figure 1: *Co-movement of discount rate proxies across asset classes*



Note: Pairwise correlation coefficients between the dividend-price ratio, rent-price ratio and corporate bond spread – each demeaned at country level – over rolling centered decadal windows (e.g. the 1875 value covers the window 1870–1880). Shaded areas are 95% confidence intervals.

misses the most important part of the picture: the asset-specific component of excess volatility. Explaining this asset-specific volatility will likely require moving away from standard approaches and the focus on cross-asset variation in macro-financial risk. I find empirical support for two such alternative mechanisms: first, that asset-specific volatility is driven by quantities of capital moving across segmented markets (Gabaix and Koijen, 2020; Greenwood, Hanson, and Liao, 2018); and second, that it is driven by the volatility in the expectation formation process itself, for example through overreaction to asset-specific news (Bordalo, Gennaioli, Ma, and Shleifer, 2020).

To study these empirical relationships in the broadest possible setting, I introduce a novel dataset of asset prices and cashflows across all major advanced economies and risky asset classes covering years 1870–2016. The housing and equity data come from Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2019a), and corporate bond data are from Kuvshinov (2021).[1] I first test whether in this broad setting, prices of risky assets are in fact more volatile than fundamentals. To do this, I run predictive regressions within asset classes, testing for example whether elevated equity valuations are followed by predictable increases in dividends (fundamentals) or falls in stock returns (discount rates). The second step is to test whether this non-fundamental variation is correlated across asset classes. To do this, I first study the correlations between proxies for asset-specific expected returns, and then examine the ability of asset-specific valuations and macroeconomic risk factors to predict returns on multiple asset classes, for example the ability of dividend-price ratios to predict future housing returns.

I find that excess volatility is ubiquitous: all three of equity, housing and corporate bond returns are predictable by, respectively, the dividend-price ratio, the rent-price ratio, and the bond spread.

[1] While the Kuvshinov (2021) paper is in preparation, a summary description of the corporate bond data is provided in Section 3 and the Data Appendix B.

This holds under a vast battery of robustness checks, across different time periods and under alternative estimation techniques and return definitions. Consistent with existing estimates for the US, a 1 standard deviation increase in the asset-specific yield forecasts 2–2.5 ppts lower real total returns one year ahead and 6–10 ppts lower cumulative returns 5 years ahead. But contrary to the consensus for US equities (Cochrane, 2008), cashflow growth is also robustly predictable. A 1 standard deviation higher dividend-price ratio predicts 4.8 percentage points lower year-ahead dividend growth, and higher rent-price ratios predict low future growth in rents. Put differently, if asset valuations are high, we can on average expect both low future returns and high cashflow growth for the specific asset class. A Campbell and Shiller (1988) variance decomposition shows that non-fundamental (expected return) variation is responsible for 45% of the variance in dividend-price ratios, 65% of variance in rent-price ratios and 70% of the variance in corporate bond spreads.

The within-asset-class return predictability shows that the seminal "excess volatility" puzzle of Shiller (1981) is a salient feature of risky asset markets across 17 advanced economies, three major asset classes, and 146 years. But the presence of cashflow predictability makes the low correlations between asset yields in Figure 1 more difficult to interpret: it could be the case that cashflows co-move negatively and expected returns positively, with these two effects netting out to result in the near-zero asset yield correlation. I show that this is not the case. To do this, I first follow Campbell (1991) and decompose each year's unexpected returns (the difference between the realised return and a VAR forecast from the predictive regression) on each asset class into cashflow and discount rate news. It turns out that, if anything, cashflows are more correlated than discount rates: while housing and equity cashflow news display a significant positive correlation of around 0.2, the correlation coefficient between discount rate news on the three asset classes is statistically insignificant and below 0.1. While both discount rate and cashflow correlations are higher during world wars and equity and corporate bond discount rates are correlated in the aftermath of banking crises, other time periods and measurement methods result in consistently low co-movement.

I test for discount rate co-movement more formally using cross-asset-class predictive regressions. The results confirm the central finding of this paper: expected returns on different asset classes do not co-move. Under the baseline specification, none of the cross-asset-class predictive relationships are significant at 5% level, only one (bond spreads predicting equity returns) is significant at 10% level, and the economic size of the effects is at most a 1 percentage point return increase following a 1 standard deviation rise in the yield, with some predictive return coefficients negative rather than positive. Structural-break-adjusted rent-price ratios and bond spreads do show some predictive power for future stock returns, but the R^2 and economic significance of the impact is small, and this predictive power goes away at longer horizons. This lack of cross-asset return predictability extends to a range of alternative discount factor proxies such as consumption growth and credit growth. I show that such macro-financial factors predict returns on individual asset classes, but not across the three classes of risky assets. Taken together, my findings suggest that while discount rate co-movement can sometimes be found for specific samples or time periods, the lion share of excess asset price volatility is asset-specific.

The extent to which expected returns lack co-movement is puzzling. In the presence of trading and information frictions, measurement error and market segmentation, we would not expect asset valuations or expected return proxies to co-move perfectly. But the fact that discount rates co-move less than cashflows, and that the lack of co-movement is pervasive across a variety of time periods, asset class pairs and testing methods is rather unexpected in light of standard theory. It suggests that to understand the drivers of excess asset price volatility, we need to explain what drives asset-specific rather than common variation in expected returns.

In the final part of my paper, I explore several potential candidates for such asset-specific excess volatility: time-varying asset risk or beta, capital flows, and volatile expectations. Variation in the quantity of risk is commonly recognised as an important driver of *level* differentials in expected returns the the cross-section of stocks (Fama and French, 1993). But when it comes to *time variation* in expected returns, I show that changes in the quantity of asset-specific risk over time are strongly positively correlated. I also show that market segmentation per se is not enough to generate the asset-specific discount rate movements: for this, we need some factors which make the discount rates in individual asset markets more volatile than implied by consumption of individual investors.

One candidate for such excess volatility is time variation in quantities of capital supplied and demanded on specific markets. Recent work by Gabaix and Koijen (2020) and Greenwood et al. (2018) has shown that in the presence of segmentation, small changes in asset quantities can generate large changes in asset prices. In my data, I show that capital inflows into the stock market – measured as high net equity issuance – consistently predict low future stock returns, but do not forecast any meaningful changes in housing or corporate bond returns. This is consistent with the evidence in Gabaix and Koijen (2020), who use a granular instrumental variable method to show that exogenous inflows of capital into the equity market can substantially increase stock prices and hence reduce expected equity returns.

The final set of explanations concerns a set of theories which I loosely label "volatile expectations". The idea behind these is that information processing biases or frictions applied to asset-specific news can, in turn, result in asset-specific excess volatility. I use the *Survey of Professional Forecasters* to show that, first, forecasts of future returns on different asset classes (equities, treasuries, AAA bonds and BAA bonds) are uncorrelated, and second, forecast updates display what I label asset-specific overreaction. Using the methods of Coibion and Gorodnichenko (2012) and Bordalo, Gennaioli, Ma, and Shleifer (2020), I show that individual forecaster forecasts overreact to revisions (news) in the forecast for the specific asset class but not for other asset classes, consistent with forecasters overreacting to asset-specific news.

My findings most closely relate to two strands of existing literature. The first strand studies variation in expected returns, discount rates and risk premia within asset classes through return and cashflow predictability regressions. A large literature starting with Shiller (1981) has documented that US stock prices vary more than dividends and that stock returns are predictable (see Cochrane, 2011, for a summary). Even though the current consensus is that US equity cashflows are not predictable and hence all the variation in the dividend-price ratio is accounted for by expected returns (Cochrane, 2008), a number of papers point out that dividends are predictable for different time periods, countries and data definitions (Engsted and Pedersen, 2010; Golez and Koudijs, 2018; Chen, 2009). There is also evidence for return and rent growth predictability in markets for residential and commercial real estate (Campbell, Davis, Gallin, and Martin, 2009; Ghysels, Plazzi, Valkanov, and Torous, 2013; Knoll, 2017) as well as return and spread growth predictability in corporate bond markets (Greenwood and Hanson, 2013; López-Salido, Stein, and Zakrajšek, 2017).

In sum, there is evidence that expected returns on a broad range of asset classes vary over time, but there is a lack of consensus on the relative importance of expected return and cashflow variation, and on the pervasiveness of return predictability beyond US equities. My study shows that return predictability is ubiquitous and stretches to a sample covering all major asset classes, 17 advanced economies and the last 146 years. But variation in expected cashflows also matters, with time-varying dividend growth accounting for roughly half of the variation in dividend-price ratios in long-run cross-country data.

The second strand of the literature relates to the co-movement of expected returns and risk premia across asset classes. Here, consensus is much more difficult to find. On the one hand, Fama and French (1993) and numerous subsequent studies have shown that the risk factors driving the level of expected return on individual stocks are different to those on individual bonds. But when it comes to the focus of my study – the time variation expected returns – some initial studies highlighted commonality, with Fama and French (1989) showing positive co-movement between US equity and corporate bond risk premia – while others such as Shiller (1982) have emphasised differences. More recent studies are no closer to agreement: while some emphasise common cross-asset expected return variation derived through, for example, value and momentum (Asness, Moskowitz, and Pedersen, 2013) or intermediary balance sheets (Baron and Muir, 2018), others show that a common discount factor is unable to explain all the time variation in expected returns on different assets (Haddad, Kozak, and Santosh, 2017; Giglio and Kelly, 2018).

The key question is then the following: how much of the excess volatility is common to all asset classes and how much is asset-specific, in the broadest possible setting? My paper shows that when we consider the most important components of risky household wealth in a long-run cross-country sample, common factors are relatively unimportant and what stands out is a lack rather than a presence of co-movement. Even if there is some commonality in expected return movements during certain time periods, or for certain countries or risk factors, we need to better understand what drives the hitherto unexplored elephant in the room – the asset class specific component of expected return. After all, this asset-specific excess volatility is responsible for most of the variation in asset prices across some 6,000 country-asset-class-year observations studied in this paper.

2. Testing for discount rate co-movement

I start by setting out the framework for testing for expected return variation within and across asset classes. Asset prices should equal the present value of expected future cashflows:

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

Above, $P_{i,t}$ is the price of asset i at time t, $CF_{i,t+s}$ are future cashflows in the form of dividends, rents or coupon payments, and $R_{i,t+s}$ is the asset-specific discount rate.

Asset-specific cashflows $CF_{i,t}$ can vary in an idiosyncratic manner. But to rule out arbitrage, discount rates $R_{i,t}$ on different risky assets have to move together. More specifically, the standard "fundamental equation of asset pricing" states that expected returns on different assets should all be proportional to a single cross-asset discount factor m:

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

The discount factor m reflects the relative price of cashflows across time and states of nature. Existence of such a discount factor ensures that all risky assets are priced in a consistent manner, and cashflows from one asset are not arbitrarily valued higher than those from another.[2] Expected returns across all asset classes should then move in line with m as follows:

$$\mathbb{E}_t \left(R_{i,t+1} \right) = \frac{1}{\mathbb{E}_t \left(m_{t+1} \right)} (1 + \sigma_i), \tag{3}$$

where $\sigma_i = -cov(R_i, m)$ is an asset-specific risk correction.

The variation in asset prices can then be split into two components: asset-specific cashflows and common cross-asset discount factor movements scaled up by the appropriate risk correction. The consensus in the literature is that expected cashflow variation is not an important driver of asset prices, and that the discount factor m rather than the risk correction σ drives the time variation in expected returns (Cochrane, 2011, 2017). In light of this consensus, the absence of co-movement in cross-asset price-to-fundamental ratios shown in Figure 1 is puzzling. Equations (1)–(3) imply that under stable $\mathbb{E}(CF_i)$ and $\sigma_i > 0$, variation in these asset yields should be driven by a common discount factor m, and the correlations in yields on different classes of risky assets should be close to 1.

The consensus that expected cashflow movements do not matter is primarily based on post-1926 US data. The new data in this paper pose a new challenge. In order to see whether the lack of asset yield co-movement is, in fact, surprising, we need to first establish whether in this long-run data, this asset yield variation is in fact driven by time-varying expected returns rather than cashflows.

[2]The conditions for equation 2 are, on the surface, minimal: the law of one price for m to exist and absence of arbitrage for $m > 0$ (see, for example Ross, 1976).

After documenting the extent of non-fundamental (expected return) volatility within asset classes, I turn to testing whether it is driven by common cross-asset factors or not.

1. Testing for variation in expected returns and cashflows within asset classes The first part of the paper checks for the relative importance of variation in cashflows and expected returns *within* each risky asset class. This test is based on a log-linearised version of the present value identity in (1) derived by Campbell and Shiller (1988):

$$dp_{i,t} \approx \mathbb{E}\sum_{s=0}^{\infty}\rho_i^s r_{i,t+1+s} - \mathbb{E}\sum_{s=0}^{\infty}\rho_i^s dg_{i,t+1+s} \tag{4}$$

This equation holds for both equity and housing, with asset yield dp the log of the dividend-price or rent-price ratio, r the log total return, and dg the log dividend or rent growth. Nozawa (2017) shows that a version of equation (4) holds for corporate bonds, with dp the price premium (spread) over government bonds, r the excess return over government bonds and dg the credit losses given default.

The intuition behind equation (4) is the same as that behind equation (1): asset prices (P or $pd = -dp$) can be high either because of high expected cashflows or a low discount rate. In absence of direct data on investor expectations, this correspondence can be tested empirically by forecasting future returns and cashflows using today's asset yield dp (Cochrane, 2008; Nozawa, 2017; Campbell et al., 2009). I do this by running the following predictive regressions:

$$r_{i,j,t+1} = \beta_{i,j,1} + \beta_{i,2}dp_{i,j,t} + u_{i,j,t} \tag{5}$$

$$dg_{i,j,t+1} = \gamma_{i,j,1} + \gamma_{i,2}dp_{i,j,t} + e_{i,j,t}, \tag{6}$$

The regressions are run separately for each asset class i using a panel of 17 countries j across the period $t = \{1870, 2015\}$. For corporate bonds, I additionally run a regression of future spread growth – a proxy for excess return – on today's spread, which helps avoid some of the measurement error present in the corporate bond return series. For the US, I also study the relationship between future corporate bond default rates (which proxy for dg) and today's spread.

If expected return variation is an important driver of asset prices, the $\beta_{i,2}$ coefficient on dp should be positive and significant. If expected cashflow variation is important, the $\gamma_{i,2}$ coefficient should be negative and significant. If both expected returns and cashflows matter, we can assess their relative importance by estimating the discounted sums of expected future returns $\mathbb{E}\sum_{s=0}^{\infty}\rho_i^s r_{i,t+1+s}$ and cashflows $\mathbb{E}\sum_{s=0}^{\infty}\rho_i^s dg_{i,t+1+s}$ in equation (4). To do this I again follow the standard procedure in the literature and estimate a constrained VAR in returns r, cashflows dg and valuations dp, and use the long-run VAR forecasts of these variables to calculate the corresponding discount rate and cashflow news components of (4) (see, for example, Golez and Koudijs, 2017; Campbell, 1991, and a more detailed descirption of the method in Appendix C.2). After computing these forecasts, I calculate the proportion of variation in dp that is explained by future expected returns and cashflows.

2. Testing for co-movement in expected returns across asset classes The current consensus in the literature is that time-varying discount rates are a key driver of variation in asset prices. If this is the case, expected return variation should not only be an important driver of asset valuations – in terms of a high discount rate news variance share in the Campbell-Shiller decomposition in (4) – but it should also be common across the different risky asset classes. From equation (3), expected returns on any two risky assets should be proportional to a common discount factor m, such that expected return on asset i is equal to the expected return on asset k times the ratio of the two assets' risk corrections:

$$\mathbb{E}_t\left(R_{i,t+1}\right) = \mathbb{E}_t\left(R_{k,t+1}\right) * \frac{1+\sigma_i}{1+\sigma_k} \tag{7}$$

I test for the extent to which expected returns across asset classes co-move in two steps. First, instead of correlating asset valuations as in Figure 1, I separately correlate the discount rate and cashflow news estimates from the VAR constructed following Campbell (1991), as described in Appendix C.2. I then study whether discount rate news on different asset classes strongly positively correlated, and whether discount rate news are more or less correlated compared to the asset-specific cashflow news.

Second, I run cross-asset predictive regressions where I use valuations of asset $k1$ and $k2$ (e.g. housing and corporate bonds) to predict returns on another asset class i (e.g. equities):

$$r_{i,j,t+1} = \beta_{i,j,1} + \beta_{k1\neq i} dp_{k1,j,t} + \beta_{k2\neq i} dp_{k2,j,t} + u_{i,j,t} \quad i \ = \{eq, hous, bond\} \tag{8}$$

If expected returns are driven by a common cross-asset discount factor m – for example relating to macro-financial risk, as in most of the prominent macro-finance theories – the coefficients β_k should all be positive and significant, and – as long as the coefficients are standardised or asset-specific risk corrections are similar – be similar in terms of magnitude.

Asset-specific dps could, however, be a poor proxy for the cross-asset discount factor m. For example, Lettau and Ludvigson (2002) show that the consumption-wealth ratio may be a better proxy for the macro-financial risk factor than the dividend-price ratio. In light of this, I also test whether alternative proxies for m predict future returns across all three asset classes in the right direction by running the following set of regressions for each asset class:

$$r_{i,j,t+1} = \beta_{i,1} + \sum_{\tilde{m}=1}^{\tilde{M}} \beta_{m,i} \tilde{m}_{j,t} + e_{i,t} \quad i \ = \{eq, hous, bond\}, \tag{9}$$

Above, $\tilde{m}$ denotes discount factor proxies relating to, for example, consumption and balance sheet strength of financial intermediaries. Cross-asset expected return co-movement would, in this case, mean that some macro-financial factor $\tilde{m}$ predicts returns on all three asset classes in the right direction, with high risk corresponding to high future returns.

If there is within-asset class return predictability but no cross-asset-class return predictability, this means that expected returns vary over time but do not co-move. Consequently, much expected return variation and the associated excess volatility is then asset-specific, and not driven by a common cross-asset risk factor.

3. Long-run data on cross-asset yields, returns and cashflows

There is substantial debate in the literature about how much return predictability exists within asset classes, and whether cross-asset excess volatility can be explained by a single discount factor (Cochrane, 2008; Goyal and Welch, 2008; Asness et al., 2013; Haddad et al., 2017). One reason for these disagreements is that findings often depend on a specific data samples used – with results from the recent US period arguably not applicable to broader cross-country data (Chen, 2009; Engsted and Pedersen, 2010) – or are imprecise even for a relatively long sample of data (Stambaugh, 1999). To ensure my findings are accurate and representative, I make use of new long-run cross-country data covering asset yields dp, cashflows dg and returns r 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 2016. Appendix Table A.1 summarises the data coverage by country and asset class. A brief description of the sources follows below.

Equity The data consist of total returns, dividends, and dividend-price ratios of listed equities, all taken from Jordà et al. (2019a), with the addition of a new data series for 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 the 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. Chen (2009) shows that allowing dividends to be reinvested within the year can bias the predictive coefficient on dividend growth towards zero by making it affected by predictable return variation. To guard against this bias, my dividend growth figures generally refer to non-reinvested dividends.

Housing The data consist of total returns, rents, and rent-price ratios for residential real estate, all taken from Jordà et al. (2019a). 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 for the housing and equity data, see Jordà et al. (2019a).

Table 1: *Risky asset returns, cashflows and yields*

Panel 1*: Real total returns*			
	Equity	Housing	Corporate bonds
Mean	7.08	6.95	3.00
Standard deviation	22.30	9.97	9.71
Geometric mean	4.78	6.51	2.53
Excess return over bills	6.49	6.49	2.17
Panel 2*: Cashflows*			
	Real dividend growth	Real rent growth	Corporate default rate
Mean	3.55	1.24	0.99
Standard deviation	29.08	7.80	1.51
Panel 3*: Asset yields*			
	Dividend-price ratio	Rent-price ratio	Corporate bond spread
Mean	3.86	5.06	1.05
Standard deviation	1.69	1.81	1.13
Observations	1506	1506	1506

Note: Pooled sample of 17 countries, 1870–2016. All figures are in percentage points. The corporate default rate is for the US only and measures the par value of bonds in default relative to total.

Corporate bonds Kuvshinov (2021) introduces a dataset of yields, spreads, and holding period returns on bonds issued by private sector creditors, targeting 10-year maturity. The data cover all private fixed-rate bonds traded on the secondary market. To ensure appropriate coverage, in some cases these are supplemented by issue yields and data from over the counter markets. The data exclude foreign bonds, foreign currency bonds, bonds with explicit government guarantees, and – when separately identifiable – excludes mortgage bonds issued by credit institutions or special purpose vehicles, and includes bonds issued by non-financial corporations backed by real estate. The spread is the yield-to-maturity differential vis-a-vis 10-year government bonds, and the return is the 1-year holding period return. Most of the corporate bond data were constructed from primary sources, by aggregating yields and returns on individual bonds traded on the domestic stock exchange. Appendix B provides further detail on these data.

The inclusion of countries other than US allows me to test whether the return predictability prevalent in the US market (Cochrane, 2008) or the dividend growth predictability documented for a number of other markets (Engsted and Pedersen, 2010; Golez and Koudijs, 2018) are the more prevalent feature of the data. The inclusion of housing and corporate bonds allows me to study the excess volatility within these two less explored risky asset classes, and to ultimately assess the degree of cross-asset co-movement of expected returns. Including three rather than two risky asset classes also allows me to evaluate whether discount rate co-movement is only present or absent between certain asset class pairs, or is a more general feature of the data. Finally, for the purpose of this study I focus on risky assets with positive risk premia, and abstract from movements in convenience yields, which means that I do not include government bonds in the study (Table 9, however, shows that the government bond risk premium – the term spread – also has little cross-asset predictive power).

Table 1 summarises the main features of the data. Panel 1 shows that three the assets earn a positive risk premium and exhibit high volatilities, and can therefore be classified as risky. Returns on housing and equity are similar at around 7% p.a., while those on corporate bonds are lower at around 3% p.a. but still substantially above the bill rate. Panel 2 shows that cashflows on these assets are also volatile and it is therefore not a given that variation in the asset yield dp primarily reflects expected returns. Panel 3 of Table 1 shows that asset yields do vary over time but are less volatile than realised returns and cashflows. This is to be expected because yields reflect ex ante expected movements in smoothed future returns and cashflows rather than their one-year realisations. At the same time, these yield measures display substantial variability of 1–2 ppts p.a.. The next section investigates whether this variability in asset yields relates to systematically predictable future movements in returns and cashflows.

4. Return predictability within asset classes

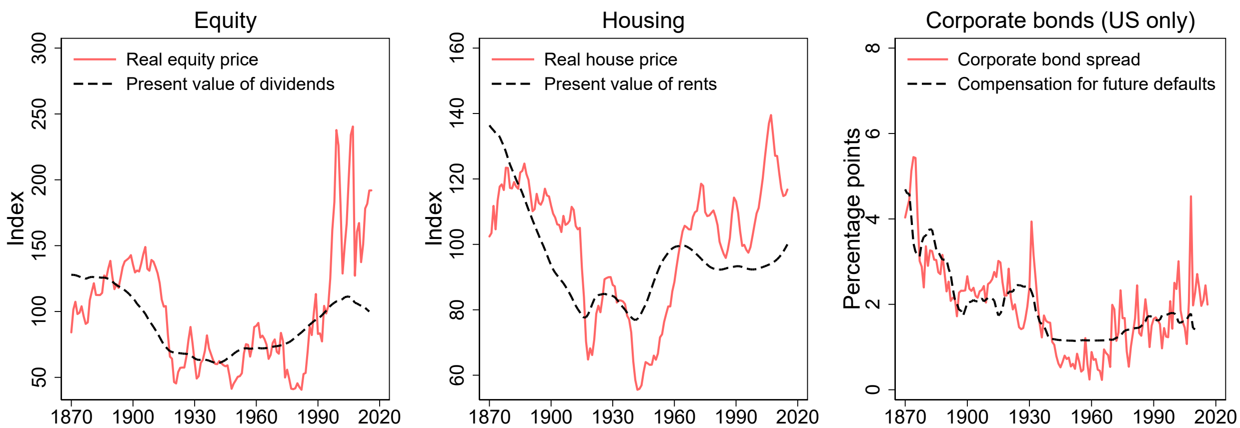
Are swings in risky asset prices driven by time varying fundamentals, or non-fundamental factors such as discount rates? If financial volatility is purely fundamentals-driven, the lack of co-movement between asset valuations in Figure 1 simply corresponds to idiosyncratic cashflows, and is not in itself puzzling. As a first pass of answering this question, I follow Shiller (1981) and compare the variation in observed asset prices with that of counterfactual "fundamental prices" $P^*_{i,t}$. For housing and equity, these equal the constant-discount-rate present value of future cashflow for the specific asset i from year t onwards:

$$P^*_{i,t} = \sum_{s=1}^{\infty} \overline{R}_i^{-s} CF_{i,t+s}, \tag{10}$$

where the discount rate $\overline{R}_i$ is equal to the average asset-specific rate observed in the data, $\overline{R}_i = 1/(1+\overline{dp}_i)$. 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.

Figure 2 shows the corresponding observed asset price or spread (solid red line) and the present value of fundamentals (dashed black line). As in Shiller (1981), I detrend real prices using an exponential trend, and set both observed and fundamental prices to equal 100 on average throughout the sample. This benchmarking effectively fixes cashflow growth beyond the end of the sample to a rational expectations benchmark which equates averaged observed and fundamental asset prices but as also shown in Shiller (1981), changing these benchmarking or end-point assumptions only affects the trend and not the volatility comparisons. The equity and housing data are an unweighted average of 17 countries and corporate bond data cover the US only with long-run default data sourced from Giesecke, Longstaff, Schaefer, and Strebulaev (2014).

Figure 2: *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. 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.

Prices of all three risky assets fluctuate much more than fundamentals. Even though the observed and fundamental series do track each other somewhat over the long run – showing a U shape reminiscent of the advanced-economy wealth-to-income ratio trend identified by Piketty and Zucman (2014) – observed prices and spreads also display substantial short- and medium- run deviations from their fundamental values. The question then becomes: is there something systematic about this non-fundamental variation in asset prices? Put differently, can we use today's asset yields to predict future mean-reversion via returns, or fundamental-based cashflow movements?

To answer these questions, Table 2 presents the results of predictive regressions using today's asset yields to forecast year-ahead returns and cashflow growth within each asset class, as specified in equations (5)–(6). The numbers in the first two columns correspond to the predictive coefficients β_2 in (5) and δ_2 in (6) for equities, columns 3 and 4 present the same numbers for housing, column 5 presents the return β_2 for corporate bonds and column 6 presents the β_2 for an alternative bond return proxy – the spread growth. To make results comparable across asset classes, I standardise all the coefficients in columns 1–5 to a one standard deviation increase in the asset yield. Column 6 displays the predictable percentage point change in the spread 1 year ahead following a 1 percentage point higher spread today. To help interpret the coefficients on log returns, the row titled "percentage point impact" shows the impact expressed in terms of percentage points (log return change times mean return in the sample times 100). The results for corporate bond cashflow predictability regressions, for the US only, are shown in the Appendix Table A.2.

Returns on all three risky asset classes are predictable. Column 1 shows that a one standard

Table 2: *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	0.024***	-0.048***				
	(0.009)	(0.010)				
Rent-price ratio			0.021***	-0.007**		
			(0.003)	(0.003)		
Bond spread					0.021***	-0.287***
					(0.006)	(0.039)
Percentage point impact	2.49	-4.84	2.19	-0.74	2.19	-0.29
R^2	0.014	0.043	0.049	0.010	0.044	0.139
Observations	2290	2288	1816	1816	1906	1912

Note: OLS regressions with country fixed effects. Coefficients in columns 1–5 are standardised to a 1 standard deviation increase in the predictor variable; column 6 is not standardised. Predictor (x) variables in rows are in logs for the dividend- and rent-price ratios, and percentage points for the bond spread. 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 corporate bond spread. Percentage point impact is the resulting percentage point change in return or cashflow growth after a one standard deviation increase in the asset yield (x variable). All variables are demeaned at the country level. Driscoll-Kraay standard errors clustered by country and year and adjusted for autocorrelation in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

deviation increase in the dividend-price ratio – equivalent to about 1.5 percentage points – predicts 2.5 percentage point higher real equity returns one year ahead (the regression coefficient 0.024 times the mean gross return of 1.048 and converted to percentage points through multiplying by 100). Returns on housing and corporate bonds (columns 3 and 5) are also predictable, with similarly-sized effects to to those for equities. Column 6 further shows that this return predictability is associated with substantial mean reversion: a 1 percentage point higher corporate bond spread predicts a 0.287 percentage point spread decline 1 year ahead, with almost one-third of these elevated spreads mean-reverting within a year.

Not only returns, but cashflows are also predictable, with the effect being strongest for the equity market. A 1 standard deviation increase in the dividend-price ratio predicts 4.8 percentage points lower real dividend growth 1 year ahead. A similar increase in the rent-price ratios, however, only forecasts 0.7 percentage points lower growth in rents, and the Appendix Table A.2 shows that corporate bond yields in the US are only weakly associated with future default rates, consistent with the findings of Giesecke et al. (2011). The evidence for return predictability mirrors the consensus for long-run data on US equities in Cochrane (2008) and 400 years of evidence for a global financial center in Golez and Koudijs (2018). Contrary to the consensus for the US equities however (Cochrane, 2008), I show that cashflows are also predictable across a broad range of countries and asset classes.

The reasons why I find dividend growth predictability are that my sample covers more countries and longer time periods – including times of disasters and substantial macroeconomic and cashflow

Table 3: *The relative importance of time varying discount rates and cashflows*

	(1) Equity	(2) Housing	(3) Corporate bonds
The share of total variation in asset valuations explained by:			
Discount rate news	45	65	70
Cashflow news	55	35	30

Note: Ratios of discount rate and cashflow news variance to total dividend-price, rent-price and bond spread variance, per cent. Discount rate news refer to predictable movements in future returns (or spread growth for bonds), and cashflow news to predictable movements in future cashflows (for bonds, a residual). Equity and housing shares are estimated using a constrained VAR, and corporate bond share is estimated using OLS forecasts of up to 10 years ahead.

volatility – and does not reinvest dividends or rents, which tends to bias down the cashflow growth coefficients as discussed by Chen (2009). The evidence for cashflow predictability is consistent with studies featuring longer time horizons (Golez and Koudijs, 2018) and other countries (Engsted and Pedersen, 2010). My results show that in the broad long-run perspective, dividend growth predictability is ubiquitous and is much stronger than that for cashflows in other asset classes such as rents. Taken together, the results in Table 2 show that the asset price variation in Figure 2 is driven by both time-varying cashflows and non-fundamental factors (expected returns).

Table 3 shows the relative importance of expected return (discount rate news) and cashflow news variation for each asset class. Consistent with the Campbell-Shiller identity in equation (4), the discount rate and cashflow news shares are calculated as, respectively, ratios of the variance in long-run cashflow and return forecasts $\sum_{s=0}^{\infty} \rho_i^s r_{t+1+s}$ and $\sum_{s=0}^{\infty} \rho_i^s dg_{t+1+s}$ in proportion to the variance of the asset yield dp_i. For housing and equity, these long-run forecasts are estimated by iterating a one-year forecast within a VAR of returns, cashflow growth and yields (as, for example, in Golez and Koudijs, 2017, described in more detail in Appendix C.2). For corporate bonds, the discount rate news share is the ratio of variance in predictable future spread growth (summed over the future 10 years and discounted by ρ) to the total variance of the spread.

For equities, roughly half of the variation in the dividend-price ratios is accounted for by future returns. The discount rate news share is higher for housing, at 65%, and highest for corporate bonds at 70%. Even though realised equity returns are much more volatile than those on housing and corporate bonds (Table 1), much of this volatility can be attributed to future dividend movements rather than mean-reversion through time-varying expected returns. All three asset classes are excessively volatile, but this non-fundamental volatility becomes more important as we move from the relatively liquid and well-informed equity market to the more frictional housing and corporate bond markets. The importance of discount rate news in the corporate bond market is consistent with existing literature for the US which emphasises the importance of mean-reverting sentiment swings in driving credit spread movements (Greenwood and Hanson, 2013; López-Salido et al.,

Table 4: *Within-asset-class predictability: alternative specifications*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	5-year average	Excess returns	VAR	Post-1950	Structural breaks	Year Effects
Equity:							
r_{t+1}	0.024***	0.018**	0.017**	0.029***	0.030***	0.037***	0.028***
	(0.009)	(0.007)	(0.008)	(0.005)	(0.009)	(0.007)	(0.006)
dg_{t+1}	-0.048***	-0.033***		-0.040***	-0.051***	-0.062***	-0.062***
	(0.010)	(0.005)		(0.009)	(0.010)	(0.010)	(0.013)
Housing:							
r_{t+1}	0.021***	0.020***	0.025***	0.021***	0.018***	0.020***	0.022***
	(0.003)	(0.003)	(0.005)	(0.002)	(0.005)	(0.005)	(0.003)
dg_{t+1}	-0.007**	-0.013***		-0.007***	-0.006	-0.009**	-0.007**
	(0.003)	(0.004)		(0.002)	(0.005)	(0.004)	(0.003)
Corporate bonds:							
r_{t+1}	0.021***	0.012**	0.028***		0.011**	0.023***	0.018***
	(0.006)	(0.005)	(0.005)		(0.004)	(0.004)	(0.003)
$\Delta spread_{t+1}$	-0.287***	-0.131***			-0.402***	-0.546***	-0.284***
	(0.039)	(0.014)			(0.045)	(0.050)	(0.037)

Note: Predictive coefficents on the log dividend-price ratio for equity, log rent-price ratio for housing, and percentage point spread for bonds. Dependent (y) variables in rows. Specifications in columns. Coefficients in the top 5 rows are standardised to a 1 standard deviation increase in the predictor (x) variable; bottom row is not standardised. r_{t+1} is log real total return; dg_{t+1} is log real dividend or rent growth, Δspread_t is the percentage point change in the corporate bond spread. Baseline is OLS with country fixed effects. 5-year averages regresses average return, cashflow or spread growth in years $t+1$ to $t+5$ on the yield at t . Excess returns are net of the government bond return. VAR estimates the return and cashflow regressions jointly subject to present value moment constraints. Structural breaks demean the predictors (x variables) by both time period and country using the Bai and Perron (2003) procedure. Year effects has both country and year fixed effects. Standard errors clustered by country-year and adjusted for autocorrelation in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

2017).

Table 4 shows that these findings hold under a variety of different estimation methods and across different time periods. Again, the coefficients in rows 1–5 are standardised to a one standard deviation increase in the yield, with the percentage point impact being roughly 100 times the reported coefficient, and the bottom-row coefficient corresponds to a 1 percentage point change in the spread. The 5-year-ahead average growth coefficients in column 2 are similar to the year-ahead coefficients in column 1, which means that the cumulative predictable return and cashflow movements become substantially larger over time. For example, a 1 standard deviation increase in the dividend-price ratio corresponds to 9.4 percentage points higher cumulative stock returns and 16.5 percentage points lower cumulative dividend growth.

Excess return predictability (column 3) is also similar to that for total returns, meaning that much of the expected return variation corresponds to risk premium rather than safe rate movements. Estimating the return and cashflow predictive regressions jointly in a VAR (column 4) leads to similar results. Return and spread growth predictability also becomes stronger after 1950 (column 5) and after adjusting the asset yield (predictor) variables for structural breaks as suggested by Lettau and Van Nieuwerburgh (2008) in column 6. Adding year fixed effects to control for common cross-country variation in yields, returns and cashflows (column 7) leaves results little changed relative to baseline.

Appendix Table A.3 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 statistically insignificant in some countries due to the relatively lower power of within-country samples. However, if we adjust the country data for structural breaks as in the Appendix Table 2, the predictive coefficients on returns are significant in almost every country across the three asset classes. Note that further adjusting the data to exclude periods of rent control which may lead to non-market-induced movements in house prices and rents, using the classification in Knoll (2017), also leaves both housing returns and rents predictable (results available from author upon request).

Return predictability is ubiquitous, and the Shiller (1981) excess volatility puzzle extends to the near-universe of advanced economies and risky asset classes studied in this paper. Risky cashflows are, however, also predictable, especially when it comes to equities. Because asset yields reflect future cashflows as well as discount rates, some of the lack of co-movement in asset yields shown in Figure 1 could correspond to asset-specific cashflows rather than expected returns. The next section tests for the cross-asset co-movement of expected returns directly by studying correlations of discount rate news and cross-asset-class predictability regressions.

5. Discount rate co-movement across asset classes

5.1. Discount rate correlations

Most theories in macro-finance attribute expected return variation to a common cross-asset discount factor typically linked to the evolution of macro-financial risk (e.g. consumption volatility, risk aversion, or disaster risk). If this is the case, expected returns (or discount rates) on different asset classes should not only vary over time, but also be strongly positively correlated. Cashflow news, on the contrary, may be asset-specific and do not need to display such positive correlation. Since both returns and cashflows are predictable, the fact that asset yields do not co-move (Figure 1) could be attributable to the highly asset-specific nature of cashflow shocks.

To see if this is the case, we can extract the cashflow and discount rate news components of the asset yield using predictive regressions and the method of Campbell (1991), which uses the VAR forecast to split the unexpected return at time t, $r_{i,t} - \mathbb{E}_{t-1}(r_{i,t})$, into future discount rate and future cashflow innovations, estimated as changes in the corresponding long-run return and cashflow growth forecasts $\mathbb{E} \sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s}$ and $\mathbb{E} \sum_{s=0}^{\infty} \rho_i^s dg_{i,t+1+s}$ (Appendix C.2 provides further detail). Table 5 then correlates these discount rate and cashflow news components separately in the pooled

Table 5: *Correlations of discount rate and cashflow news across asset classes*

	(1)	(2)	(3)	(4)	(5)
	Discount rate news			Cashflow news	
	Equity	Housing	Corporate bonds	Equity	Housing
Equity	1			1	
Housing	0.05	1		0.22***	1
Corporate bonds	0.04	0.05	1		

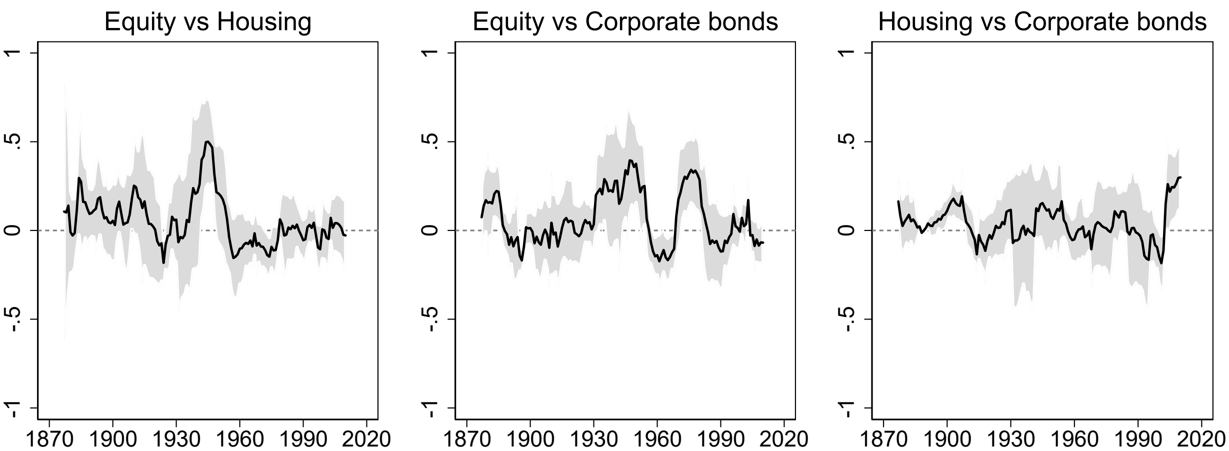
Note: Pairwise correlation coefficients. Discount rate and cashflow news for equities and housing are estimated as the innovations to the present value of, respectively, expected future returns and cashflows for each asset class, where expectations are computed using a VAR forecast. Discount rate news for bonds are the change in the bond spread. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$, using country-year clustered autocorrelation-adjusted standard errors.

cross-country sample. Note that because of the lack of corporate bond default data, I only compute the cashflow news correlation for equity and housing, and take the whole of the bond spread innovation to correspond to discount rate news.

It turns out that, if anything, discount rate news are not only uncorrelated across asset classes, but also less correlated than cashflow news. Table 5 columns 1–3 show that the discount rate news correlation across asset class pairs is below 0.1 and not statistically significant, whereas the cashflow news correlation in column 4 is a statistically significant 0.23. Figure 3 further checks how the discount rate news correlation has evolved over time by computing rolling 10-year correlations across asset class pairs in a way similar to Figure 1. Asset-specific discount rates are even less correlated than the raw valuation ratios shown in Figure 1. The correlation is also more stable over time and across asset classes, staying at around zero throughout the majority of the sample period and only spiking during the two world wars for some of the asset class pairs. The fact that discount rate co-movement is present during wartime suggests that cross-asset factors such as disaster risk can affect expected returns, but that these influences are largely confined to the disaster periods themselves.

Table 6 checks for presence of discount rate and cashflow news co-movement across different discount rate measures and time periods. Column 1 reports the baseline results from Table 5, and Column 2 correlates 3-year moving averages of discount rate and cashflow news to smooth over timing idiosyncracies across asset classes: for example, housing transactions may take longer to complete, generating a delay in the house price response to the discount rate innovation. Column 3 deals with the possible sluggish reaction of housing returns to discount factor innovations by letting it react one year later than all other variables. The correlations remain low. Column 4 computes the discount rate and cashflow news using a VAR where the asset yields are adjusted for structural breaks. Even though return and cashflow predictability is much stronger under this specification (see Table 4), cross-asset-class discount rate news remain uncorrelated.

Figure 3: *Co-movement of cross-asset discount rate news through time*



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 95% confidence intervals, using country-clustered standard errors. Discount rate news correspond to changes in the present value of predicted future returns for housing and equity, and as the change in the spread for bonds.

Table 6: *Discount rate and cashflow news correlations, alternative specifications*

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	3-year MA	3-year MA, housing lag	Structural breaks	Wars	Banking Crises
Discount rate news:						
Equity, housing	0.05	0.11	0.15**	0.01	0.28*	0.06
Equity, corporate bonds	0.04	0.08*	0.08*	0.04	0.08*	0.24**
Housing, corporate bonds	0.05	0.08	0.09	0.01	0.11***	0.11
Cashflow news:						
Equity, housing	0.22***	0.34***	0.25***	0.18***	0.59***	0.02

Note: Pairwise correlations. 3-year MA correlates 3-year moving averages of discount rate and cashflow news. 3-year MA, housing lag specification correlates housing data at t to t+2 with equity and bond data at t-1 to t+1, effectively allowing for a lagged housing response. Structural breaks uses discount rate and cashflow news obtained from VAR where the predictor variables are adjusted for structural breaks. Wars only considers periods during world wars. Banking crises consdiers periods within 3 years of the start of the crisis. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$, using country-year clustered autocorrelation-adjusted standard errors

Table 6 column 5 shows that correlations are generally larger during world wars, consistent with the visual evidence in Figure 3, though cashflows news remain more strongly correlated than discount rates even during wartime. Column 6 instead looks at correlations during the three years at the start of a systemic banking crisis, using the narrative definition of Schularick and Taylor (2012). Consistent with Muir (2017), I find that both bond spreads and dividend-price ratios tend to increase in crises, generating some positive discount rate news correlation. However the correlation remains low owing to the fact that even though spreads and dividend-price ratios increase on average, in many crises one of these asset classes is much more affected than the other. Consistent with findings of Jordà et al. (2019b), the housing discount rate remains relatively uncorrelated with both bonds and equities even during crises. Overall, discount rate co-movement is weak and is confined to specific time periods such as world wars and, to a lesser extent, banking crises.

Appendix Table A.6 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. Consistent with findings of Fama and French (1989), US corporate bond and equity discount rate news do show some positive correlation, especially after 1950 (Table A.7. But as with the wartime and crisis periods shown in Table 6, this positive correlation is not representative of the broader patterns in the data. All other countries show lower – and some negative – correlations, and the equity and housing discount rate correlation in the US is close to zero.

5.2. Cross-asset return predictability

The extent of expected return co-movement can be tested more formally within the framework of cross-asset predictive regressions. In principle, valuations of one asset class could predict returns on other asset classes even if the cross-asset valuations are themselves uncorrelated, thereby capturing some co-movement in expected return that is not seen in the simple correlations studied in Section 5.1. Table 7 tests for the presence of cross-asset return predictability in the data. As in Table 2, each column corresponds to a different asset class, and each row – to a different predictor; but this time the predictors correspond to yields on *other* asset classes. As before, the predictors are standardised to a one standard deviation increase, in order to make results comparable across assets and to the within-asset-class regressions in Table 2. In each column, r_{t+1} corresponds to the one-year-ahead log total real return, and $\overline{r_{t+1,t+5}}$ – to the five-year-ahead average return.

Consistent with the discount rate correlation evidence in Figure 3 and Table 5, the estimates in Table 7 show that there is very little cross-asset return predictability in the data. Although valuations of some asset classes are positively correlated with returns on other asset classes, most of these correlations are statistically insignificant and economically small. For example, high rent-price ratios are positively correlated with one-year-ahead equity returns (column 1), but negatively correlated with five-year-ahead equity and corporate bond returns (columns 2 and 6). The predictive R^2 is also small and much lower than that for the within-asset-class predictive regressions in Table 2. Based on this evidence, there is very little cross-asset discount rate co-movement in the data.

Table 7: *Predictability of returns across asset classes*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity		Housing		Corporate bonds	
	r_{t+1}	$\overline{r_{t+1,t+5}}$	r_{t+1}	$\overline{r_{t+1,t+5}}$	r_{t+1}	$\overline{r_{t+1,t+5}}$
Dividend-price ratio			-0.000	0.000	0.011	0.007
			(0.004)	(0.003)	(0.008)	(0.007)
Rent-price ratio	0.010	-0.004			0.000	-0.005
	(0.008)	(0.006)			(0.005)	(0.004)
Bond spread	0.010*	0.003	-0.001	0.001		
	(0.006)	(0.005)	(0.002)	(0.002)		
R^2	0.004	0.002	0.000	0.001	0.012	0.015
Observations	1527	1454	1503	1414	1507	1413

Note: OLS regressions with country fixed effects. All coefficients are standardised to a 1 standard deviation increase in the predictor variable. Dependent (y) variables in columns. r_{t+1} is the 1-year ahead log real total return, and $\overline{r_{t+1,t+5}}$ is the average 5-year ahead log real total return on the specific asset class. Predictor (x) variables are the yields on other asset classes. Standard errors clustered by country-year and adjusted for autocorrelation in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

Table 8 tests for presence of cross-asset return predictability across different regression specifications, return definitions and time periods. The columns correspond to different regression specifications and rows – to different asset classes and predictors. The top two rows show the regression coefficients from predicting equity returns with housing and corporate bond valuations, the next two – from predicting housing returns with equity and bond valuations, and the bottom two – from predicting corporate bond returns with equity and housing valuations. Even under these alternative specifications, cross-asset predictability is rare and the cross-asset predictive regressions sometimes carry the wrong sign (e.g. high dividend-price ratios predicting low rather than high future excess housing returns in column 3).

Table 8 column 2 conditions on the own asset valuation (e.g. the dividend-price ratio for equities) in the regression, in which case even the borderline cross-asset predictability shown in Table 7 disappears. Cross-asset predictability is weak or goes in the wrong direction for excess returns (column 3) and the post-1950 sample period (column 4). Adjusting the data for structural breaks (column 5) does result in some cross asset predictability, improving the forecasting power of the rent-price ratio and the bond spread for future equity returns. But even this predictability almost disappears at the 5-year ahead horizon (column 6).

Still, the presence of some cross-asset predictability under the structural break specification calls for a further investigation. How widespread is this predictability across asset class pairs and time, and how does it compare in strength to the within-asset predictability? To assess this, I estimate the predictable change in returns following a one standard deviation increase in the break-adjusted yield on the own asset class, and yields on other asset classes, at horizons $h = 1$ to 10 years ahead, using the regressions in (5) and (8) but replacing the return variable with the cumulative return

Table 8: *Predictability of returns across asset classes: alternative specifications*

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Conditional	Excess returns	Post 1950	Structural breaks	Breaks, 5-yr ahead
Equity r_{t+1}:						
Rent-price ratio	0.010	0.003	0.011	0.010	0.028***	0.010*
	(0.008)	(0.008)	(0.009)	(0.012)	(0.008)	(0.005)
Bond spread	0.010*	0.007	0.022**	0.010	0.019***	0.008**
	(0.006)	(0.006)	(0.009)	(0.008)	(0.007)	(0.004)
Housing r_{t+1}:						
Dividend-price ratio	-0.000	-0.003	-0.014*	-0.001	-0.003	-0.000
	(0.004)	(0.004)	(0.008)	(0.005)	(0.004)	(0.002)
Bond spread	-0.001	-0.003	0.011	-0.000	-0.004**	-0.002
	(0.002)	(0.002)	(0.009)	(0.003)	(0.002)	(0.001)
Corporate bond r_{t+1}:						
Dividend-price ratio	0.011	0.009	0.001	-0.001	0.011***	0.006
	(0.008)	(0.008)	(0.002)	(0.005)	(0.004)	(0.004)
Rent-price ratio	0.000	-0.001	0.001	-0.006	0.013**	0.000
	(0.005)	(0.005)	(0.002)	(0.005)	(0.006)	(0.005)

Note: Predictive coefficents of log real total returns on one asset class at $t+1$ regressed on the yields of other asset classes at t. Coefficients are standardised to a 1 standard deviation increase in the asset yield. Predictor (x) variables in rows, specifications in columns. Conditional specification conditions on the own asset yield at t (e.g. the dividend-price ratio for equity returns). Excess returns are in excess of the government bond return. Structural breaks demean asset yields (x variables) by both time period and country using the Bai and Perron (2003) procedure. Breaks, 5-year predicts 5-year ahead returns using predictors adjusted for structural breaks. OLS regressions with country fixed effects. Standard errors clustered by country-year and adjusted for autocorrelation in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

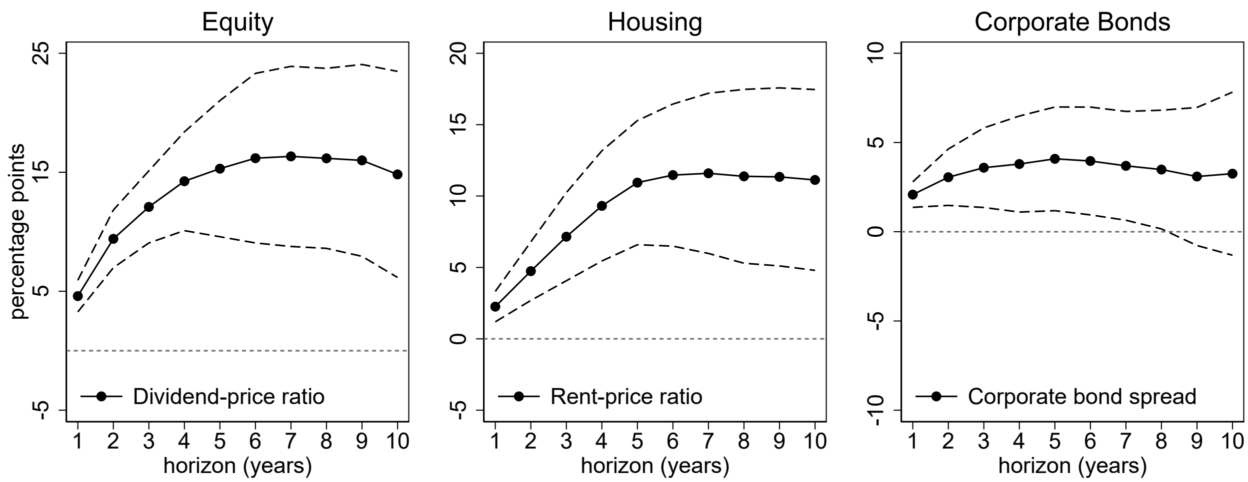
from year t to year $t+h$. To give the cross-asset predictability relationships the best chance of succeeding, I adjust all predictor variables for structural breaks and do not condition on the own valuation ratio in the cross-asset predictive regression, i.e. the regressions are specified exactly as in equations (5) and (8). Since all the responses are standardised to a 1 standard deviation increase in the break-adjusted valuation ratio dp and all regressions are run on a consistent sample, the magnitudes of the coefficients are comparable across predictors and asset classes.

Figure 4a shows the predictive coefficients on the own valuation ratio. Consistent with evidence in Section 4, the predictive coefficients are economically large and statistically significant, with a one standard deviation increase in the own asset yields dp predicting 3–5 ppt higher real returns 1 year ahead and 4–15 percentage points higher cumulative real returns 5–10 years ahead. The impact is persistent, with all the coefficients bar that on corporate bonds significant at all horizons at 5% level, and the corporate bond coefficient significant at 5% level for years 1–7.

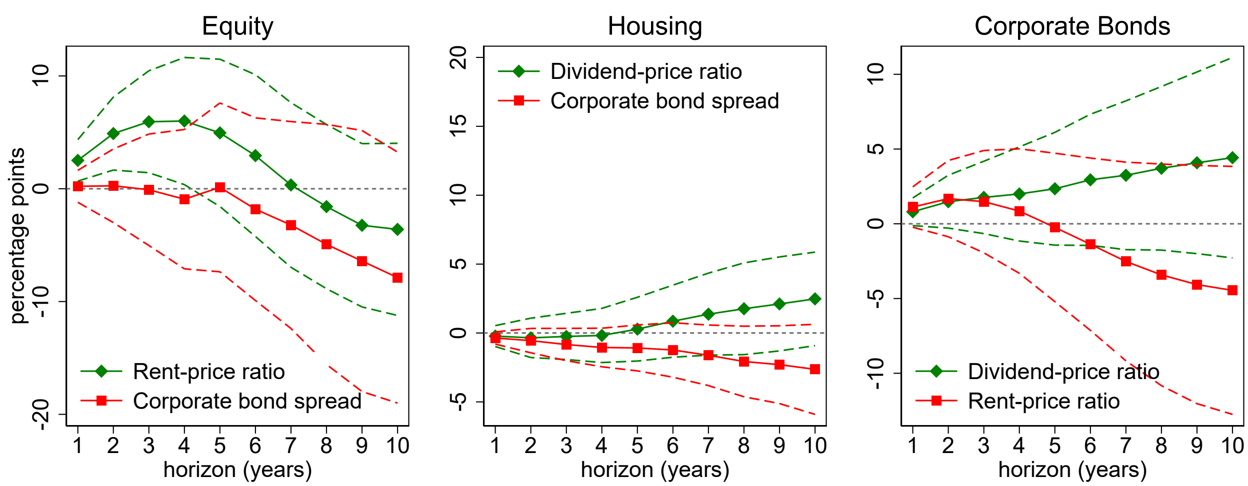
Figure 4b shows the predictive power of valuations of other asset classes, for example regressing equity returns on the rent-price ratio and bond spreads (left-hand panel). Most of the coefficients are both small and statistically insignificant. The corporate bond spread does not predict any

Figure 4: *Within-and cross-asset predictability at different horizons, adjusting for structural breaks*

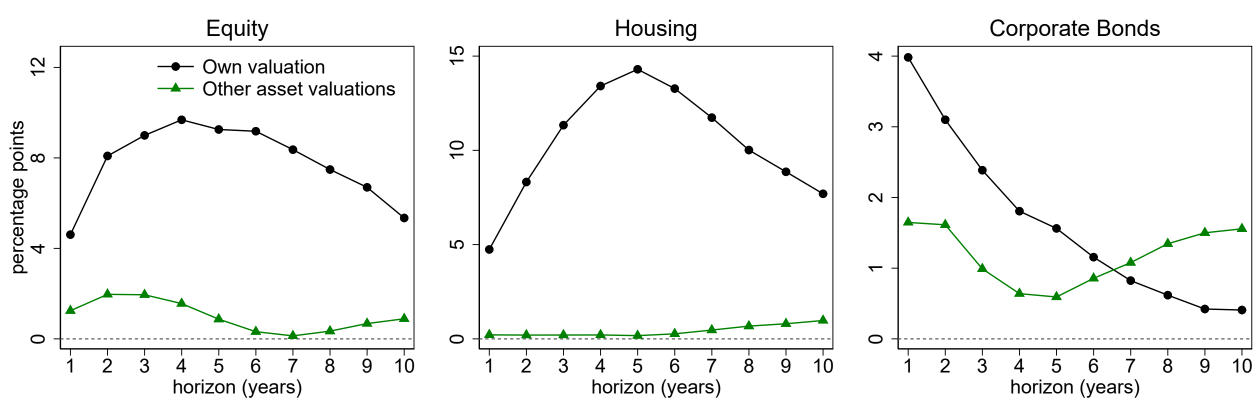
(a) *Within-asset predictability:*



(b) *Cross-asset predictability:*

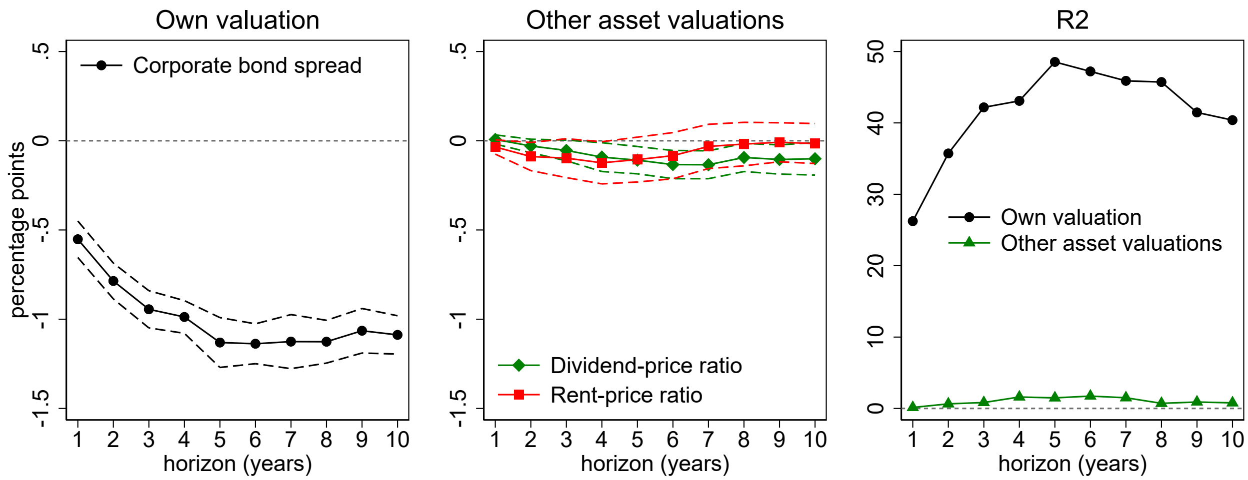


(c) *Predictive* R^2*:*



Note: Predictable cumulative return change after a one standard deviation increase in the asset yield. Standard errors clustered by country and year and adjusted for autocorrelation. All predictors are adjusted for structural breaks. Cumulative return impact estimated using the beta from regressing h-year ahead returns on either own valuation, or other asset valuations. All regressions are run on a consistent sample across assets, predictors and horizons. Dashed lines show 95% confidence bands.

Figure 5: *Corporate bond spread growth predictability, adjusting for structural breaks*



Note: Left and middle panel: predictable cumulative change in the spread after a 1 ppt higher bond spread (left panel), rent-price or dividend-price ratio (middle panel). Dashed lines show 95% confidence bands. Standard errors are clustered by country and year and adjusted for autocorrelation. All predictors are adjusted for structural breaks. Cumulative spread growth impact estimated using the beta from regressing h-year ahead spread growth on today's asset yields. All regressions are run on a consistent sample across predictors and horizons.

economically meaningful variation in future returns on housing or equities. The break-adjusted rent-price ratio does have some short-run predictive power for future stock returns, with a positive and significant predictive coefficient in the left-hand panel of Figure 4b. But this coefficient actually turns negative at longer horizons, and insignificant at 5% level from year 5 onwards. High dividend-price ratios predict high future corporate bond returns (Figure 4b), but the coefficients are not significant at the 5% level. Figure 4c further compares the R^2 of predictive regressions using own asset valuation to that using valuations of other asset classes. Own valuations have much larger explanatory power for future returns. Equity and housing do show an R^2 similar to the bond spread at longer horizons, but much of it comes from the rent-price ratio predicting future bond returns with the wrong sign (Figure 4b right panel).

Because the corporate bond returns for a large part of the sample are approximated from spread movements, this measurement error biases down the predictive coefficients on corporate bond returns in Figure 4b. To correct for this, Figure 5 shows the results of forecasting changes in the bond spread rather than the bond return. The left panel shows the cumulative predictable change in future spreads following a 1 percentage point higher break-adjusted spread today, the middle panel shows the predictable change in the spread following 1 percentage point higher dividend-price and rent-price ratios (without conditioning on the bond spread), and the right-hand panel compares the R^2 of these two predictive regressions. The predictive power of bond spreads is much stronger when it comes to future spread growth, and much larger than that of the dividend- and rent-price ratios. Furthermore, a 1 percentage point higher break-adjusted bond spread today is followed by a roughly 1 percentage point predictable cumulative decline in the bond spread after 5 years. This suggests that nearly all the variation in the bond spreads is driven by discount rate news, but that these discount rate news are highly specific to the corporate bond asset class.

Taken together, cross-asset-class return predictability is limited and much less economically meaningful than the within-asset-class return predictability. It could, however, be the case that cross-asset discount rate co-movement is not absent, but is simply not captured by asset-specific yields dp_i. To see if this is the case, I construct a number of alternative proxies for the cross-asset discount rate, related to direct measures of macro-financial risk, and examine their ability to forecast returns across all three risky asset classes by running the regressions in (9).

I draw on existing empirical and theoretical literature to determine the list of factors, subject to data availability for my historical sample. These consist of consumption-related variables which aim to discern between periods of relatively high and low effective risk aversion through consumption growth and proxies for habit and the consumption-wealth ratio. Intermediary-based factors aim to capture the possibility that financial intermediaries are the relevant marginal investor in these markets and try to proxy for their risk appetite through 3-year growth in bank leverage, real bank assets and real credit. Other factors include a set of variables which have been shown to predict stock returns in the US and internationally such as the term spread (Campbell, 1991) and the stock market capitalization to GDP ratio (Kuvshinov and Zimmermann, 2020). Appendix D.2 provides a more detailed description of how each factor is constructed.

Table 9 reports the outcomes of forecasting regressions using these factors to predict future returns on all three asset classes as in in equation (9), again standardising the macro-financial factors to a one standard deviation increase in order to ease comparability. Because elevated levels of some factors correspond to high, and others to low values of the discount factor m, the table also includes the theoretically correct signs of regression coefficients in brackets. The cross-asset predictive power of macro-financial risk factors is limited. Some factors are important for individual asset classes – for example, high market capitalization predicts low future equity returns, and high bank asset growth predicts low future corporate bond returns. But none predict returns on all three asset classes, and the magnitude of the predictive coefficients is small relative to that of the own asset valuations show in Table 2.

The consumption-wealth ratio and bank leverage growth do have the right sign on the predictive relationship for all three asset classes – consistent with the model of Lettau and Ludvigson (2002) and the empirical findings of Baron and Muir (2018) – although the coefficients are relatively small and some are insignificant. Appendix Figure A.2 compares the predictive power of these two variables to own asset valuations at different regression horizons, first predicting future real returns and then future bond spread growth. Neither of these two factors predict meaningful future return variation across multiple asset classes. Leverage growth is a good predictor of future corporate bond returns, outperforming the bond spread for some regression specifications, which suggests that it is a useful proxy for credit market risk appetite or sentiment (López-Salido et al., 2017; Baron and Xiong, 2017). But when it comes to predicting a cleaner measure of future mean-reversion in bond spreads – the future bond spread growth – the bond spread vastly outperforms leverage growth

Table 9: *Cross-asset predictive power of macro-financial risk factors*

	(1)	(2)	(3)
	Equity r_{t+1}	Housing r_{t+1}	Corporate bond r_{t+1}
Consumption-based factors:			
$\Delta_3 Real\ Consumption_t(-)$	-0.025	0.019*	-0.012
	(0.019)	(0.010)	(0.014)
$Surplus\ Consumption_t(-)$	-0.001	-0.006	-0.013
	(0.025)	(0.009)	(0.010)
$cay_t(+)$	0.004	0.006	0.015**
	(0.005)	(0.004)	(0.006)
Financial intermediary factors:			
$\Delta_3 Bank\ Leverage_t(-)$	-0.008	-0.006*	-0.019**
	(0.013)	(0.003)	(0.008)
$\Delta_3 Real\ Bank\ Assets_t(-)$	-0.005	0.003	-0.009
	(0.007)	(0.006)	(0.007)
$\Delta_3 Real\ Credit_t(-)$	-0.002	0.009	0.013
	(0.016)	(0.006)	(0.009)
Other factors:			
$log(MCAP_t/GDP_t)(-)$	-0.030**	0.001	0.001
	(0.012)	(0.004)	(0.007)
$Term\ Spread_t(+)$	0.003	0.007***	-0.003
	(0.008)	(0.002)	(0.003)
R^2	0.030	0.046	0.066
Observations	1475	1391	1266

Note: OLS regressions with country fixed effects. All coefficients are standardised to a 1 standard deviation increase in the predictor variable. Dependent (y) variable is the log real total return on the specific asset class, in columns. Predictor (x) variables together with the theoretically correct sign of the regression coefficient in rows. $\Delta_3 Real\ Consumption_t$ is the log growth 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 household 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 yield differential between long- and short-term government bonds. Standard errors clustered by country-year and adjusted for autocorrelation in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

as a predictor. Of course, the measures of both these variables in my long-run data are much less precise than those in Lettau and Ludvigson (2002) and Baron and Muir (2018) – for example, I do not have a good proxy for human wealth, and my leverage growth measure relates to commercial banks rather than broker-dealers. This means that the results should be interpreted with caution, but they do suggest that asset-specific excess volatility remains important even after conditioning on these cross-asset macro-financial factors.

Taken together, the analysis in this section has shown that asset-specific discount rates do not co-move. The correlation of cross-asset-class discount rate news is close to zero, and while returns within asset class are robustly predictable, there is no meaningful return predictability across asset classes. Some cross-asset expected return variation is present in the data – for example during specific time periods such as world wars – but it remains very much the exception rather than the rule. The vast bulk of excess asset price volatility is asset class specific. The next section explores the potential underlying drivers of this asset-specific expected return variation.

6. The co-movement puzzle

Expected returns on different risky asset classes vary over time, but they do not co-move. This suggests that much of the excess volatility in financial markets, and the associated expected return variation is asset-class-specific. This asset-specific excess volatility represents a new asset pricing anomaly which cannot be explained by time variation in a common cross-asset discount factor. This "co-movement puzzle" can be most easily illustrated within the framework of the standard consumption CAPM but also applies to a broad range other theories in macro-finance, which I briefly discuss below.

Standard consumption-based theory links the variation in expected returns and asset prices to the marginal utility of the representative investor. In the simple representative-agent model, the stochastic discount factor m takes the following form:

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

Under this formulation, expected returns on all asset classes are driven by the representative investor's marginal utility, and should therefore be strongly positively correlated.[3] The simple consumption-based model is therefore unable to generate the asset-specific discount rate variation observed in the data. It is also, however, unable to explain a number of other stylised asset pricing facts pertaining to the high level and volatility of risk premia (Mehra and Prescott, 1985; Cochrane, 2017).

A number of modifications proposed to this model are able to generate high risk premium levels and volatility, but would still – at least without substantial further modification – be unable to explain the co-movement puzzle. In what follows, I briefly review the implications for expected return co-movement arising from the most common modifications of the standard model. I then consider several alternative mechanisms for generating asset-specific expected return variation and explaining the co-movement puzzle.

Time-varying risk aversion This set of theories augment the investor's utility with an additional parameter referring to the level of past consumption (habit), as in Campbell and Cochrane (1999), or

[3] In fact, as seen from equation (2), under a constant risk correction σ_i the correlation between changes in expected returns should be equal to 1.

the composition of consumption between different goods, for example housing and non-housing expenditure in Piazzesi et al. (2007). Because marginal utility now depends on past consumption or its composition, this additional parameter H also affects the price of risk and expected returns:

$$\mathbb{E}(R_{i,t+1}) = f(H_{t+1}/H_t)$$

This means that effective risk aversion varies over time and asset prices should be low, and expected returns high, at times of temporarily low consumption (habit) or low consumption share of certain goods. Movements in H should affect prices of all risky assets and therefore generate co-movement of expected returns.

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

$$\mathbb{E}(R_{i,t+1}) = f(\sigma_{C,t})$$

Again, time-varying consumption risk should affect all categories of risky assets and result in expected return co-movement.[4]

Rare disasters Risk of potential large future declines in consumption during disasters can increase expected returns and risk premia even outside of these disaster periods (Barro, 2006). Time variation in disaster risk can cause expected returns to vary over time. Gabaix (2012) provides the following formula for the disaster risk driven expected return:

$$\mathbb{E}(R_{i,t+1}) = R_t^{safe} + p_t^{dis}\mathbb{E}_t\left[(B_{t+1}^{-\gamma}(1 - R_{i,t+1}^{dis})\right]$$

Here, p_t^{dis} is the time-varying disaster probability, γ is risk aversion, B_{t+1} captures consumption losses in a disaster and $R_{i,t+1}^{dis}$ is the disaster-specific asset return. Even though this theory can generate different levels of risk premia across asset classes based on different values of $R_{i,t+1}^{dis}$, the time variation in expected returns through p_t^{dis} should be common to all risky assets and induce a strong co-movement in discount rates of asset classes with positive risk premia. Note also that the relatively high discount rate co-movement during world wars suggests that disaster risk can drive cross-asset variation in expected returns, but this influence is largely confined to the periods of the disasters themselves.

Idiosyncratic risk and preferences Theories in which a representative household prices all risky assets tend to generate high co-movement in expected returns. This co-movement is, however,

[4] Because long-run risk reflects movements in long-run *consumption* which affect current utility through time non-separability, it should also affect prices of shorter-duration assets such as corporate bonds as well as longer-dated assets such as housing and equity.

typically still present in many theories which allow consumption (Constantinides and Duffie, 1996) and preferences (Gârleanu and Panageas, 2015) to vary across investors, as long as the actions of individual investors in different markets are tied together by a no-arbitrage condition akin to that in equation (2). In this case high cross-sectional dispersion of consumption risk or a high market share of risk-averse investors would typically increase the price of risk and expected returns along the lines of the following expression:

$$\mathbb{E}(R_{i,t+1}) = f(\sigma(\Delta c)_{cross,t}, \bar{\gamma}_t),$$

where $\sigma(\Delta c)_{cross,t}$ is the cross-sectional consumption dispersion and $\bar{\gamma}_t$ a weighted average of individual investor risk aversion. But even in this case, expected returns on all assets should be high during periods of high idiosyncratic consumption risk and a high market share of risk-averse investors. Generating asset-specific discount rate movements under such conditions requires additional frictions, for example in the form of market segmentation.

Intermediary asset pricing Rather than being priced by a representative household, many assets are priced by financial intermediaries or market makers. In this set of theories, the pricing kernel *m* should correspond to financial intermediary risk appetite, usually tied to their balance sheet characteristics *bs* such as leverage (He and Krishnamurthy, 2013):

$$\mathbb{E}(R_{i,t+1}) = f(bs_t)$$

Without any other frictions, time-varying intermediary appetite should affect all risky assets and generate expected return co-movement. However, if assets differ in the extent to which they are intermediated and cross-market frictions generate some segmentation across markets for different asset classes, asset-specific expected return variation can arise. For example, in the model of Haddad and Muir (2021), some asset classes are priced by intermediaries and others by households, resulting in two different discount factors. Haddad and Muir (2021) provide additional evidence to showing that expected returns on some asset classes are more responsive to financial intermediary factors than others. The evidence in Table 9 also suggests that intermediary-based factors can play a role in generating asset-specific excess volatility, in particular for returns on corporate bonds. My results also show, however, that even after conditioning on financial intermediary factors, a substantial amount of asset-specific excess volatility remains.

In light of the difficulties faced by a number of standard theories when it comes to resolving the puzzle, the rest of this section investigates several alternative mechanisms for generating the type of asset-specific expected return variation observed in the data.

Table 10: *Correlations between proxies for asset-specific risk*

	(1)	(2)	(3)	(4)	(5)	(6)
	Consumption beta			Return volatility		
	Equity	Housing	Corporate Bonds	Equity	Housing	Corporate Bonds
Equity	1			1		
Housing	0.85	1		0.83	1	
Corporate bonds	0.75	0.80	1	0.89	0.86	1

Notes: Pairwise correlations between estimates of asset-specific consumption beta (columns 1–3) and realised return volatility (columns 4–6). The consumption beta is the covariance between log excess return on the specific asset class and log real consumption growth. Volatility is the annual standard deviation of log excess return on the specific asset class. The betas and volatilities are estimated over 25-year rolling windows for the pooled sample of returns and consumption. All correlations are significant at 1% level.

6.1. Time-varying risk exposures

Expected return on an asset class i is a product of the discount factor m and the risk correction σ_i (equation (3)). Put differently, changes in expected returns can correspond not only to variation in the discount factor m, but also to time-varying asset-class-specific exposures to this factor σ_i. An extensive literature following Fama and French (1993) has relied on differences in risk corrections to explain the differences in *levels* of expected returns across assets. However, when it comes to *time variation* in expected returns, most standard models rely on changes in the discount factor rather than the exposure to this factor. In some sense this is understandable: time variation in σ_i requires that return distributions on whole asset classes vary at high frequency in a predictable manner, so a constant σ_i is a natural starting point. But a number of recent papers have used time variation in the risk correction and macroeconomic risk exposure to explain differences in expected and realised returns over time.

Lettau, Maggiori, and Weber (2014) augment the standard CAPM with an additional downside-risk beta, with the risk correction at time t effectively an average of the risk corrections for downside-risk and exposure to the standard market risk factor. An increase in downside risk increases the relative riskiness of asset classes which are more exposed to this factor, such as fixed-income securities, driving up their expected returns relative to those on the other asset classes.

Time-varying risk at the level of whole asset classes is generally difficult to measure in the data. I construct two proxies for the time-varying asset class beta: the consumption beta of annual asset returns – the covariance between asset excess return and consumption growth divided by consumption growth variance – and the unconditional annual excess return volatility, both estimated using 25-year rolling windows of pooled cross-country data. The estimates of asset-specific risk do vary over time, but they display strong co-movement across different asset classes. Table 10 columns 1–3 show the pairwise correlations between the consumption betas of different asset classes, and columns 4–6 show the correlation between asset class level volatilities. All the correlations are positive and significant, and most are close to 1. This suggests that on the level of broad classes of risky assets, time-varying risk exposures may not be the main force generating the asset-specific time variation in expected returns.

6.2. Capital flows across segmented markets

If there are frictions to moving capital across markets, the discount rate on asset class i, m_i, will be asset-specific:

$$1 = \mathbb{E}_t \left(m_{i,t+1} R_{i,t+1} \right), \tag{11}$$

But what determines this market-specific m_i? One possible explanation is that the discount rate is still determined as in standard theory – for example through risk aversion or long-run risk – but these risk factors now correspond to the consumption process of the marginal investor in market i. For example, Mankiw and Zeldes (1991) show that consumption of households which own equities is more volatile, helping rationalise the high equity premium. If the consumption risk of investors in one asset class is uncorrelated with that of investors in other asset classes, and if markets are highly segmented, this can generate asset-specific movements in discount rates and expected returns.

Appendix Table A.8, however, shows that while consumption growth of different types of households can be very different on average, the time variation in these growth rates tends to be highly correlated. Using data from Piketty, Saez, and Zucman (2018), Table A.8 shows that the consumption rates at the top, middle and bottom of the income distribution – with the top and middle, correspondingly, thought of as the representative equity and housing investors – is highly correlated, even though these income groups have experienced widely different average income growth rates since the 1960s. Furthermore, as shown by recent studies (Martínez-Toledano, 2019; Garbinti, Goupille-Lebret, and Piketty, 2020), most wealthy households own different types of risky assets – for example, the wealthy own some housing and bonds as well as equity – meaning that their discount factor variation should affect all asset classes. This makes household-level consumption volatility a relatively unlikely candidate for explaining the puzzle.

Another potential driver of expected returns in segmented markets is variation in the *quantity* of capital supplied or demanded. Greenwood et al. (2018) show that in partially segmented markets, shocks to the supply of capital can generate asset-specific movements in expected returns which take some time to dissipate. Gabaix and Koijen (2020), instead, focus on demand. Under their framework, capital inflows into a specific market put upward pressure on prices, with the price effects being larger the more inelastic the market supply schedule is. These propositions are difficult to test in my aggregate data since capital inflows are a combination of both demand and supply, and supply and demand induced movements carry the opposite predictions for expected returns. Greenwood et al. (2018) argue that evidence from price impacts of changes in bond supply during quantitative easing provides support for this channel. Gabaix and Koijen (2020) use a granular instrumental variable method drawing on portfolio data for individual investors to show that changes in demand

Table 11: *Predictive power of net equity issuance*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity		Housing		Corporate bonds	
	r_{t+1}	$\overline{r_{t+1,t+5}}$	r_{t+1}	$\overline{r_{t+1,t+5}}$	r_{t+1}	$\overline{r_{t+1,t+5}}$
Net equity issuance / GDP	-0.030***	-0.018***	0.005	-0.000	-0.009**	-0.001
	(0.006)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
R^2	0.021	0.036	0.002	0.000	0.006	0.000
Observations	1657	1578	1371	1301	1400	1305

Notes: OLS regressions with country fixed effects. All coefficients are standardised to a 1 standard deviation increase in the log of net equity issuance relative to GDP. Net issuance is gross issues minus redemptions, from Kuvshinov and Zimmermann (2020). r_{t+1} is the 1-year ahead real total return, and $\overline{r_{t+1,t+5}}$ is the average 5-year ahead log real total return on the specific asset class. Standard errors clustered by country-year and adjusted for autocorrelation in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

for specific assets from certain investor groups have very large price effects, with higher demand increasing prices and lowering the expected return.

In my aggregate data, I test whether capital flows can explain variation in expected returns by regressing future returns on all asset classes on net capital inflows into the stock market, measured as net equity issuance relative to GDP. The net issuance data are from Kuvshinov and Zimmermann (2020) and capture gross issues minus redemptions at market value, either in actual data or as the difference between market capitalization growth and capital gains, as in Goyal and Welch (2008). The resulting movement in expected returns will be positive if issuance is primarily a shock to supply, negative if it is driven by demand, and zero if equity capital flows do not affect prices, or if the two effects cancel out. Table 11 reports the coefficients from regressing one- and five- year ahead returns on the three asset classes on net equity issuance relative to GDP, again standardised to a one standard deviation increase to ease comparability.

Table 11 shows that high equity issuance predicts low future equity returns, and has very little predictive power for the other two asset classes (there is some predictive power for corporate bonds 1-year ahead, but the coefficient size and R^2 are very small and there is no predictive power for bonds 5 years ahead). The effects are economically significant: a one standard deviation increase in issuance predicts 3.1 percentage points lower equity returns 1 year ahead and 9.4 percentage points lower returns 5 years ahead; and similar in magnitude to those of the dividend-price ratio. This effect is also something of a lower bound since it mixes up supply and demand factors. Appendix Table A.9 shows that this predictability is also highly robust, with the predictive power of equity issuance holding up even when conditioning on structural-break-adjusted own asset valuations. This suggests that in these macroeconomic data, capital inflows can induce asset-specific movements in expected returns and that demand effects tend to dominate over supply effects.

The negative issuance predictability, however, also has an alternative interpretation. Baker and Wurgler (2000) show that a high equity share in new issues predicts low future returns, but argue that this is because firms time the market to issue at the peak, and issuance acts as a proxy for investor sentiment. The negative return predictability in Table 11 could therefore be driven by asset-specific sentiment as well as the price impact of capital flows. I explore the possibility that asset-specific return variation is, more generally, driven by volatile investor expectations next.

6.3. Volatile expectations

Excess volatility can arise through variation in expectations that is not linked to future fundamentals. Behavioural theories and theories allowing for learning permit these expectations to depart from the full-information rational benchmark such that investors form their forecasts of future cashflows using an operator $\mathbb{E}^*$ which differs from the full-information rational forecast $\mathbb{E}^{rational}$:

$$\mathbb{E}^*(R_{i,t+1}) = f^*(I_{i,t}) \neq f^{rational}(I_{i,t}) = \mathbb{E}^{rational}(R_{i,t+1}) \tag{12}$$

Above, $\mathbb{E}^*$ is the volatile-expectation forecast based on a biased or incomplete information processing function f^*, $\mathbb{E}^{rational}$ is the rational-expectation forecast based on the information processing function $f^{rational}$, and I is the information available when the forecast is made. A volatile expectation forecast $\mathbb{E}^*$ can generate the excess volatility and return predictability patterns observed in the data. For example, stock prices may be high – and equity yields dp low – at time t because investors incorrectly forecast high future dividends based on existing information I. At time $t+1$, new information I arrives and the incorrect forecast is revised, lowering the stock price and resulting in low returns, potentially generating the type of return predictability observed in the data.

One notable feature of theories involving volatile expectations is that such biases or frictions apply to asset-specific information I_i, and therefore generate asset-specific variation in expected returns. For example, investors may be extrapolating past returns for a specific asset class (Barberis, Greenwood, Jin, and Shleifer, 2015; Barberis and Shleifer, 2003; Adam, Beutel, and Marcet, 2017), overreacting to asset-specific return surprises (Bordalo, Gennaioli, La Porta, and Shleifer, 2019), or overweighting the recent history of returns on a specific asset or portfolio (Malmendier and Nagel, 2011; Nagel and Xu, 2019). This asset-specificity is often seen as a shortcoming of these theories (Cochrane, 2017), but in the case of the co-movement puzzle it actually confers an advantage. Even though the exact reason for expectation volatility will differ according to the precise model of expectation formation, the central idea unifying many of these theories is that of extrapolation and overreaction to – often asset-specific – news.

Existing empirical studies have documented such extrapolation and overreaction patterns within specific asset classes. In a recent paper, Andonov and Rauh (2020) study the asset-specific return expectations of public pension funds and show that these display within-asset-class extrapolation: for example, if the fund had experienced relatively high past stock returns on its portfolio, it also submits a high expected future equity return on its GASB 67 disclosure. That being said, few papers have studied whether extrapolation and overreaction for one asset class also "spills over" into

Table 12: *Cross-asset correlations of expected excess returns in the Survey of Professional Forecasters*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Forecasts				Forecast errors			
	Equities	Treasuries	AAA bonds	BAA bonds	Equities	Treasuries	AAA bonds	BAA bonds
Equities	1				1			
Treasuries	-0.29***	1			0.05	1		
AAA bonds	0.09	0.03	1		0.15	0.23**	1	
BAA bonds	0.08**	-0.10	0.07	1		0.32	0.20**	1

Note: Pairwise correlation coefficients, SPF forecasts and forecast errors. A more positive correlation coefficient means more correlated expectations across the two asset classes. Signs on all bond yield variabless reversed to proxy for expected returns. Equity return is in excess of the bill rate, 10 years ahead. Treasury yield is in excess of the bill rate, 10 years ahead. AAA yield is in excess of treasuries, 5 quarters ahead. BAA yield is in excess of AAA, 5 quarters ahead. Expectation error is the difference between realised return or yield and the forecast. Forecasts and errors net out forecaster fixed effects. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$, using forecaster-quarter clustered standard errors.

other assets. In what follows, I use data from the *Survey of Professional Forecasters* (SPF) to compute correlations between professional forecaster expectations of returns on different asset classes, and provide evidence for overreaction to asset-specific information akin to $f^*(I_{i,t})$ in equation (12).

The SPF provides quarterly forecasts for a range of real-economy and financial variables, at the level of individual forecasters. For the purpose of my analysis, I take the forecasts for future stock returns, as well as yields on government bonds, bills, AAA and BAA rated corporate bonds. The stock forecasts are only available annually for a long horizon of 10 years, government bond and bill forecasts are available for both long (10-year) and short (1 quarter to 2 years) horizons, and corporate bond forecasts are only available for short horizons (1 quarter to 2 years ahead). All forecasts apart from the BAA bonds are available from 1990, with BAA bonds available from 2010.

To ease comparability, I convert all these forecasts into proxies for excess returns. For equities, I compute the equity return forecast minus the bill rate forecast; for treasuries, the negative of the long-term yield forecast minus the bill forecast (since yields vary inversely to bond returns); both at the 10-year horizon. I also compute shorter-horizon proxies for the excess return on treasuries (a negative of the treasury minus the bill rate forecast 5 quarters ahead), the excess return of AAA bonds over treasuries and BAA bonds over AAA bonds. As well as the forecasts themselves, I calculate the forecast errors by comparing the forecast with the eventual realisation (eg the 10-year ahead equity return forecast in 2000 to the average return over 2000–2010). Armed with these data, I study the correlations between forecasts and forecast errors across different assets in Table 12, and the degree to which these forecasts over- or under-react to forecast revisions in Table 13.

Table 12 reports pairwise correlations between excess return forecasts (columns 1–4) and forecast errors (columns 5–8) on different assets: equities, long-term treasuries, AAA bonds and BAA bonds. The equity forecast is always for 10 years ahead (as these are the only equity data available in the

SPF), the treasury forecast is 10 years ahead when correlated with equities and 5 quarters ahead when correlated with corporate bonds, and AAA and BAA forecasts are always 5 quarters ahead.[5] The forecasts net out forecaster fixed effects to control for systematically pessimistic or optimistic forecasters, though this has little effect on the correlations. As described above, I invert the yield forecasts to proxy for bond returns.

If return expectations are correlated across asset classes – for example, if they were driven by a common cross-asset discount factor – the correlation coefficients in Table 12 should all be high and positive. This, however, is not the case. The correlations between return expectations in columns 1–4 are close to zero, and the only large correlation is negative rather than positive: when forecasters expect high excess stock returns, they also expect a high term premium on long-term treasuries, and hence a low excess treasury return. Correlations are stronger when it comes to forecast errors in columns 5–8, but still low, around 0.1–0.2 for most asset class pairs. These positive correlations are, however, driven by realisations and not the forecasts. Put differently, the forecasters appear to underestimate the degree to which returns and yields on different assets are correlated, and expectations are less correlated than realised returns – similar to the lower correlation of discount rate news compared to cashflow news documented in Table 5.

Why are asset-specific return expectations uncorrelated? In what follows, I test for one potential channel: *asset-specific overreaction* to new information. For this, I build on the framework of Coibion and Gorodnichenko (2012) and Bordalo, Gennaioli, Ma, and Shleifer (2020) and test for correlation between forecast revisions and forecast errors, both within and across asset classes. The general idea is that if forecasters overreact to news, they may revise their forecast too much, thereby creating a forecast error in the opposite direction: for example, revise their equity return expectation up to the extent that it is above the future realised value, and hence the positive forecast revision is followed by a negative forecast error. To test for this, Bordalo et al. (2020) run the following regression:

$$\underbrace{x_{t+h} - x^n_{t+h|t}}_{FE_{t+h}} = \beta^n_0 + \beta^n_1 \underbrace{(x^n_{t+h|t} - x^n_{t+h|t-1})}_{FR_{t+h}} + u^n_{t,t+h} \tag{13}$$

Above, x is the variable that is being forecast – e.g. the stock return – FE is the forecast error, FR is the forecast revision – the difference between the h-ahead forecast made at times $t-1$ and t – and β^n_0 are forecaster fixed effects, with the regression being run at the level of individual forecaster n. A negative β^n_1 is evidence that forecasters revise their forecast too much in response to news, i.e. they overreact. What I do is to in addition test for overreaction to news on other asset classes, by

[5] Because BAA forecasts are only available from 2010 onwards, I cannot correlate them with equity expectation errors since computing equity errors requires stock price realisations 10 years ahead, i.e. 2020 onwards for the post-2010 sample.

Table 13: *Asset-specific overreaction in the Survey of Professional Forecasters*

	(1)	(2)	(3)	(4)
	Equities forecast error	Treasuries forecast error	AAA bonds forecast error	BAA bonds forecast error
Equities forecast revision	-0.53***	0.05	-0.00	-0.02
	(0.13)	(0.04)	(0.02)	(0.04)
Treasuries forecast revision	0.29**	-0.31***	0.03	0.00
	(0.13)	(0.11)	(0.08)	(0.07)
AAA bond forecast revision	0.19	-0.13	-0.39***	-0.35*
	(0.56)	(0.29)	(0.10)	(0.19)
BAA bond forecast revision				-0.98***
				(0.17)
R^2	0.07	0.07	0.08	0.45
Observations	164	113	263	68

Notes: Forecast revision is the change in the forecast for quarter $t+h$ between quarter t and $t-1$ for bonds and year t and $t-1$ for equities. Forecast error is the realised value at $t+h$ minus the forecast made at t. Forecast horizons are 10 years for equities and 5 quarters for bonds. Regressions with individual forecaster fixed effects, standard errors clustered by forecaster and quarter. Since BAA spread forecast data start in 2010, I do not include them in regressions 1–3 in order to maintain a large enough sample size. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

regressing an asset-specific forecast error on other assets' forecast revisions as follows:

$$\underbrace{x^i_{t+h} - x^{i,n}_{t+h|t}}_{FE^i_{t+h}} = \beta^n_0 + \beta^n_{own}\underbrace{\left(x^{i,n}_{t+h|t} - x^{i,n}_{t+h|t-1}\right)}_{FR^{own}_{t+h}} + \beta^n_{cross}\underbrace{\left(x^{j,n}_{t+h|t} - x^{j,n}_{t+h|t-1}\right)}_{FR^{cross}_{t+h}} + u^n_{t,t+h} \tag{14}$$

Above, FE^i is the forecast error on asset i – e.g. equities – FR^{own} is the within-asset-class (e.g. equity forecast) revision, and FR^{cross} are forecast revisions for other asset classes. If overreaction to news is asset-specific, we should see $\beta^n_{own} < 0$ and $\beta^n_{own} \geq 0$. I run these regressions for each asset class i, using horizons of 10 years for equities and treasuries, and horizons of 5 quarters for corporate bonds.[6] Because the forecasts are uncorrelated, running the within and cross-asset-class specifications together, as in Table 13, shows similar results to running them separately.

Table 13 shows the results of regressing the forecast error on within-asset-class and cross-asset-class forecast revisions.[7] Within asset classes, there is consistent evidence of overreaction: the estimates of β^n_{own} on the diagonal are all negative and significant, with magnitudes similar to those documented by Bordalo et al. (2020). This confirms the evidence in Bordalo et al. (2020) that while

[6] 5 quarters is the longest horizon for which I can calculate the revision term FR from consecutive 5- and 6-quarter ahead forecasts. For 10-year ahead forecasts, I simply take the difference between 10-year ahead forecasts in year t and $t-1$ (since stock market forecasts are only available for the 10-year horizon).

[7] As before, because the BAA yield forecast data only start in 2010, I do not include it in the regressions in Table 13 columns 1–3 to keep a large enough sample for those estimates.

aggregate forecasts studied by, among others, Coibion and Gorodnichenko (2012) may display underreaction ($\beta^n_{own} > 0$), forecaster-level forecasts – especially those for financial variables – often display overreaction. But my findings also show that this overreaction is asset-class-specific. The off-diagonal β^n_{cross} estimates are mostly insignificant, small in magnitude, and often positive rather than negative (e.g. equity forecasts underreact to treasury forecast revisions).

The only negative and significant estimate is for the BAA-AAA spread reaction to the AAA-treasury spread forecast revisions in column 4 (coefficient of -0.35), suggesting that BAA bond yields overreact to news related to AAA bonds. This evidence is consistent with forecaster overreaction within asset class (since AAA and BAA are both corporate bonds), but not across asset classes. Interestingly, the BAA bond spread regression also displays the highest overreaction R^2, similar to the high discount rate news share and mean-reversion coefficient for the within-asset-class corporate bond spread predictability regressions in Table 3 and Figure 5.

If expectation formation is volatile because of learning or biases and information is asset-specific, these volatile expectations can generate asset-specific volatility in expected returns. The evidence presented above suggests that one mechanism behind such sentiment variation – overreaction to asset-specific news – is present in the SPF survey data, and generates expected return variation that is specific to a particular asset class.

6.4. Other asset-specific factors

In what follows, I briefly discuss two other factors – non-monetary payoffs and credit constraints – which can generate asset-specific variation in expected returns.

Liquidity, convenience and housing utility Asset valuations depend not only on monetary cashflows, but also on any additional non-monetary payoffs provided by the asset. These include liquidity and the utility flow of services for housing. Time-varying liquidity premia should affect the price differential of liquid vs illiquid assets, generating a wedge in expected returns between these two asset categories. Bao, Pan, and Wang (2011) show that liquidity premia form an important component of the corporate bond spread, and Piazzesi and Schneider (2016) show that housing assets are illiquid with housing turnover generally around a tenth of that in the stock market. In addition to liquidity and convenience premia, housing may generate additional utility services – for homeowners – which are not well measured by monetary rents.

Credit constraints Whereas equity and bond purchases are often financed by cash, house purchase is typically financed by credit, with the importance of mortgage finance rising substantially over recent decades (Jordà, Schularick, and Taylor, 2016a). Variation in credit conditions can therefore explain some of the variation in demand for housing assets, and with it the time variation in housing-specific expected returns (Favilukis, Ludvigson, and Van Nieuwerburgh, 2017).

Table 14: *Predictability using proxies for housing utility, credit conditions and liquid asset supply*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity		Housing		Corporate bonds	
	r_{t+1}	$\overline{r_{t+1,t+5}}$	r_{t+1}	$\overline{r_{t+1,t+5}}$	r_{t+1}	$\overline{r_{t+1,t+5}}$
Rent expenditure/GDP	0.004	-0.005	0.003	0.001	0.010***	0.005
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mortgage loan growth	0.008	0.003	0.011***	0.001	0.008	0.006
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Public debt/GDP	0.023***	0.016**	-0.002	0.000	0.014**	0.010**
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
R^2	0.013	0.032	0.018	0.001	0.035	0.041
Observations	1651	1578	1633	1544	1408	1313

Notes: OLS regressions with country fixed effects. All coefficients are standardised to a 1 standard deviation increase in the predictor variable. Predictor (x) variables in rows. Rent-GDP and public debt-GDP ratios are in logs. Mortgage loan growth is the log cumulative 3-year growth in mortgage credit net of inflation. Dependent (y) variables in columns. r_{t+1} is the 1-year ahead log real total return, and $\overline{r_{t+1,t+5}}$ is the average 5-year ahead log real total return on the specific asset class. Standard errors clustered by country-year and adjusted for autocorrelation in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

Table 14 tests the importance of these asset-specific factors by using proxies for housing utility, housing credit conditions, and liquid asset supply to predict future returns across the three asset classes. Following Piazzesi et al. (2007), the value of housing utility is proxied by the share of rental expenditure in GDP, with rents being a proxy for total housing-related expenses. Housing credit conditions are proxied as the 3-year cumulative growth in real mortgage credit. Following Krishnamurthy and Vissing-Jorgensen (2012), I use the public debt to GDP ratio as a rough proxy for the supply of liquid assets, with the idea being that if public liquid assets are plentiful, demand for liquidity is easy to satisfy and liquidity premia – and hence the expected returns on illiquid assets – ought to be low.

Table 14 shows that these factors have some influence on asset-specific expected returns, but this influence is limited. A high rental expenditure share forecasts high year-ahead corporate bond returns (column 5) but not those at other horizons or asset classes. Mortgage loan growth does forecast higher housing returns in the short run – in line with higher demand for housing driven by this higher credit availability – but not in the long run. High public debt forecasts high rather than low returns on equities and corporate bonds, suggesting that these assets may be pricing a high macroeconomic risk exposure rather than a low liquidity premium. The R^2 statistics of the predictive regressions are low – though of course, more precise proxies of these different factors may do a better job of forecasting returns.

Taken together, this section has shown that the co-movement puzzle is difficult to reconcile with the most prominent asset pricing theories, since they tend to rely on a single risk factor, generally relating to macro-financial risk, to generate expected return variation across all asset classes. Simple modifications of these theories introducing additional frictions, time-varying risk exposures and investor heterogeneity also appear to fall somewhat short of generating the type of asset-specific expected return variation observed in the data. Instead, looking at conceptually different types of drivers of excess volatility – namely, capital flows and volatile expectations – offers a promising way of resolving the puzzle.

7. Conclusion

This paper has used long-run data spanning 17 countries, 146 years and 3 major risky asset classes to assess the underlying drivers of asset price volatility. This analysis has confirmed the ubiquity of Shiller (1981)'s volatility puzzle: prices of all major risky asset classes vary more than fundamentals in a highly predictable manner. For equities, the volatility puzzle is not quite as pervasive as previously thought, with time-varying dividend growth accounting for around half of the variation in dividend-price ratios. For housing and corporate bonds however, non-fundamental variation is by far the dominant force behind observed asset price movements.

The main contribution of this paper is to document a new asset pricing anomaly which should ultimately help pin down the underlying source of this excess volatility. I find that the discount rates – or expected returns – on different asset classes do not co-move. The low degree of co-movement is highly pervasive, stretching across different time periods, countries and holding up under a variety of alternative testing methods. It is difficult to reconcile with many of the established asset pricing theories which attribute excess volatility to a variation in a common cross-asset discount factor. I show that most observed excess volatility is, in fact, asset-specific and therefore not attributable to common macroeconomic forces such as disasters and risk aversion. Instead, my findings point to the importance of conceptually different sources of asset price variation in the form of time varying capital flows and volatility in the expectation formation process itself.

References

Adam, Klaus, Johannes Beutel, and Albert Marcet. 2017. Stock Price Booms and Expected Capital Gains. *American Economic Review* 107(8): 2352–2408.

Andonov, Aleksandar, and Joshua D. Rauh. 2020. The Return Expectations of Institutional Investors. Stanford University Graduate School of Business Research Paper.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse H. Pedersen. 2013. Value and Momentum Everywhere. *Journal of Finance* 68(3): 929–985.

Bai, Jushan, and Pierre Perron. 2003. Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics* 18(1): 1–22.

Baker, Malcolm, and Jeffrey Wurgler. 2000. The Equity Share in New Issues and Aggregate Stock Returns. *Journal of Finance* 55(5): 2219–2257.

Bansal, Ravi, and Amir Yaron. 2004. Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles. *Journal of Finance* 59(4): 1481–1509.

Bao, Jack, Jun Pan, and Jiang Wang. 2011. The Illiquidity of Corporate Bonds. *Journal of Finance* 66(3): 911–946.

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer. 2015. X-CAPM: An Extrapolative Capital Asset Pricing Model. *Journal of Financial Economics* 115(1): 1–24.

Barberis, Nicholas, and Andrei Shleifer. 2003. Style Investing. *Journal of Financial Economics* 68(2): 161–199.

Baron, Matthew, and Tyler Muir. 2018. Intermediaries and Asset Prices: Evidence from the US, UK, and Japan, 1870-2016. Working paper.

Baron, Matthew, and Wei Xiong. 2017. Credit Expansion and Neglected Crash Risk. *Quarterly Journal of Economics* 132(2): 713–764.

Barro, Robert J. 2006. Rare Disasters and Asset Markets in the Twentieth Century. *Quarterly Journal of Economics* 121(3): 823–866.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer. 2019. Diagnostic Expectations and Stock Returns. *Journal of Finance* 74(6): 2839–2874.

Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer. 2020. Overreaction in Macroeconomic Expectations. *American Economic Review* 110(9): 2748–82.

Campbell, John. 1991. A Variance Decomposition for Stock Returns. *Economic Journal* 101(405): 157–79.

Campbell, John Y., and John H. Cochrane. 1999. By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. *Journal of Political Economy* 107(2): 205–251.

Campbell, John Y., and Robert J. Shiller. 1988. The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *Review of Financial Studies* 1(3): 195–228.

Campbell, Sean D., Morris A. Davis, Joshua Gallin, and Robert F. Martin. 2009. What Moves Housing Markets: A Variance Decomposition of the Rent–Price Ratio. *Journal of Urban Economics* 66(2): 90–102.

Chen, Long. 2009. On the Reversal of Return and Dividend Growth Predictability: A Tale of Two Periods. *Journal of Financial Economics* 92(1): 128–151.

Cochrane, John H. 2008. The Dog That Did Not Bark: A Defense of Return Predictability. *Review of Financial Studies* 21(4): 1533–1575.

Cochrane, John H. 2011. Presidential Address: Discount Rates. *Journal of Finance* 66(4): 1047–1108.

Cochrane, John H. 2017. Macro-Finance. *Review of Finance* 21(3): 945–985.

Coibion, Olivier, and Yuriy Gorodnichenko. 2012. What Can Survey Forecasts Tell Us about Information Rigidities? *Journal of Political Economy* 120(1): 116–159.

Constantinides, George M., and Darrell Duffie. 1996. Asset Pricing with Heterogeneous Consumers. *Journal of Political Economy* 104(2): 219–240.

Engsted, Tom, and Thomas Q. Pedersen. 2010. The Dividend-Price Ratio Does Predict Dividend Growth: International Evidence. *Journal of Empirical Finance* 17(4): 585–605.

Fama, Eugene F., and Kenneth R. French. 1989. Business Conditions and Expected Returns on Stocks and Bonds. *Journal of Financial Economics* 25(1): 23–49.

Fama, Eugene F., and Kenneth R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33(1): 3–56.

Favilukis, Jack, Sydney C. Ludvigson, and Stijn Van Nieuwerburgh. 2017. The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk Sharing in General Equilibrium. *Journal of Political Economy* 125(1): 140–223.

Gabaix, Xavier. 2012. Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance. *Quarterly Journal of Economics* 127(2): 645–700.

Gabaix, Xavier, and Ralph S.J. Koijen. 2020. In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis. Working Paper. Available at SSRN 3686935.

Garbinti, Bertrand, Jonathan Goupille-Lebret, and Thomas Piketty. 2020. Accounting for Wealth-Inequality Dynamics: Methods, Estimates, and Simulations for France. *Journal of the European Economic Association* Jvaa025.

Gârleanu, Nicolae, and Stavros Panageas. 2015. Young, Old, Conservative, and Bold: The Implications of Heterogeneity and Finite Lives for Asset Pricing. *Journal of Political Economy* 123(3): 670–685.

Ghysels, Eric, Alberto Plazzi, Rossen Valkanov, and Walter Torous. 2013. Chapter 9 – Forecasting Real Estate Prices. In *Handbook of Economic Forecasting*, edited by Elliott, Graham, and Allan Timmermann, volume 2, 509–580. Cambridge, Mass.: Elsevier.

Giesecke, Kay, Francis A. Longstaff, Stephen Schaefer, and Ilya Strebulaev. 2011. Corporate Bond Default Risk: A 150-year Perspective. *Journal of Financial Economics* 102(2): 233–250.

Giesecke, Kay, Francis A. Longstaff, Stephen Schaefer, and Ilya A. Strebulaev. 2014. Macroeconomic Effects of Corporate Default Crisis: A Long-term Perspective. *Journal of Financial Economics* 111(2): 297–310.

Giglio, Stefano, and Bryan Kelly. 2018. Excess Volatility: Beyond Discount Rates. *Quarterly Journal of Economics* 133(1): 71–127.

Golez, Benjamin, and Peter Koudijs. 2017. Four Centuries of Return Predictability. NBER Working Paper 20814.

Golez, Benjamin, and Peter Koudijs. 2018. Four Centuries of Return Predictability. *Journal of Financial Economics* 127(2): 248–263.

Goyal, Amit, and Ivo Welch. 2008. A Comprehensive Look at the Empirical Performance of Equity Premium Prediction. *Review of Financial Studies* 21(4): 1455–1508.

Greenwood, Robin, and Samuel G. Hanson. 2013. Issuer Quality and Corporate Bond Returns. *Review of Financial Studies* 26(6): 1483–1525.

Greenwood, Robin, Samuel G. Hanson, and Gordon Y. Liao. 2018. Asset Price Dynamics in Partially Segmented Markets. *Review of Financial Studies* 31(9): 3307–3343.

Haddad, Valentin, Serhiy Kozak, and Shrihari Santosh. 2017. Predicting Relative Returns. NBER Working Paper 23886.

Haddad, Valentin, and Tyler Muir. 2021. Do Intermediaries Matter for Aggregate Asset Prices? *Journal of Finance* Forthcoming.

He, Zhiguo, and Arvind Krishnamurthy. 2013. Intermediary Asset Pricing. *American Economic Review* 103(2): 732–70.

Jordà, Òscar, Katharina Knoll, Dmitry Kuvshinov, Moritz Schularick, and Alan M. Taylor. 2019a. The Rate of Return on Everything, 1870–2015. *Quarterly Journal of Economics* 134: 1225–1298.

Jordà, Òscar, Katharina Knoll, Dmitry Kuvshinov, Moritz Schularick, and Alan M. Taylor. 2019b. The Total Risk Premium Puzzle. NBER Working Paper 25653.

Jordà, Òscar, Björn Richter, Moritz Schularick, and Alan M. Taylor. 2017. Bank Capital Redux: Solvency, Liquidity, and Crisis. NBER Working Paper 23287.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. 2016a. The Great Mortgaging: Housing Finance, Crises and Business Cycles. *Economic Policy* 31(85): 107–152.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. 2016b. Macrofinancial History and the New Business Cycle Facts. In *NBER Macroeconomics Annual 2016, Volume 31*, edited by Martin Eichenbaum, Jonathan A. Parker, 213–263. Chicago, Ill.: University of Chicago Press.

Klovland, Jan Tore. 2004. Bond Markets and Bond Yields in Norway 1820–2003. In *Historical Monetary Statistics for Norway 1819–2003. Norges Bank Occasional Paper No. 35*, edited by Øyvind Eitrheim, Jan T. Klovland, and Jan F. Qvigstad, chapter 4, 99–181.

Knoll, Katharina. 2017. *Our Home in Days Gone By: Housing Markets in Advanced Economies in Historical Perspective*. Ph.D. thesis, Free University of Berlin. Chapter 3. As Volatile As Houses: Return Predictability in International Housing Markets, 1870–2015.

Krishnamurthy, Arvind, and Annette Vissing-Jorgensen. 2012. The Aggregate Demand for Treasury Debt. *Journal of Political Economy* 120(2): 233–267.

Kuvshinov, Dmitry. 2021. The Corporate Bond Premium. Manuscript, in preparation.

Kuvshinov, Dmitry, and Kaspar Zimmermann. 2020. The Big Bang: Stock Market Capitalization in the Long Run. CEPR Discussion Paper 14468.

Lettau, Martin, and Sydney Ludvigson. 2002. Consumption, Aggregate Wealth, and Expected Stock Returns. *The Journal of Finance* 56(3): 815–849.

Lettau, Martin, Matteo Maggiori, and Michael Weber. 2014. Conditional Risk Premia in Currency Markets and Other Asset Classes. *Journal of Financial Economics* 114(2): 197–225.

Lettau, Martin, and Stijn Van Nieuwerburgh. 2008. Reconciling the Return Predictability Evidence. *Review of Financial Studies* 21(4): 1607–1652.

López-Salido, David, Jeremy C. Stein, and Egon Zakrajšek. 2017. Credit-Market Sentiment and the Business Cycle. *Quarterly Journal of Economics* 132(3): 1373–1426.

Malmendier, Ulrike, and Stefan Nagel. 2011. Depression Babies: Do Macroeconomic Experiences Affect Risk Taking? *Quarterly Journal of Economics* 126(1): 373–416.

Mankiw, N. Gregory, and Stephen P. Zeldes. 1991. The Consumption of Stockholders and Nonstockholders. *Journal of Financial Economics* 29(1): 97–112.

Martínez-Toledano, Clara. 2019. House Price Cycles, Wealth Inequality and Portfolio Reshuffling. Working paper.

Mediobanca. Various years. Indici e Dati Relativi ad Investimenti in Titoli Quotati.

Mehra, Rajnish, and Edward C. Prescott. 1985. The Equity Premium: A Puzzle. *Journal of Monetary Economics* 15(2): 145–161.

Muir, Tyler. 2017. Financial Crises and Risk Premia. *Quarterly Journal of Economics* 132(2): 765–809.

Nagel, Stefan, and Zhengyang Xu. 2019. Asset Pricing with Fading Memory. NBER Working Paper 26255.

Nozawa, Yoshio. 2017. What Drives the Cross-Section of Credit Spreads?: A Variance Decomposition Approach. *Journal of Finance* 72(5): 2045–2072.

Piazzesi, M., and M. Schneider. 2016. Chapter 19 – Housing and Macroeconomics. volume 2 of *Handbook of Macroeconomics*, 1547–1640. Elsevier.

Piazzesi, Monika, Martin Schneider, and Selale Tuzel. 2007. Housing, Consumption and Asset Pricing. *Journal of Financial Economics* 83(3): 531–569.

Piketty, Thomas, Emmanuel Saez, and Gabriel Zucman. 2018. Distributional National Accounts: Methods and Estimates for the United States. *Quarterly Journal of Economics* 133(2): 553–609.

Piketty, Thomas, and Gabriel Zucman. 2014. Capital is Back: Wealth-Income Ratios in Rich Countries 1700–2010. *Quarterly Journal of Economics* 129(3): 1255–1310.

Plazzi, Alberto, Walter Torous, and Rossen Valkanov. 2010. Expected Returns and Expected Growth in Rents of Commercial Real Estate. *The Review of Financial Studies* 23(9): 3469–3519.

Ross, Stephen A. 1976. The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory* 13: 341–360.

Schularick, Moritz, and Alan M. Taylor. 2012. Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *American Economic Review* 102(2): 1029–61.

Shiller, Robert J. 1981. Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *American Economic Review* 71(3): 421–436.

Shiller, Robert J. 1982. Consumption, Asset Markets and Macroeconomic Fluctuations. *Carnegie-Rochester Conference Series on Public Policy* 17: 203–238.

Shiller, Robert J. 2000. *Irrational Exuberance*. Princeton, N.J.: Princeton University Press.

Stambaugh, Robert F. 1999. Predictive regressions. *Journal of Financial Economics* 54(3): 375–421.

Appendix

A. Data coverage

Table A.1: *Data coverage*

Country	Equity	Housing	Corporate Bonds
Australia	1870–2016	1901–2015	1915–2016
Belgium	1870–2016	1890–2015	1870–2016
Canada	1870–2016		1905–2016
Denmark	1872–2016	1875–2015	1991–2016
Finland	1912–2016	1920–2015	1922–2015
France	1870–2016	1870–2015	1870–2016
Germany	1870–2016	1870–2015	1870–2016
Italy	1870–2016	1927–2015	1873–2016
Japan	1886–2016	1931–2015	1900–2016
Netherlands	1900–2016	1870–2015	1870–2016
Norway	1880–2016	1871–2015	1903–2016
Portugal	1870–2016	1948–2015	1905–2016
Spain	1899–2016	1900–2015	1884–2016
Sweden	1871–2016	1883–2015	1871–2016
Switzerland	1875–2016	1901–2015	1925–2016
UK	1870–2016	1895–2015	1870–2016
USA	1871–2016	1890–2015	1870–2016

B. Corporate bond data description

Corporate bond data include yields, spreads and holding period returns on bonds issued by private sector creditors, targeting 10-year maturity. The corporate bond discount rate proxy is the spread, equal to the yield to maturity differential between corporate and government bonds:

$$\text{spread}_t = YTM_{\text{corporate},t} - YTM_{\text{government},t} \tag{A.1}$$

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:

$$r^{holding}_{bond,t+1} = C_{bond,t+1}/P_{bond,t} + (P_{bond,t+1} - P_{bond,t})/P_{bond,t} \tag{A.2}$$

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:

$$r^{implied}_{bond,t+1} = -(\text{spread}_{t+1} - \text{spread}_t) \tag{A.3}$$

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.

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.[8] 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. (2019a). 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, described in the next section. 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.

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.

[8] 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.

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.

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 sample, the biases arising from uncertainty around maturity dates are likely to be small.

Comparison to existing datasets 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. 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.

C. Return predictability within asset classes: additional results

C.1 Additional predictive regressions

Table A.2: *Predicting corporate default rates with yield spreads, US data*

	(1)	(2)
	Default rate, t+1	Δ Default rate, t+1
spread$_t$	1.485***	
	(0.274)	
Δ spread$_t$		0.195
		(0.331)
R^2	0.430	0.002
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. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

Table A.2 shows that high spreads are positively correlated with future corporate bond defaults in the US, though this relationship is only significant in levels and not in changes. Table A.3 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 2. 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. But if we adjust the data for structural breaks as in table A.4, returns are predictable for almost every country and asset class. In the break-adjusted regression, dividends are strongly predictable whereas evidence for rent growth predictability is rather weak. Note also that the non break adjusted US equity return coefficient in Table A.3 is insignificant contrary to the findings of Cochrane (2008). This is largely explained by the different sample used in this paper – rather than using the CRSP data which go back to 1926, I use the Shiller (2000) S and P 500 data going back to 1870. As also shown by Chen (2009) and Golez and Koudijs (2018), in this sample dividend predictability becomes stronger and return predictability – weaker. In any case, consistent with Lettau and Van Nieuwerburgh (2008), both returns and dividends become predictable once we adjust the US data for structural breaks.

Table A.3: *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	0.032**	-0.020*	0.009	-0.008	0.025**	-0.385***
	(0.013)	(0.011)	(0.007)	(0.006)	(0.010)	(0.081)
Belgium	0.033	-0.027	-0.024*	-0.043***	0.018**	-0.589***
	(0.025)	(0.043)	(0.014)	(0.012)	(0.009)	(0.113)
Canada	0.024*	-0.059***			0.027***	-0.211*
	(0.014)	(0.018)			(0.008)	(0.125)
Denmark	-0.003	-0.051**	0.025***	-0.001		
	(0.018)	(0.024)	(0.006)	(0.003)		
Finland	0.036	-0.069*	0.047***	-0.016	0.020*	-0.385**
	(0.033)	(0.041)	(0.013)	(0.013)	(0.012)	(0.165)
France	0.093***	0.028	0.034***	0.018***	0.036***	-0.184
	(0.019)	(0.029)	(0.008)	(0.006)	(0.008)	(0.117)
Germany	-0.022	-0.157***	0.038***	0.003	0.049***	-0.217***
	(0.024)	(0.027)	(0.009)	(0.004)	(0.017)	(0.073)
Italy	0.029	-0.062	0.030***	-0.020	0.034**	-0.559***
	(0.035)	(0.038)	(0.008)	(0.016)	(0.014)	(0.126)
Japan	0.030	-0.052**	0.019***	-0.007	0.014	-0.462***
	(0.023)	(0.021)	(0.007)	(0.004)	(0.013)	(0.174)
Netherlands	0.016	-0.063***	0.023***	-0.008	0.024***	-0.266***
	(0.021)	(0.024)	(0.007)	(0.005)	(0.006)	(0.066)
Norway	0.005	-0.057**	0.024***	0.004	0.042***	-0.418***
	(0.020)	(0.024)	(0.008)	(0.005)	(0.008)	(0.103)
Portugal	0.028	-0.012	0.003	-0.025**	0.032*	-0.340***
	(0.035)	(0.069)	(0.012)	(0.010)	(0.018)	(0.099)
Spain	0.053***	-0.057**	0.026**	-0.006	-0.032***	-0.144*
	(0.021)	(0.026)	(0.011)	(0.006)	(0.008)	(0.080)
Sweden	0.001	-0.091***	0.014**	-0.004	0.034***	-0.254***
	(0.018)	(0.016)	(0.007)	(0.004)	(0.007)	(0.058)
Switzerland	0.007	-0.060***	0.008	-0.008*	0.021**	-0.256**
	(0.019)	(0.020)	(0.005)	(0.004)	(0.009)	(0.106)
UK	0.046**	-0.021***	0.022***	-0.000	0.009	-0.390***
	(0.019)	(0.006)	(0.006)	(0.005)	(0.008)	(0.112)
USA	0.021	-0.039***	0.024***	-0.007	0.034***	-0.156***
	(0.015)	(0.012)	(0.009)	(0.005)	(0.006)	(0.057)
Significant/Total	5/17	13/17	13/16	4/16	14/16	15/16

Note: OLS regressions at country level. Predictor (x) variables are the log dividend-price ratio, log rent-price ratio and the percentage point corporate bond spread, all standardised to a 1 standard deviation increase. 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. Danish corporate bond regression omitted as the bond series start in 1990. Heteroskedasticity-robust standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

Table A.4: *Return and cashflow predictability in individual countries, adjusted for structural breaks*

	(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	0.028**	-0.038***	0.017***	-0.020**	0.032***	-0.617***
	(0.014)	(0.012)	(0.007)	(0.009)	(0.008)	(0.092)
Belgium	0.030	-0.037	-0.040**	-0.057***	0.015*	-0.652***
	(0.024)	(0.041)	(0.017)	(0.012)	(0.009)	(0.105)
Canada	0.039***	-0.075***			0.026***	-0.318**
	(0.011)	(0.017)			(0.008)	(0.155)
Denmark	0.030*	-0.038	0.021***	-0.004		
	(0.016)	(0.026)	(0.006)	(0.006)		
Finland	0.064**	-0.116***	0.052***	0.002	0.007	-0.833***
	(0.032)	(0.037)	(0.016)	(0.014)	(0.011)	(0.189)
France	0.103***	0.019	0.024***	0.002	0.038***	-0.523***
	(0.020)	(0.024)	(0.008)	(0.007)	(0.008)	(0.174)
Germany	-0.026	-0.186***	0.027*	-0.005	0.058***	-0.334***
	(0.025)	(0.022)	(0.014)	(0.004)	(0.019)	(0.079)
Italy	0.035	-0.066	0.009	-0.021	0.018	-0.821***
	(0.036)	(0.042)	(0.006)	(0.015)	(0.012)	(0.151)
Japan	0.033	-0.081**	0.020**	0.003	0.024***	-0.617***
	(0.030)	(0.032)	(0.010)	(0.008)	(0.009)	(0.164)
Netherlands	0.043**	-0.085***	0.024***	-0.009	0.029***	-0.382***
	(0.021)	(0.023)	(0.006)	(0.006)	(0.007)	(0.101)
Norway	0.023	-0.047**	0.036***	0.008*	0.029***	-0.572***
	(0.020)	(0.023)	(0.007)	(0.005)	(0.009)	(0.104)
Portugal	0.079***	-0.011	0.003	-0.020*	0.032	-0.554***
	(0.030)	(0.071)	(0.007)	(0.011)	(0.021)	(0.091)
Spain	0.056***	-0.071***	0.031***	-0.011	-0.010	-0.458***
	(0.018)	(0.024)	(0.011)	(0.007)	(0.009)	(0.151)
Sweden	0.027	-0.091***	0.029***	-0.001	0.023***	-0.432***
	(0.020)	(0.016)	(0.006)	(0.004)	(0.008)	(0.082)
Switzerland	0.018	-0.067***	0.012**	-0.002	0.018**	-0.438***
	(0.018)	(0.019)	(0.005)	(0.003)	(0.009)	(0.130)
UK	0.067***	-0.018***	0.031***	-0.001	0.013	-0.594***
	(0.016)	(0.005)	(0.007)	(0.005)	(0.008)	(0.121)
USA	0.034**	-0.062***	0.030***	-0.007*	0.018***	-0.405***
	(0.013)	(0.012)	(0.009)	(0.004)	(0.007)	(0.107)
Significant/Total	10/17	12/17	14/16	5/16	11/16	16/16

Note: OLS regressions at country level. Predictor (x) variables are the log dividend-price ratio, log rent-price ratio and the percentage point corporate bond spread, all adjusted for structural breaks and standardised to a 1 standard deviation increase. 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. Danish corporate bond regression omitted as the bond series start in 1990. Heteroskedasticity-robust standard errors in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

C.2 Discount rate and cashflow news, VAR estimation

Equation (4) 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:

$$\mathrm{Var}(dp_{i,t}) = \underbrace{\mathrm{Var}(\mathbb{E}\sum_{s=0}^{\infty}\rho_i^s r_{i,t+1+s})}_{\text{DR news}} + \underbrace{\mathrm{Var}(\mathbb{E}\sum_{s=0}^{\infty}\rho_i^s dg_{i,t+1+s})}_{\text{CF news}} - 2\mathrm{Cov}(\mathbb{E}\sum_{s=0}^{\infty}\rho_i^s r_{i,t+1+s}, \mathbb{E}\sum_{j=0}^{\infty}\rho_i^s dg_{i,t+1+s}) \tag{A.4}$$

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 $[r_{i,t}, dg_{i,t}, dp_{i,t}] \equiv z_{i,t}$:

$$z_{i,t} = Az_{i,t-1} + u_{i,t} \tag{A.5}$$

$$z_{i,t} = [r_{i,t}, dg_{i,t}, dp_{i,t}]' \tag{A.6}$$

$$\mathbb{E}(zz') = \Gamma; \quad \mathbb{E}(uu') = \Sigma; I = (e1, e2, e3) \tag{A.7}$$

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

$$E[(z_{i,t+1} - z_{i,t}) \otimes z_{i,t}] = 0 \tag{A.8}$$

The present value relation in (4) imposes three additional moment restrictions:

$$(e1' - e2' + \rho e3')A = e3' \tag{A.9}$$

I estimate the VAR using 6-equation GMM subject to the constraints in (A.9), 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 (A.4):

$$\mathrm{Var}(dp_{i,t}) = e3\Gamma e3 = \underbrace{e1'A(I-\rho A)^{-1}\Gamma e3}_{\text{DR news}} - \underbrace{e2'A(I-\rho A)^{-1}\Gamma e3}_{\text{CF news}} \tag{A.10}$$

Here, A is the VAR coefficient matrix, and Γ is the covariance matrix of the regressors in (A.7).

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 $r_{i,t+1} - \mathbb{E}r_{i,t+1}$:

$$r_{i,t+1} - \mathbb{E}r_{i,t+1} = \underbrace{-e1'\rho_i A(I-\rho_i A)^{-1}u_{i,t+1}}_{\text{DR news}} + \underbrace{(e1 + e1'\rho_i A(I-\rho_i A)^{-1})u_{i,t+1}}_{\text{CF news}} \tag{A.11}$$

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:

$$\mathrm{Var}(\mathrm{spread}_t) = \mathrm{Var}(\sum_{s=1}^{s=9}\rho_{bond}^s \Delta\mathrm{spread}_{t+s}) + \text{Cashflow news} \tag{A.12}$$

Table A.5: *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	0.101***	0.018	-0.086**	0.207***	-0.012	-0.230***
	(0.032)	(0.043)	(0.038)	(0.047)	(0.029)	(0.045)
dg_t	-0.004	-0.044	-0.042	0.156***	0.445***	0.304***
	(0.027)	(0.051)	(0.045)	(0.044)	(0.044)	(0.046)
dp_t	0.061***	-0.085***	0.887***	0.066***	-0.022***	0.957***
	(0.012)	(0.018)	(0.017)	(0.007)	(0.007)	(0.008)
Variance decomposition of dp_t:						
DR share			45			65
CF share			55			35
Observations			2266			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. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.

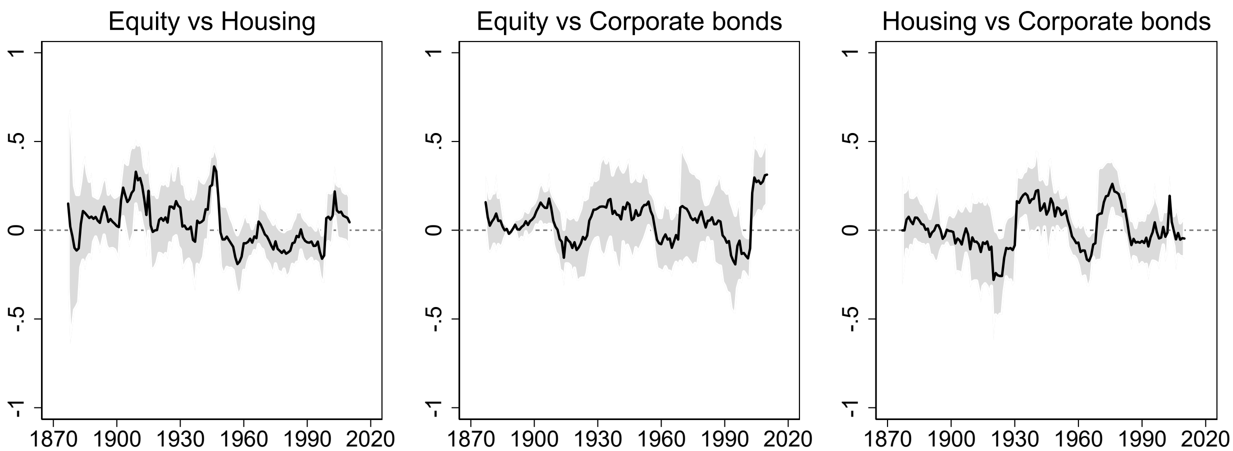
An alternative way of assessing the importance of expected returns is simply to regress the ten-year ahead credit spread growth on the current credit spread – an exercise that, similarly to the long-horizon regressions in Table 4, show that almost all of the variation in credit spreads can be accounted 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.5 shows the estimated VAR for housing and equity, using GMM specified in equations (A.8) and (A.9), and the corresponding variance decomposition ratios in equation (A.10). Dependent variables $z_{i,t+1}$ are in columns, and predictor variables $z_{i,t}$ are in rows. As in Table 2, the first two columns present the predictive coefficients on next period's real equity returns $r_{i,t+1}$ and real dividend growth $dg_{i,t+1}$ – but unlike in Table 2, the coefficients are not standardised. The bottom row uses the dividend-to-price ratio $dp_{i,t}$ as a predictor, so the estimates in the first two columns row 3 are the non-standardised versions of the OLS estimates in the first two columns row 1 in Table 2. Compared to OLS, the VAR estimates a richer dynamic structure, but the magnitudes of the coefficients of interest are very similar across the two specifications (Table 4).

D. Discount rate co-movement: additional results

D.1 Discount rate correlations

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



Note: Pairwise correlation coefficients between 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 95% confidence intervals, using country-clustered standard errors.

Table A.6: *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	0.01	0.05	0.16	0.15
Belgium	0.47***	0.12**	0.24***	0.54***
Canada		0.22***		
Denmark	−0.03	−0.04	0.16	0.06
Finland	0.14*	−0.40**	−0.07	0.20**
France	0.15**	0.09	−0.06	0.33***
Germany	0.10	0.03	−0.12*	0.06
Italy	0.18	0.25**	0.10	0.29
Japan	0.08	−0.02	−0.30*	0.19
Netherlands	−0.14	0.06	0.05	0.02
Norway	−0.07	0.08	−0.06	0.15
Portugal	−0.12	0.02	0.08	0.29
Spain	−0.27**	−0.23	0.14	0.02
Sweden	0.11	0.18	0.06	0.10
Switzerland	−0.12	0.00	0.11	0.13
UK	−0.13**	0.29*	0.04	0.24**
USA	0.11	0.36***	0.02	0.33***
Sig. >0 / Total	3/16	5/17	1/16	5/16
Sig. <0 / Total	2/16	1/17	2/16	0/16
Not sig. / Total	11/16	11/17	13/16	11/16

Note: Pairwise correlation coefficients. 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.7: *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	−0.01	0.08	0.17	0.10
Belgium	0.14	−0.10	0.04	0.22*
Canada		0.29***		
Denmark	0.10	−0.04	0.16	0.24**
Finland	0.07	−0.39*	−0.04	0.07
France	0.11	0.08	−0.20*	0.05
Germany	−0.27**	−0.02	−0.12	0.16
Italy	−0.04	0.26*	0.06	0.13
Japan	0.13	0.01	−0.31*	0.08
Netherlands	−0.14	0.09	−0.08	−0.03
Norway	−0.13	0.12	−0.02	0.12
Portugal	−0.12	0.03	0.08	0.29
Spain	−0.23*	−0.08	0.06	0.06
Sweden	0.01	0.30	−0.06	−0.06
Switzerland	−0.21*	−0.01	0.08	−0.03
UK	−0.14	0.34*	0.02	0.14
USA	−0.03	0.50***	0.03	0.30**
Sig. >0 / Total	0 /16	4 /17	0 /16	3 /16
Sig. <0 / Total	3 /16	1 /17	2 /16	0 /16
Not sig. / Total	13 /16	12 /17	14 /16	13 /16

Note: Pairwise correlation coefficients in the post-1950 sample. 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. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$

D.2 Cross-asset return predictability

Predictive power of macro-financial risk factors The consumption-based factors include 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.[9] 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, 2016b), stock market capitalization data come from Kuvshinov and Zimmermann (2020), and housing wealth data are from Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2019a).

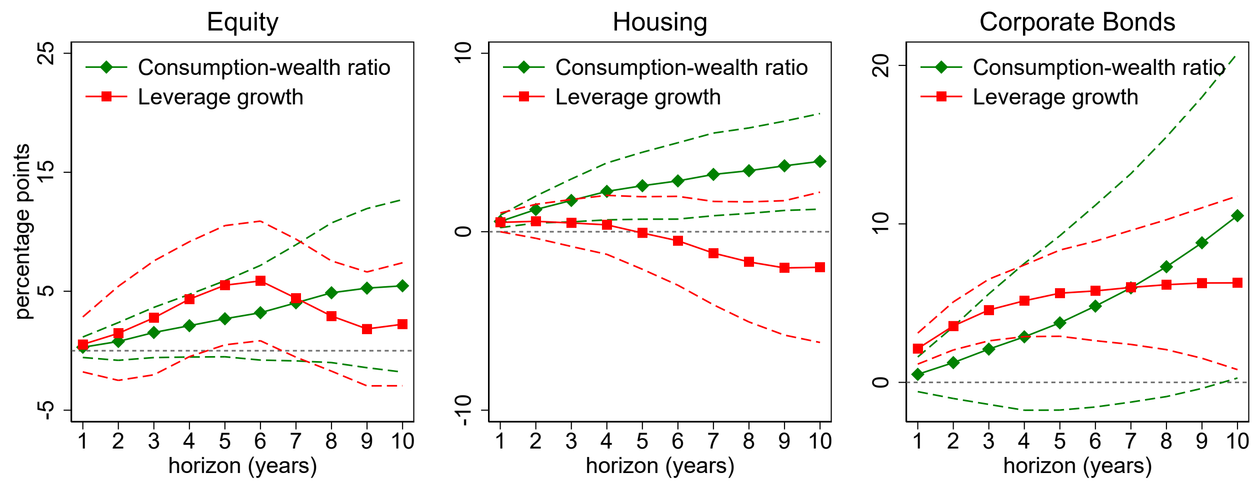
A series of recent papers suggest that high risk appetite by financial intermediaries affects prices of risky assets, both in theory and in the data (He and Krishnamurthy, 2013; Baron and Muir, 2018). Most measures of risk appetite either correspond to balance sheet strength, or balance sheet growth 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 (2017), while bank asset and credit data come from (Jordà, Schularick, and Taylor, 2016b).

I also 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 (2020) 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 9 shows that only two of the macro-financial risk factors have the right predictive sign for year-ahead returns across the three asset classes – the consumption-wealth ratio and bank leverage growth. Figure A.2 evaluates their predictive power at different horizons, for future returns (panels (a) and (b)) and corporate bond spread growth (panel (c)).

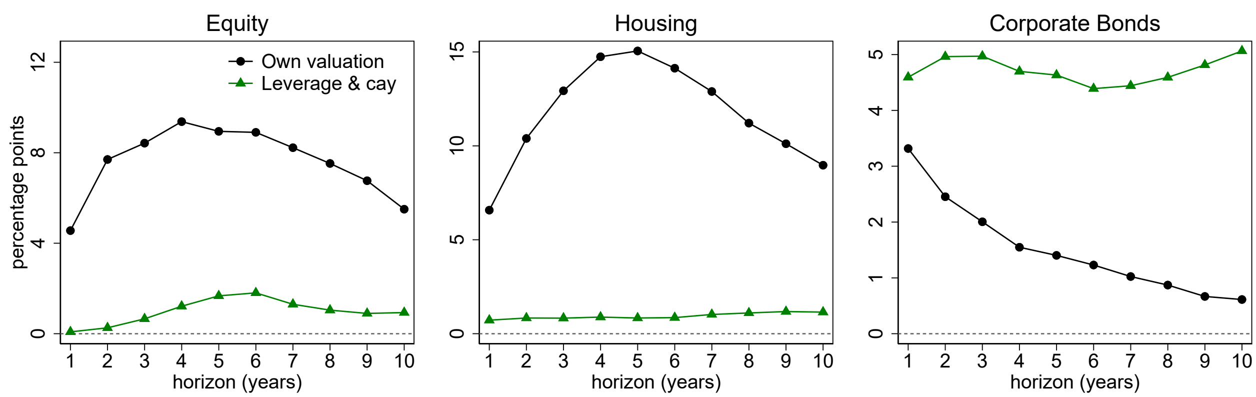
[9] Because of the lack of data on other classes of wealth, or total income for my historical sample, I restrict the analysis to stock market and housing wealth, and use wages rather than total labour income to proxy the flow of human wealth.

Figure A.2: *Predictive power of macro-financial risk factors at different horizons*

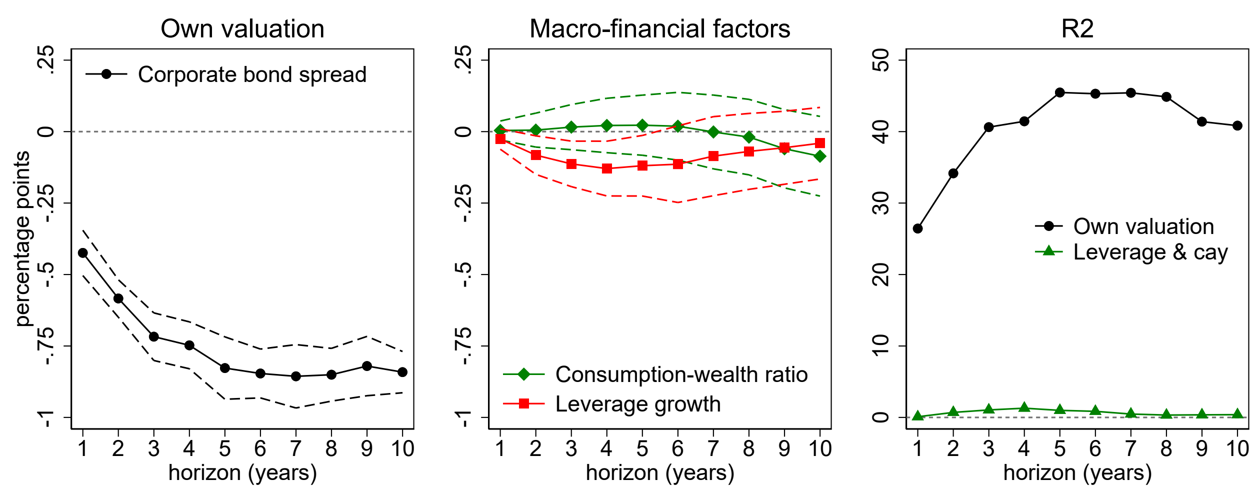
(a) *Return predictability:*



(b) *Return predictive R^2:*



(c) *Bond spread growth predictability:*



Note: Predictable cumulative return and spread growth change after a 1 standard deviation increase in the predictor variable, or a 1 percentage point increase in the bond spread for panel (c) left-hand graph. Standard errors clustered by country and year and adjusted for autocorrelation. Dashed lines show 95% confidence bands. The dividend-price ratio, rent-price ratio and bond spread are adjusted for structural breaks. Cumulative return impact estimated using the beta from regressing h-year ahead returns on either the own asset yield, or selected macro-financial risk factors. All regressions are run on a consistent sample across assets, predictors and horizons.

E. The co-movement puzzle: additional results

Table A.8: *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.

Table A.9: *Predictive power of net equity issuance: conditioning on own asset valuation*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity		Housing		Corporate bonds	
	r_{t+1}	$\overline{r_{t+1,t+5}}$	r_{t+1}	$\overline{r_{t+1,t+5}}$	r_{t+1}	$\overline{r_{t+1,t+5}}$
Net equity issuance / GDP	-0.026***	-0.016***	0.006*	0.001	-0.009**	-0.001
	(0.006)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
Dividend-price ratio	0.038***	0.023***				
	(0.007)	(0.005)				
Rent-price ratio			0.018***	0.021***		
			(0.004)	(0.004)		
Corporate bond spread					0.017***	0.007**
					(0.004)	(0.003)
R^2	0.054	0.095	0.040	0.140	0.034	0.014
Observations	1657	1578	1363	1293	1398	1303

Notes: OLS regressions with country fixed effects. All coefficients are standardised to a 1 standard deviation increase in the predictor variable. Predictor (x) variables in rows. Net issuance is the log of net equity issuance relative to GDP, from Kuvshinov and Zimmermann (2020). Dividend-price ratios, rent-price ratios and bond spreads are adjusted for structural breaks. r_{t+1} is the 1-year ahead real total return, and $\overline{r_{t+1,t+5}}$ is the average 5-year ahead log real total return on the specific asset class. Standard errors clustered by country-year and adjusted for autocorrelation in parentheses. *: $p < 0.1$ **: $p < 0.05$ ***: $p < 0.01$.