The Co-Movement Puzzle *

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Abstract

This paper studies the co-movement between discount rates on housing, equity, and corporate bonds, in long-run data covering 17 countries over 150 years. Standard macro-finance theories imply strongly positive co-movement attributable to changes in the stochastic discount factor but in the data, this co-movement is absent. I show that asset-class-specific discount rates are uncorrelated, and asset valuations predict returns within individual asset classes, but not across asset classes. Variance decompositions attribute most asset price movements to asset-class-specific discount rates, a considerable part to cashflows, and almost none to cross-asset discount rate variation. My findings suggest that cross-asset-class factors such as risk aversion and consumption risk are not the key driver of asset prices. I conclude by discussing several alternative risk-based and behavioral mechanisms consistent with the facts.

Keywords: discount rates, risk premia, co-movement, return predictability, excess volatility, equities, corporate bonds, real estate

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

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1. Introduction

Prices of risky assets fluctuate substantially over time. Most of this variation is excessive relative to changes in cashflows such as dividends, rents, and corporate debt payments (Shiller, 1981; Plazzi, Torous, and Valkanov, 2010; Greenwood and Hanson, 2013). The dominant explanation for such "excess volatility" is that the rate at which investors discount cashflows changes over time. Cochrane (2011) called the understanding of why discount rates vary "the central organizing question of current asset-pricing research". Standard macro-finance theories attribute discount rate movements to changes in the stochastic discount factor, reflecting general willingness to save and bear risk (Cochrane, 2017). The literature has offered numerous reasons for why this macroeconomic discount factor should vary, including changes in risk aversion (Campbell and Cochrane, 1999), long-run consumption risk (Bansal and Yaron, 2004), disaster risk (Wachter, 2013), and intermediary risk appetite (He and Krishnamurthy, 2013).

But are changes in the macroeconomic discount factor really a key driver of asset prices? Empirical studies have offered support for this by showing that discount rates for one specific asset class, typically US equities, vary over time, and equity returns are predictable with dividend-price ratios (e.g., Cochrane, 2008; Van Binsbergen and Koijen, 2010; Golez and Koudijs, 2018). An important, and largely unexamined, feature of discount factor variation, however, is that it should induce price movements that are correlated across risky asset classes (e.g., Ross, 1978; Chen, Collin-Dufresne, and Goldstein, 2008). For example, high risk aversion should lead to high discount rates and low prices not just for equities, but also for housing and corporate bonds. Similarly, proxies for the equity discount rate should predict returns not only in the stock market, but also in housing and corporate bond markets (Fama and French, 1989). Yet when it comes to the empirical studies of asset price volatility and predictability, this question has received relatively little attention.

This paper studies the co-movement between discount rates on three major risky asset classes: equity, housing, and corporate bonds, in a novel long-run dataset covering 17 advanced economies for years 1870–2020. The corporate bond data are new in this paper, and the equity and housing data are an updated version of those in Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2019). I use these data to, first, test whether discount rates within each asset class vary over time, and, second, whether discount rates on different asset classes co-move. My main empirical analysis is done through predictive regressions. I first run these regressions within asset classes, testing, for example, whether dividend-price ratios predict future stock returns and dividend growth. This allows me to test whether changes in asset prices are driven by future cashflows (in which case dividend-price ratios should forecast future dividends), or the rate at which these cashflows are discounted (in which case dividend-price ratios should forecast future equity returns). I then run these regressions across asset classes, testing, e.g., whether dividend-price ratios predict future housing or corporate bond returns. This allows me to test whether we can use the discount rate movements implied by prices of one asset class (e.g., equities) to explain the changes in prices of other major risky asset classes (e.g., housing).

My findings confirm that discount rates vary over time: returns are predictable, and prices of all major risky asset classes across 17 advanced economies vary more than the corresponding cashflows. But contrary to the above hypothesis, discount rates on different risky asset classes do not co-move. Proxies for asset-class-specific discount rates are uncorrelated, and valuations of one asset class do not predict returns on other risky asset classes. Variance decomposition attributes next to none of risky asset price movements to cross-asset-class changes in discount rates. Instead, asset-class-specific discount rate movements are key, and time variation in future cashflows is also important (with both dividend and rent growth predictable in my sample).

This paints a picture that is very different to the conventional wisdom on the drivers of asset price volatility. The consensus in the macro-finance literature is that all the asset price variation is attributable to time varying discount rates, and these discount rate movements are in turn related to time variation in a cross-asset discount factor, and the underlying changes in risk aversion or macroeconomic risk (Cochrane, 2017). But this conclusion is largely based on studies of the US equity market (see, e.g., Ang and Bekaert, 2007; Cochrane, 2008; Koijen and Van Nieuwerburgh, 2011). When we study multiple risky asset classes together in a large cross-country long-run sample, a very different conclusion emerges: that cross-asset-class discount rate movements are not important, that cashflow variation matters, and that asset-class-specific discount rate movements are key.

This implies that changes in asset prices may have little to do with cross-asset macroeconomic factors such as risk aversion and aggregate macroeconomic risk related to consumption and real activity. Instead, they are driven by asset-class-specific factors. In the final part of the paper, I provide suggestive evidence on the likely economic drivers of these factors, with important implications for both risk-based and behavioral theories of asset price formation. For risk-based theories, my findings point to the importance of asset-class-specific risks such as liquidity in the corporate bond or housing markets (Bao, Pan, and Wang, 2011; Head, Lloyd-Ellis, and Sun, 2014), or financial constraints of intermediaries specializing in a particular asset class (Haddad and Muir, 2021; Siriwardane, Sunderam, and Wallen, 2022). For behavioral theories, my findings point to the importance of subjective expectations of risk and cashflows on different assets (Bordalo, Gennaioli, La Porta, and Shleifer, 2020a; De la O and Myers, 2021, 2022; Nagel and Xu, 2021). Still, even accounting for the empirical proxies of these behavioral biases and risk factors leaves a substantial proportion of discount rate variation unexplained, leaving room for future research in explaining the drivers of asset-class-specific price volatility.

I start my analysis by studying return and cashflow predictability within asset classes. Campbell and Shiller (1988) show that time variation in asset prices scaled by fundamentals (the asset yield) should correspond to either changes in the asset-specific discount rate (expected return), in which case the asset yield should predict future returns, or cashflows, in which the asset yield should predict future cashflow growth. Applying these methods to my data, I find that all three of equity, housing, and corporate bond returns are predictable by their own asset yield (respectively, the dividend-price ratio, rent-price ratio, and the credit spread). This means that time-varying discount rates are an important driver of asset prices. A one standard deviation increase in the asset yield forecasts 2–2.5 ppts higher real total returns on the respective asset class one year ahead, and 6–10 ppts higher cumulative returns 5 years ahead, consistent with existing evidence for US equities (Cochrane, 2008).

Contrary to the consensus for US equities, I find that cashflow growth is also robustly predictable. A one standard deviation higher dividend-price ratio predicts 4.9 percentage points lower year-ahead dividend growth, and higher rent-price ratios predict low future growth in rents. These results hold across different regression specifications, variable definitions, countries, time periods, and both in and out of sample. A Campbell and Shiller (1988) variance decomposition shows that discount rates are responsible for 44% of the variation in dividend-price ratios, 66% of the variation in rent-price ratios, and 82% of the variation in corporate bond spreads.

My findings show that the seminal excess volatility puzzle of Shiller (1981) is a salient feature of three different asset markets in 17 advanced economies over 150 years. But are the drivers of this excess volatility common to all risky asset classes or not? To assess this, I first study the correlations between discount rate and cashflow news on different asset classes, calculated following Campbell (1991) as innovations to VAR forecasts of future returns and cashflow growth. I show that discount rate news on different asset classes (e.g., housing vs equity) are not only largely uncorrelated, but their correlations (0.05) are much lower than those between cashflow news (0.2). Discount rate news correlations increase somewhat during world wars and banking crises, but other time periods and specifications result in consistently low co-movement.

I test for discount rate co-movement more formally using cross-asset-class predictive regressions. The results confirm that co-movement is low. Under the baseline specification, the cross-asset-class predictive relationships are statistically and economically weak, with regression coefficients and predictive R^2s far below those of within-asset-class regressions. Cross-asset predictive power remains low within countries, across alternative regression specifications, variable definitions, and business cycle phases, as well as when we consider co-movement with another, relatively safe, asset class – government bonds. Furthermore, cross-asset-class predictability becomes weaker at longer horizons, in contrast to within-asset-class predictability which becomes stronger at horizons of beyond 1 year.

To get a sense of the relative magnitudes of within- and cross-asset-class discount rate variation, I introduce a novel variance decomposition which builds on Campbell and Shiller (1988) to decompose asset yield variation into i). predictable changes in future returns which are correlated with other asset classes, ii). predictable changes in future returns which are asset-class-specific, and iii). predictable changes in cashflows. I estimate these variance shares via direct long-run predictive regressions, and find that none of the variation in asset yields corresponds to cross-asset-class discount rates, 44–85% of asset yield variation corresponds to asset-class-specific discount rates, and 15%–50% to cashflows.

These results suggest that asset-class-specific discount rate movements are the key driver of asset price volatility. But what are the economic mechanisms behind them? I argue that this form of asset price volatility is difficult to reconcile with many standard theories in macro-finance, where prices of all risky asset classes are driven by changes in a single macroeconomic risk factor, typically related to risk aversion (e.g., Campbell and Cochrane, 1999) or macroeconomic (especially consumption) risk (Bansal and Yaron, 2004; Wachter, 2013; Constantinides and Duffie, 1996). But it is consistent with a number of alternative mechanisms, both risk-based and behavioral. Starting with risk-based mechanisms, I find some support for variation in asset-class-specific risk factors, either related to different forms of risks (e.g., liquidity, downside, and inflation risks, see Lettau, Maggiori, and Weber, 2014; Campbell, Pflueger, and Viceira, 2020; Fang, Liu, and Roussanov, 2022) or risk appetite of different marginal investors in segmented markets (e.g., households and intermediaries in Haddad and Muir, 2021). I show that empirical proxies for these risk factors predict returns on individual asset classes, but not across asset classes. However, even after accounting for this predictive power, a large proportion of discount rate movements remains unexplained.

Turning to behavioral mechanisms, I use the framework of De la O and Myers (2021, 2022) to show that what looks like an asset-class-specific discount rate movement in observed data can be driven by either an asset-class-specific cashflow forecast error (for example, investors being overly pessimistic about future dividend but not future rent growth), or an asset-class-specific risk perception (for example, investors being cautious about future equity risk). In recent data (from the Fannie Mae National Housing Survey), I show that survey-based perceptions of risk and potential of different assets vary in a predictable and asset-class-specific manner. In long-run data, a common theoretical driver of subjective expectations, past experienced returns on the specific asset class (Malmendier and Nagel, 2011; Nagel and Xu, 2021), displays asset-class-specific predictability. However, after decomposing the variance of asset yields into i). predictable movements in returns related to macro-financial risk factors (a proxy for the risk-based drivers), ii). predictable movements in returns related to past experienced returns (a proxy for behavioral drivers), and iii). cashflows, a substantial part of asset price variation remains unexplained. This points towards an important role for further unexplored drivers such as other risk factors and frictions to purchasing specific assets, other forms of behavioral bias, and demand-induced price movements in inelastic markets (Gabaix and Koijen, 2020; Gabaix, Koijen, Mainardi, Oh, and Yogo, 2022).

Related literature My findings contribute to the large empirical literature seeking to understand the drivers of asset price fluctuations. Most of these studies have focussed on price movements and predictability relationships within asset classes. The consensus is that discount rate variation is key (Cochrane, 2011), with evidence that US and international equity returns (Ang and Bekaert, 2007; Lettau and Van Nieuwerburgh, 2008; Koijen and Van Nieuwerburgh, 2011; Rapach, Strauss, and Zhou, 2013), US real estate returns (Campbell et al., 2009; Ghysels et al., 2013), and US corporate bond returns (Greenwood and Hanson, 2013; López-Salido, Stein, and Zakrajšek, 2017) are all predictable, but that US equity dividends are not (Cochrane, 2008). However, there is growing evidence of dividend predictability using alternative datasets and estimation methods for the US (Lettau and Ludvigson, 2005; Chen, 2009; Van Binsbergen and Koijen, 2010; Golez and Koudijs, 2018), and when extending the sample to other countries (Engsted and Pedersen, 2010), as well as some debate about the statistical robustness of return predictability for US stocks (Stambaugh, 1999;

Goyal and Welch, 2008).

My study helps settle these ongoing debates by studying both return and cashflow predictability in a much broader setting than before. My paper is the first to provide evidence for housing and corporate bond return predictability in long-run data outside of the US, and the first to document equity return predictability for a large long-run panel of countries. It is also the first to show that cashflow variation is important across many countries and risky assets, and that the relative importance of discount rate and cashflow movements varies by asset class.

My main contribution comes from studying these predictive relationships not within, but across asset classes, which ultimately helps us understand the underlying drivers of asset price volatility. When it comes to differences in discount rates or risk premia, there is an extensive literature on differences in *levels* of expected returns in the cross-section of stocks and bonds (Fama and French, 1993), and a somewhat smaller literature on the co-movement between *realized* returns on *risky and safe* assets, mostly US equities and Treasuries (Shiller and Beltratti, 1992; Baele, Bekaert, and Inghelbrecht, 2010). The goal of my study is different: to understand the *time variation* in *expected* returns (discount rates) on different classes of *risky* assets. This research question has received surprisingly little attention. The closest study is that of Fama and French (1989), who find common time variation in stock and bond returns in monthly post-1926 data for the US, and relate it to changes in business conditions. In my annual data for the corresponding sample, co-movement between equities and corporate bonds is larger than in the full long-run panel (though still weak). That being said, there is little co-movement between housing and either equities or corporate bonds even in post-1926 US data, and little co-movement overall in cross-country long-run data, or at longer time horizons.

Other studies have provided less direct evidence both in favor of, and against co-movement. Asness, Moskowitz, and Pedersen (2013) and Baba Yara, Boons, and Tamoni (2020) document co-movement in returns to value and momentum strategies across different financial assets (currencies, stocks, government bonds) and countries, in monthly post-1972 data. Cochrane and Piazzesi (2005) and Koijen, Lustig, and Van Nieuwerburgh (2017) show that, in the US, some cross-sectional bond risk factors are priced in the stock market. Haddad and Muir (2021) provide evidence for different asset-specific risk factors related to the wealth of households and financial intermediaries in recent data for many financial assets, and Baron and Muir (2021) provide evidence for intermediary-specific risk factors in historical data. Finally, Giglio and Kelly (2018) document asset-specific excess volatility not across asset classes, but across different maturities of the same underlying asset. A less closely related set of studies has examined the degree of market integration, i.e. to what extent different markets (typically, for stocks and bonds) share the same pricing kernel. Here, again, there is evidence both in favor of market integration (Sandulescu, 2020), and in favor of market segmentation and cross-market arbitrage opportunities (Choi and Kim, 2018; Ma, 2019; Siriwardane et al., 2022).[1]

[1]Note that while the asset-specific discount rate movements documented in my data can arise under segmented markets, they can also arise if markets are integrated but different asset classes are exposed to different risks which are uncorrelated, or investor expectation formation exhibits asset-class-specific biases.

My paper is the first to directly study the co-movement between discount rates on all major risky asset classes, and the first to do this in long-run data for many countries. This allows me to go beyond simply decomposing asset price movements into expected returns and cashflows, and towards uncovering their economic drivers. My findings suggest that even though a degree of co-movement can be found for specific countries, assets, and time horizons (as shown by previous studies), most variation in asset prices is both a). unrelated to future realized cashflows, and b). asset class specific, pointing to a potentially novel set of underlying economic drivers.

The final two contributions come from the new data on corporate bonds, and from examining the drivers of asset-class-specific price volatility. Most existing corporate bond datasets focus on the US, but recent work by Krishnamurthy and Muir (2017) and Muir (2017) has made important progress in taking this analysis to a long-run cross-section of countries. Compared to their data, my corporate bond dataset has a more extensive coverage, and focuses on bonds listed on domestic markets as opposed to international exchanges. This makes it more appropriate for analyzing co-movement with domestic equities (which are typically listed on the same exchange) and real estate.

When it comes to asset price drivers, many risk-based theories in macro-finance have focussed on cross-asset-class macroeconomic factors, typically related to risk aversion or different types of consumption risk (Campbell and Cochrane, 1999; Bansal and Yaron, 2004; Wachter, 2013). My analysis suggest that the risk factors that drive asset prices are highly asset class specific, for example related to risk appetite of investors in different markets (Haddad and Muir, 2021), or to different types of risks in integrated markets (Lettau, Maggiori, and Weber, 2014; Campbell, Pflueger, and Viceira, 2020). For behavioral theories, there are growing literatures on the importance of subjective expectations in driving price movements within asset classes (Bordalo et al., 2020a; Nagel and Xu, 2021; De la O and Myers, 2021, 2022, Adam, Pfäuti, and Reinelt, 2022), as well as the importance of changes in macroeconomic sentiment for real activity (Barsky and Sims, 2012; Angeletos, Collard, and Dellas, 2018; Lagerborg, Pappa, and Ravn, 2022). My analysis shows that the variation in subjective expectations of returns and cashflows is, to a large degree, asset class specific, and that when it comes to explaining asset price movements, it is these asset-class-specific expectations rather than general macroeconomic sentiment that are key.

2. Empirical framework

Why do asset prices vary over time? As standard in the literature, I start with the present value identity which tells us that the price P_i of an asset i should be equal to the present value of expected future cashflows CF_i (dividends, rents, or coupon payments for the three asset classes in my study) discounted at an appropriate risk-adjusted rate R_i:

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

Cashflows CF_i can vary in an asset-specific manner. But to rule out arbitrage, asset-specific discount rates R_i should be proportional to a common stochastic discount factor m (e.g., Ross, 1978):

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

Changes in the stochastic discount factor m should induce common variation (i.e., co-movement) in expected returns on different risky asset classes. This can be seen more clearly by rewriting equation (2) as

$$\mathbb{E}_t\left(R_{i,t+1}\right) = R^f_{t+1} + R^f_{t+1}\beta_{i,-m}\sigma^2_m \tag{3}$$

Above, $R^f_{t+1} = \dfrac{1}{\mathbb{E}_t\left(m_{t+1}\right)}$ is the risk-free rate, $\beta_{i,-m} = cov(R_i, -m)/\sigma^2_m$ is the exposure of asset class i to the variation in the stochastic discount factor (its systematic risk exposure), and σ^2_m is the variance of the stochastic discount factor (systematic or macroeconomic risk). As argued by Cochrane (2017), most theories in macro-finance can be seen as different reasons for why the discount factor m varies. In terms of equation (3), this should generate time variation in σ^2_m, typically through changes in macroeconomic risk or risk aversion (see Section 5 for more detail). Changes in σ^2_m should, in turn, induce perfectly correlated movements in discount rates on different risky asset classes (with risky meaning $\beta_{i,-m} > 0$). If variation in σ^2_m is an important driver of risky asset prices, asset-specific discount rates $\mathbb{E}(R_i)$ should vary over time, and they should co-move. I test for each of these hypotheses by applying the standard toolkit of predictive regressions to a multi-asset-class setting.

2.1. Testing for time variation in discount rates

As standard in the literature, the test for time varying discount rates is based on a log-linear 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 a corporate credit spread and r the excess return relative to government bonds (see Appendix A.1).

Within-asset-class predictive regressions Under rational expectations, equation (4) implies that asset yields dp should predict future returns and cashflow growth, and the relative strength of these predictive relationships determines which one is the more important driver of asset price movements (see, e.g., Cochrane, 2008).[2] I test this in the data by running the following predictive regressions for each asset class i, using a panel of countries j and years t:

[2]See Section 5.2 for how this result changes under non-rational expectations.

$$r_{i,j,t+1} = \beta_{i,j,1} + \beta_{i,2} dp_{i,j,t} + u_{i,j,t+1} \tag{5}$$
$$dg_{i,j,t+1} = \gamma_{i,j,1} + \gamma_{i,2} dp_{i,j,t} + e_{i,j,t+1} \tag{6}$$

$\beta_{i,2} > 0$ implies that asset-specific discount rates (expected returns) vary over time, and $\gamma_{i,2} > 0$ implies that expected cashflows do.

Within-asset-class variance decomposition The relative importance of discount rate and cashflow movements can be obtained by comparing the predictive power of the asset yield for future returns (discount rate news) and cashflows (cashflow news):

$$\text{Var}(dp_i) = \text{Cov}(dp_i, dp_i) = \underbrace{\text{Cov}(dp_{i,t}, \sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s})}_{\text{Discount rate news}} + \underbrace{\text{Cov}(dp_i, -\sum_{s=0}^{\infty} \rho_i^s dg_{i,t+1+s})}_{\text{Cashflow news}} \tag{7}$$

The covariances in equation (7) can be calculated by computing long-run forecasts of returns and cashflows, either directly or using a VAR, with the idea being that the more forecastable they are, the more important their contribution to asset yield (and price) movements (see, e.g., Cochrane, 2008; Golez and Koudijs, 2017, and Appendix A.1).

2.2. Testing for co-movement in discount rates

If variation in discount rates is driven by the cross-asset discount factor m, expected returns on different asset classes should co-move. From equation (3), expected excess returns (risk premia) on different risky asset classes should be directly proportional to each other:

$$\mathbb{E}_t\left(R_{i,t+1}\right) = R_{t+1}^f + \frac{\beta_{i,-m}}{\beta_{k,-m}} * \left(\mathbb{E}_t\left(R_{k,t+1}\right) - R_{t+1}^f\right) \tag{8}$$

This means that variables which predict returns on one asset class should also predict returns on other asset classes. As long as the predictors are standardized or assets earn similar risk premia on average (and hence have similar β_{-m}), the predictive coefficients in the cross-asset-class regressions should also be similar in size to those in the within-asset-class regressions in (5).

Cross-asset-class predictive regressions As a first less-formal test for discount rate co-movement, I study the correlations between discount rate news, i.e. changes in the long-run forecasts of returns $\Delta\mathbb{E} \sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s}$, on different risky asset classes (calculated using a VAR as in Campbell, 1991, see Appendix A.1). As the second more formal test, I run the following cross-asset-class predictive regressions:

$$r_{i,j,t+1} = \beta_{i,j,1} + \beta_{k1 \neq i} dp_{k1,j,t} + \beta_{k2 \neq i} dp_{k2,j,t} + u_{i,j,t+1} \tag{9}$$

For these regressions, I predict future stock returns using housing rent-price ratios and corporate bond spreads, predict housing returns using equity dividend-price ratios and corporate bond spreads, and so on. Since I standardize the regression coefficient to a one standard deviation change in the asset yield dp, under the null hypothesis of strong expected return co-movement (equation 8) the predictive the cross-asset predictive coefficients should all be positive, significant, and similar in size regardless of the predictor used.

Cross-asset-class variance decomposition The strength of cross-asset-class predictability can, ultimately, be used to gauge the relative importance of variation in cross-asset-class and asset-class-specific factors as drivers of asset prices. To study this, first consider that the return on any asset class i can be decomposed into the part that is correlated with returns on other asset classes, r_i^{other}, and the asset-class-specific residual, $r_i^{\text{asset-spec}}$:

$$r_{i,t} = \underbrace{\alpha + \beta_1 r_{k,t} + \beta_2 r_{z,t}}_{r_{i,t}^{\text{other}}} + r_{i,t}^{\text{asset-spec}} \tag{10}$$

Plugging equation (10) into the Campbell-Shiller decomposition in (4) tells us that the variation in asset prices (or yields) can, in turn be driven by the following three components: i). Discount rate movements which are correlated with those on other risky asset classes, $\mathbb{E}(r^{\text{other}})$, ii). Asset-class-specific discount rate movements, $\mathbb{E}(r^{\text{asset-spec}})$, and iii). Cashflows $\mathbb{E}(dg)$:

$$dp_{i,t} \approx \mathbb{E}\sum_{s=0}^{\infty}\rho_i^s r_{i,t+1+s}^{\text{other}} + \mathbb{E}\sum_{s=0}^{\infty}\rho_i^s r_{i,t+1+s}^{\text{asset-spec}} - \mathbb{E}\sum_{s=0}^{\infty}\rho_i^s dg_{i,t+1+s} \tag{11}$$

$$\text{Var}(dp_i) \approx \underbrace{\text{Cov}(dp_{i,t}, \sum_{s=0}^{\infty}\rho_i^s r_{i,t+1+s}^{\text{other}})}_{\text{Cross-asset DR news}} + \underbrace{\text{Cov}(dp_{i,t}, \sum_{s=0}^{\infty}\rho_i^s r_{i,t+1+s}^{\text{asset-spec}})}_{\text{Asset-specific DR news}} + \underbrace{\text{Cov}(dp_{i,t}, -\sum_{s=0}^{\infty}\rho_i^s dg_{i,t+1+s})}_{\text{CF news}} \tag{12}$$

I estimate the corresponding variance shares by, first, estimating equation (10) by regressing the realized returns of one asset class on those of the other two asset classes, and second, regressing the two components of long-run returns, $\sum_{s=0}^{s=T}\rho_i^s r_{i,t+1+s}^{\text{other}}$ and $\sum_{s=0}^{s=T}\rho_i^s r_{i,t+1+s}^{\text{asset-spec}}$ and long-run cashflow growth $\sum_{s=0}^{s=T}\rho_i^s dg_{i,t+1+s}$, on the asset yield dp (see Appendix A.1).[3]

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

Previous studies have shown that the predictive relationships in equations (5) and (6) can change depending on the sample used (Chen, 2009; Engsted and Pedersen, 2010), and can be imprecise even for long samples of within-country time series data (Stambaugh, 1999). To ensure a broad

[3]For the cross-asset-class decompositions I use direct long-run regressions with horizons of T=14 years instead of VAR (recursive 1-year) forecasts. This is because in the cross-asset-class predictive regressions in the data, the predictive coefficients for short and long horizons often switch sign (see, e.g., Figure 2b), rendering the VAR estimation inaccurate.

representative sample, I introduce a new long-run cross-country dataset of 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 the following 17 advanced economies over the period 1870 to 2020: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

The data for housing and equity are an updated version of those in Jordà et al. (2019). The data for corporate bonds are introduced in this paper. The inclusion of both housing and equity makes sure that I account for the two largest components of household wealth. The inclusion of corporate bonds ensures that I can compute expected returns on two assets (bonds and equities) which are listed on the same exchange and in principle available to the same investors. It also allows me to compare my results to existing literature which has focussed on co-movement between stocks and bonds. Appendix Table D.1 summarizes the data coverage by country and asset class. A brief description of the sources follows below. A more detailed description of the corporate bond data is provided in Appendix E.

Equity The data consist of total returns, dividends, and dividend-price ratios of listed equities, all taken from Jordà et al. (2019) with the exception of the US, where I use CRSP data with non-reinvested dividends after 1926, and a new series for Canada. The return, price and dividend data mostly consist of value-weighted all-share indices. The dividend-price ratio is measured as dividends paid during the year relative to year-end share price. Dividend growth is measured as dividends paid during the year relative to those paid in the previous year, and total return as dividends plus capital gain relative to previous year's share price. Chen (2009) shows that allowing dividends to be reinvested within the year can bias the predictive coefficient on dividend growth towards zero. To guard against this bias, my dividend growth data generally refer to non-reinvested dividends (and, similarly, the dividend-price ratio uses non-reinvested dividends in the numerator). The historical data has a few dividend-price observations of close to zero, which produce large dividend growth outliers. To ensure my results are not biased by these outliers, I winsorize the dividend growth data at 1% level (and adjust the returns and dividend-price ratios to be consistent with this winsorized growth).

Housing The data consist of total returns, rents, and rent-price ratios for residential real estate, all taken from Jordà et al. (2019). 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 total net rents paid relative to this year's house price, rental growth is this year's relative to last year's rent, and total return is rent plus capital gain relative to previous year's house price. Historical rent-price ratios are constructed by taking the national rent-price ratio in 2013, extrapolating it back and forward using data on house prices and rents, and benchmarking the series against historical estimates of net rental yields. To be consistent with my treatment of dividends, I also winsorize rent growth at the 1% level.

Corporate bonds These data are introduced in this paper and consist of yields, spreads, and holding period returns on bonds issued by private sector creditors, targeting 10-year maturity. To maintain consistency with equities, I focus on exchange-listed bonds, and to ensure sufficient coverage, I supplement these with statistics on private issues and over-the-counter trades for selected time periods. The data exclude foreign bonds, colonial bonds, foreign currency bonds, bonds with explicit government guarantees, and – when separately identifiable – exclude mortgage bonds issued by credit institutions or special purpose vehicles, and include real estate backed bonds issued by non-financial corporations.

The spread is the yield-to-maturity differential vis-a-vis 10-year government bonds. When I have evidence that corporate bond maturity is different to 10 years, I take the spread over a similar-maturity government bond instead. I construct two measures of bond returns: the holding period real total return, and the spread-implied excess return. Because the spread-implied excess return is defined more consistently across the whole sample and is more consistent with the credit spread variance decomposition in Nozawa (2017), I use this as my main measure of corporate bond returns, and show the results for holding period real returns as a robustness check. Finally, I construct a proxy for the log price spread – the log ratio of the government to corporate bond price – for the variance decomposition analysis, estimating the prices using yields to maturity. Because these prices are inevitably estimated with error, I winsorize the price spread proxies at 1% level to reduce the influence of outliers on my results.

The corporate bond data have a much broader coverage than those in previous studies. Most studies of bond return predictability have focussed on the US, with long-run international evidence provided in the online appendix of Muir (2017). Relative to these data, my sample covers more countries and years, and focuses on bonds listed on domestic exchanges rather than bonds listed on an international market such as the London Stock Exchange, which allows for a larger sample of bonds, and more comparability to domestic equities and housing. Most of the series were constructed from primary historical sources, by digitizing the prices of bonds listed on the countries' major domestic exchanges. When constructing these series, I ensure that the credit quality (e.g., the type of company that issues the bond) and maturity of the bonds does not vary at the short to medium term horizon of the predictive regressions, and that the maturity of the corporate bonds matches those of the government bond series. Appendix E provides further detail on the bond data, the construction of the series, and how I deal with the potential data quality issues relating to time-varying credit quality and maturity of the bonds.

Appendix Table D.2 summarizes the statistical properties of the data, showing that all asset classes in my sample are risky, with returns in excess of government bonds and bills, and large return volatility. Therefore, we should expect positive risk exposures $\beta_{i,-m} > 0$ for each of these asset classes, and hence positive discount rate co-movement in response to changes in the stochastic discount factor m.

3. Excess volatility within asset classes

Do risky asset prices vary more than future cashflows? Appendix Figure A.1 replicates the seminar analysis of Shiller (1981) for my sample, plotting the observed detrended real price of each asset (equity, housing, and corporate bonds) against the present value of future realized cashflows (dividends, rents, and defaults) discounted at a constant rate. For each of the three risky asset classes, prices are more volatile than the present value of future cashflows, which suggests that the rate at which these cashflows are discounted varies over time. To test for this more formally, I turn to the standard toolkit of predictive regressions (Cochrane, 2008; Lettau and Van Nieuwerburgh, 2008; Golez and Koudijs, 2018).

Within-asset-class predictability Table 1 shows the results of regressing year-ahead returns and cashflows on the asset yield, as specified in the equations (5)–(6). To make results comparable across asset classes, I standardize all the coefficients to a one standard deviation increase in the asset yield. The equity and housing regressions show predictability for both returns and cashflows, whereas the corporate bond regression shows the results of regressing two different measures of future bond returns on today's credit spread. The first of these measures is the real total return computed as the sum of the lagged yield and capital gain, net of inflation. The second is the spread-implied excess return computed as the year-ahead change in the credit spread times the negative of the average bond duration in my sample, -10.

Returns on all three risky asset classes are predictable. Table 1 column 1 shows that a one standard deviation increase in the dividend-price ratio (about 1.5 percentage points) predicts 2.4 percentage point higher real equity returns one year ahead (0.023 times the mean gross return of 1.048 times 100). Returns on housing and corporate bonds (columns 3, 5, and 6) are also predictable, with similarly-sized effects to to those for equities but higher R^2s. Not only returns, but cashflows are predictable, with this predictability the strongest for the equity market. A 1 standard deviation increase in the dividend-price ratio predicts 4.9 percentage points lower real dividend growth 1 year ahead. A similar (standardized) increase in the rent-price ratio, however, only forecasts 0.7 percentage points lower growth in rents. Appendix Table A.1 shows that corporate bond yields in the US are only weakly associated with future default rates, consistent with the findings of Giesecke, Longstaff, Schaefer, and Strebulaev (2011). This means that cashflow predictability is much stronger for listed equities than for the other two risky asset classes.

The bottom rows of Table 1 display the relative importance of expected return (discount rate news) and cashflow news variation for each asset class. They show the share of the variance of asset yields which can be explained by predictable long-run changes in return and cashflow forecasts computed using a VAR (see Appendix A.1). These variance decompositions confirm the finding that both time-varying returns and cashflows are important drivers of asset price variation. Around half of the variation in dividend-price ratios is accounted for by future returns, and the other half by cashflows. Consistent with stronger return predictability and weaker cashflow predictability for

Table 1: *Predictability of 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}	r^{spread}_{t+1}
Dividend-price ratio$_t$	0.023***	-0.049***				
	(0.008)	(0.009)				
Rent-price ratio$_t$			0.020***	-0.007**		
			(0.003)	(0.003)		
Credit spread$_t$					0.016***	0.025***
					(0.005)	(0.003)
Percentage point impact	2.42	-4.95	2.09	-0.68	1.68	2.45
Discount rate news share	44%		66%			82%
Cashflow news share	56%		34%			18%
R^2	0.012	0.043	0.046	0.009	0.028	0.115
Observations	2355	2355	1895	1895	1869	1869

Notes: OLS regressions with country fixed effects. Coefficients are standardized to a 1 standard deviation increase in the predictor variable (log changes for housing and equity, absolute changes for the credit spread). Predictor (x) variables in rows. Dependent (y) variables in columns. r is the log real total return, dg is log real dividend or rental growth, and r^{spread} is the spread-implied excess corporate bond return, calculated as -10 (average duration) times the change in the spread. Percentage point impact is the percentage point change in return or cashflow growth after a one standard deviation increase in the asset yield. All variables are demeaned at the country level. Discount rate news share is the proportion of asset yield variation explained by predictable changes in future returns, estimated using infinite-horizon VAR forecasts for housing and equity, and direct 15-year OLS forecasts for corporate bonds. Cashflow news share is the proportion relating to predictable changes in future cashflows. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

housing and corporate bonds, most of the yield variation in these markets is explained by future returns (discount rate news).

Alternative specifications Table 2 shows that these findings hold across a variety of estimation methods and time periods. Again, the coefficients are standardized to a one standard deviation increase in the yield, with the percentage point impact being roughly 100 times the reported coefficient. 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 8.9 percentage points higher cumulative stock returns and 17.2 percentage points lower cumulative dividend growth over 5 years. 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 regressions jointly in a VAR (column 4) leads to similar results. Return and spread growth predictability becomes stronger after 1950 (column 5), and after adjusting the predictor variables

Table 2: *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 fixed effects
Equity:							
r_{t+1}	0.023***	0.017**	0.017**	0.028***	0.030***	0.036***	0.027***
	(0.008)	(0.007)	(0.008)	(0.005)	(0.009)	(0.007)	(0.006)
dg_{t+1}	-0.049***	-0.034***		-0.041***	-0.054***	-0.064***	-0.063***
	(0.009)	(0.005)		(0.008)	(0.010)	(0.010)	(0.013)
Housing:							
r_{t+1}	0.020***	0.020***	0.024***	0.020***	0.018***	0.019***	0.022***
	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)	(0.005)	(0.003)
dg_{t+1}	-0.007**	-0.012***		-0.007***	-0.004	-0.008**	-0.007**
	(0.003)	(0.004)		(0.002)	(0.004)	(0.004)	(0.003)
Corporate bonds:							
r_{t+1}	0.016***	0.009*	0.019***		0.005	0.018***	0.014***
	(0.005)	(0.005)	(0.003)		(0.006)	(0.003)	(0.003)
r^{spread}_{t+1}	0.025***	0.011***	0.025***		0.030***	0.035***	0.025***
	(0.003)	(0.001)	(0.003)		(0.004)	(0.004)	(0.003)

Notes: Predictive coefficients on the log dividend-price ratio for equity, log rent-price ratio for housing, and the credit spread for bonds. Dependent (y) variables in rows. Specifications in columns. Coefficients are standardized to a 1 standard deviation change in the predictor (x) variable. r_{t+1} is log real total return; dg_{t+1} is log real dividend or rent growth, r^{spread} is the spread-implied excess corporate bond return. 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 in excess 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 period-specific means within each country, using the Bai and Perron (2003) procedure to identify the break dates. Year effects has both country and year fixed effects. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

for structural breaks (column 6), consistent with results for US equities reported by Lettau and Van Nieuwerburgh (2008). Adding year fixed effects to control for common cross-country variation in yields, returns, and cashflows (column 7) leaves results little changed.

Appendix Table A.2 shows the predictability results for individual countries. Return predictability for housing and corporate bonds, and dividend growth predictability, are ubiquitous. For equity returns, predictive coefficients are generally of similar size to baseline but are statistically insignificant in some countries due to the relatively low power of within-country samples. However, after adjusting the asset yields for structural breaks, the predictive coefficients on returns are significant in almost every country and asset class (Appendix Table A.3).[4]

[4]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 upon request).

Persistent regressors and out-of-sample predictability Two further potential statistical issues identified in the literature relate to the persistence of regressors, and out of sample performance. Stambaugh (1999) showed that the persistence of asset yields can bias up the predictive return coefficients and inflate the corresponding t statistics, as some cashflow-related innovations in the asset yield may be erroneously interpreted as changes in expected returns. Goyal and Welch (2008) showed that many regressors able to predict US stock returns in sample have negative R^2s out of sample. In Appendix A.2, I follow Cochrane (2008) and Golez and Koudijs (2018), and use Monte Carlo simulations to show that the Stambaugh (1999) bias does not materially affect my results. In Appendix A.3, I show that the regressions perform well out of sample, with all out of sample R^2s positive and significant, and substantial predictive power at 5-year-ahead horizons, similar to the findings of Golez and Koudijs (2018) for a very long time series of financial-center equity returns.

Literature comparison My finding of strong within-asset-class return predictability is consistent with existing evidence for the US (Cochrane, 2008; Ghysels et al., 2013; Greenwood and Hanson, 2013). My finding of strong cashflow predictability, especially for equities, is different to several previous studies: for example, Cochrane (2008) finds that in CRSP data, all the dividend-price ratio variation is attributable to future returns, and none to future cashflows. My findings are, however, in line with several more recent papers documenting dividend predictability for longer historical periods (Chen, 2009; Golez and Koudijs, 2018), other countries (Engsted and Pedersen, 2010), and alternative estimation methods (Van Binsbergen and Koijen, 2010). Appendix Table A.4 compares equity return predictability in the full panel with that in the US, before and after 1950. In line with Chen (2009), I find that for the US, dividend growth predictability is much weaker, and return predictability much stronger after 1950. Golez and Koudijs (2020) attribute this post-1950 increase in the relative importance of expected return variation to an increased duration of the stock market. For the full panel however, predictability of both equity returns and dividends is similar before and after 1950.

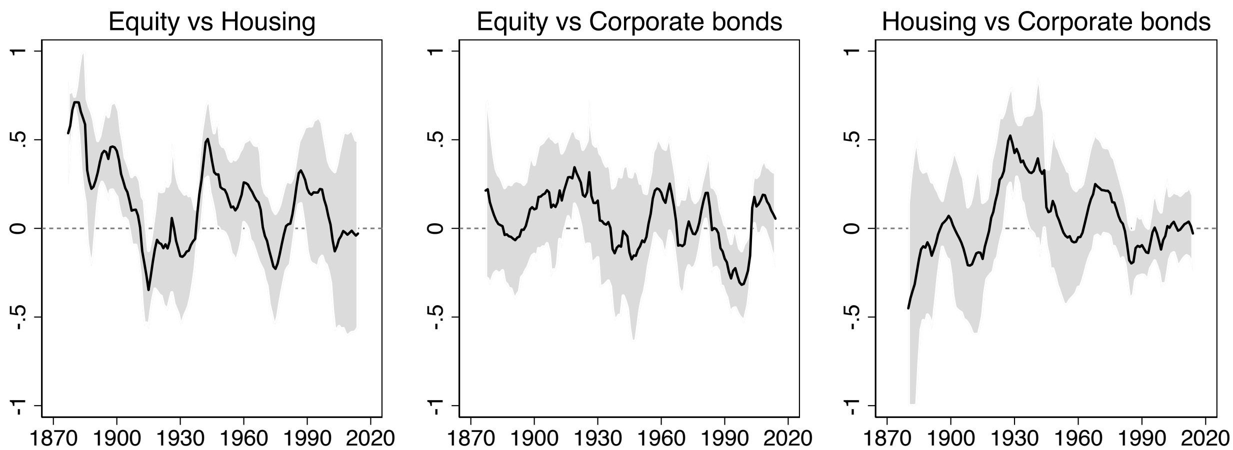
4. Discount rate co-movement across asset classes

4.1. Discount rate correlations

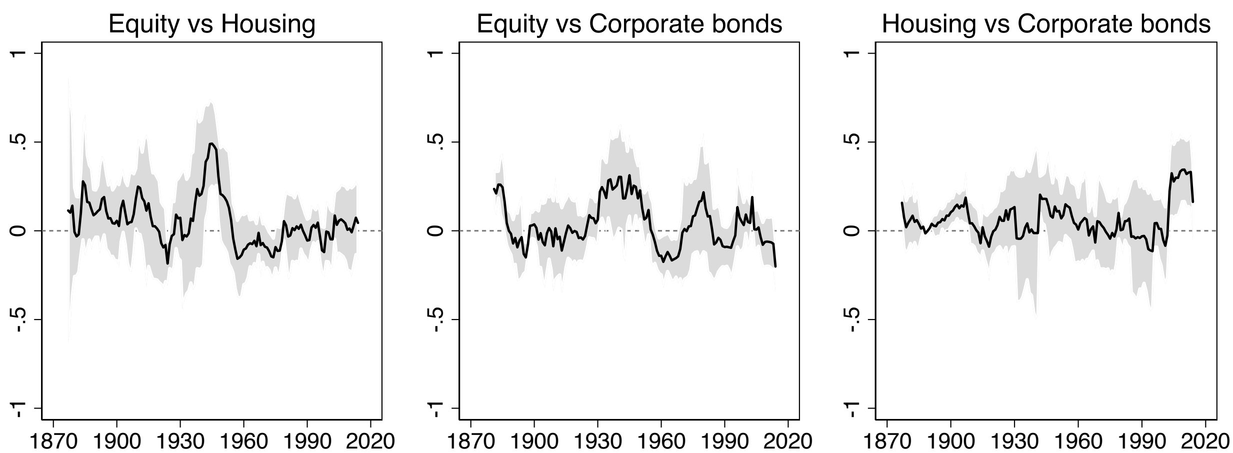
Within asset classes, time varying discount rates are a key driver of asset price movements. But are these discount rate movements common to all risky asset classes or not? I start by studying the correlations between discount rate proxies for different asset classes, and proceed to analyze co-movement more formally using cross-asset-class predictive regressions and variance decompositions. Figure 1a shows the correlations between the raw yields on the three different risky asset classes in my study: the dividend-price ratio, rent-price ratio, and corporate bond spread. These correlations are centered around zero and statistically weak. However, the level of the asset yield may be affected by time trends, and is influenced by cashflows as well as discount rates. To get a cleaner measure of

Figure 1: *Correlations between discount rate proxies for different asset classes*

(a) *Raw asset yields:*



(b) *Discount rate news:*



Note: Pooled sample of 17 advanced economies, 1870–2020. Solid lines show pairwise correlation coefficients between discount rate proxies for equity, housing, and corporate bonds over rolling centered decadal windows (e.g., 1870–1880 for year 1875). Shaded areas show 95% confidence bands using country-clustered standard errors. Asset yields are the dividend-price ratio, rent-price ratio, and corporate bond spread, demeaned at country level. Discount rate news are changes in the present value of predicted future returns on housing and equity (as in Campbell, 1991), and the change in the credit spread for corporate bonds.

asset-class-specific discount rates, I follow Campbell (1991) and compute the change in the long-run VAR forecast of future returns for each asset class, country, and year – the "discount rate news" component of the unexpected return (see Appendix A.1 for details). Figure 1b shows that the correlations between these discount rate news proxies are even smaller than those between the raw asset yields, suggesting that some of the positive correlations in Figure 1a are driven by cashflow news or common long-run trends. Appendix Figure A.2 shows that first-differencing the asset yields leads to similarly low correlations.

Table 3: *Correlations between discount rate and cashflow news on different asset classes*

	(1) Baseline	(2) 3-year MA	(3) 3-year MA, housing lag	(4) Structural breaks	(5) Wars	(6) Banking crises
Discount rate news:						
Equity, housing	0.05	0.11	0.15**	0.02	0.27*	0.07
Equity, corporate bonds	0.05	0.08*	0.08*	0.03	0.12**	0.22**
Housing, corporate bonds	0.03	0.07	0.09*	0.02	0.15***	0.08
Cashflow news:						
Equity, housing	0.21***	0.32***	0.24***	0.17***	0.59***	0.01

Notes: Pairwise correlations, pooled 17-country sample. Discount rate news are changes in the present value of predicted future returns on housing and equity, and the change in the credit spread. Cashflow news are changes in the present value of predicted future rent and dividend growth. Baseline correlates 1-year discount rate and cashflow news. 3-year MA correlates 3-year moving averages. 3-year MA, housing lag correlates housing data at t to t+2 with equity and bond data at t-1 to t+1. Structural breaks uses discount rate and cashflow news obtained from asset yields adjusted for structural breaks. Wars only considers the periods of world wars. Banking crises considers periods within 3 years of the start of the crisis, using the Schularick and Taylor (2012) crisis definition. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively, using country-year clustered autocorrelation-adjusted standard errors.

Table 3 considers the correlations between discount rates alongside those between cashflow news on different asset classes. Column 1 displays the correlations in the pooled sample of my data, and columns 2–6 show the results for alternative calculation methods and time periods. Discount rate news on different assets are less correlated than cashflow news, with a (baseline) correlation coefficient of around 0.05 for discount rates compared to 0.2 for cashflows. This pattern persists if we use three-year moving averages of discount rate and cashflow news (Table 3 column 2), allow housing discount rate news to respond with a lag since housing transactions take longer to complete (column 3), or extract discount rate and cashflow news from a VAR where the predictors are adjusted for structural breaks (column 4). In line with Figure 1b, I do find higher discount rate correlations around World Wars (column 5) and systemic banking crises (column 6), although the banking-crisis co-movement is largely confined to equities and corporate bonds (consistent with Muir (2017), who finds that both credit spreads and dividend yields spike during banking crises).

Appendix Table A.7 shows that the low discount rate news and (relatively) high cashflow news correlations are also the predominant feature of the data within individual countries, including the US. Consistent with Fama and French (1989) and Chen et al. (2008), US corporate bond and equity discount rate news do show some co-movement. However even this relatively modest positive correlation is not representative of the broader patterns in the data, with correlations between discount rate news in other countries and for other asset class pairs close to zero and sometimes negative.

Table 4: *Predictability of returns across asset classes*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity r_{t+1}		Housing r_{t+1}		Corporate bond r^{spread}_{t+1}	
Dividend-price ratio$_t$		0.034***	0.001	-0.003	0.003	0.001
		(0.012)	(0.004)	(0.004)	(0.002)	(0.003)
Rent-price ratio$_t$	0.015**	0.008		0.024***	0.000	-0.002
	(0.007)	(0.008)		(0.004)	(0.001)	(0.002)
Credit spread$_t$	0.002	-0.000	-0.002	-0.004*		0.028***
	(0.008)	(0.008)	(0.002)	(0.003)		(0.004)
P-value: equal βs		0.03		0.00		0.00
R^2	0.004	0.024	0.001	0.048	0.002	0.130
Observations	1507	1507	1504	1504	1482	1482

Notes: OLS regressions with country fixed effects. All coefficients are standardized to a 1 standard deviation increase in the predictor variable (log changes for dividend- and rent-price ratios, absolute changes for the credit spread). Dependent (y) variables in columns. r is the log real total return, and r^{spread} is the spread-implied corporate bond return. Predictor (x) variables in rows. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. P-value: equal βs tests for equality of the predictive coefficients on the dividend-price ratio, rent-price ratio, and the credit spread.

4.2. Cross-asset-class return predictability

The extent of discount rate co-movement can be tested more formally through cross-asset-class predictive regressions, with the results shown in Table 4. As in Table 1, each column corresponds to a different asset class, and each row – to a different predictor; but this time the predictors include the yields on other asset classes. Columns 1, 3, and 5 do not control for the own asset yield, while columns 2, 4, and 6 do. As before, the predictors are standardized to a one standard deviation increase, r corresponds to the real total return, and r^{spread} to the spread-implied excess return on corporate bonds.

In line with the low correlations reported in Section 4.1, there is very little cross-asset-class return predictability in the data. Even though yields on some asset classes are positively correlated with future returns on other asset classes, these relationships are statistically weak and economically small. Rent-price ratios show some predictive power for year-ahead stock returns (column 1), but this power goes away when controlling for the dividend-price ratio (column 2) or at longer forecasting horizons (Table 5 column 2). All the cross-asset-class predictive coefficients are smaller in magnitude than the within-asset coefficients, and the tests for coefficient equality are rejected at the 5% significance level (P-value: equal βs < 0.05). The R^2 statistics of the cross-asset-class regressions in columns 1, 3, and 5 are also substantially smaller than those of the within-asset-class regressions in Table 1, as well as the regressions including all three predictors in columns 2, 4, and 6 of Table 4.

Alternative specifications Table 5 tests for cross-asset-class return predictability across different regression specifications, return definitions, and time periods. The columns correspond to different

Table 5: *Cross-asset-class predictability: alternative specifications*

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	5-year average	Excess returns	Post 1950	Structural breaks	Year fixed effects
Equity r_{t+1}:						
Rent-price ratio$_t$	0.015**	-0.000	0.017**	0.014	0.029***	0.008*
	(0.007)	(0.006)	(0.009)	(0.012)	(0.007)	(0.004)
Credit spread$_t$	0.002	0.003	0.008	-0.003	0.009	0.000
	(0.008)	(0.007)	(0.007)	(0.012)	(0.007)	(0.006)
Housing r_{t+1}:						
Dividend-price ratio$_t$	0.001	-0.000	-0.009	-0.001	-0.002	0.008*
	(0.004)	(0.003)	(0.007)	(0.005)	(0.004)	(0.004)
Credit spread$_t$	-0.002	0.001	0.003	-0.001	-0.005**	-0.002
	(0.002)	(0.003)	(0.006)	(0.003)	(0.002)	(0.003)
Corporate bond r^{spread}_{t+1}:						
Dividend-price ratio$_t$	0.003	0.003**	0.003	0.003	0.002	0.001
	(0.002)	(0.001)	(0.002)	(0.004)	(0.003)	(0.002)
Rent-price ratio$_t$	0.000	0.001	0.000	0.001	0.003	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)

Notes: OLS regressions with country fixed effects. The table shows predictive coefficients of regressing log real total returns on one asset class at $t+1$ on the yields of other asset classes at t. Coefficients are standardized to a 1 standard deviation increase in the asset yield. Predictor (x) variables in rows, specifications in columns. Baseline is the unconditional specification in columns 1, 3, and 5 of Table 4. 5-year averages regresses the average return for years $t+1$ to $t+5$ on the yields at t. 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 to identify the break dates. Year effects has both country and year fixed effects. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

specifications, and the rows – to different asset classes and predictors. The top two rows show the regression coefficients from predicting equity returns with rent-price ratios and credit spreads, the next two – from predicting housing returns with dividend-price ratios and credit spreads, and the bottom two – from predicting corporate bond returns with dividend- and rent-price ratios. Even under these alternative specifications, cross-asset-class predictability is rare, and the cross-asset predictive regressions sometimes carry the wrong sign. The predictive power for 5-year ahead returns (column 2) is even weaker than for 1-year ahead returns. Cross-asset-class predictability is weak or goes in the wrong direction for excess returns (column 3) and in the post-1950 sample period (column 4). Adjusting the data for structural breaks (column 5) improves the ability of rent-price ratios to forecast stock returns, but the other predictive coefficients remain small, insignificant, or even turn significantly negative. Cross-asset-class coefficients remain small after adding year fixed effects in column 6. Appendix A.3 further shows that the own asset yield substantially outperforms both the yields on other assets, and past average returns when forecasting out of sample.

Table 6: *Cross-asset-class predictability during different business cycle phases*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Recession	Expansion	War	No war	Crisis	No crisis
Equity r_{t+1}:							
Rent-price ratio$_t$	0.015**	-0.006	0.021**	0.063**	0.013*	0.003	0.016*
	(0.007)	(0.017)	(0.009)	(0.027)	(0.007)	(0.014)	(0.009)
Credit spread$_t$	0.002	0.040***	-0.013	0.017	-0.002	0.017	-0.003
	(0.008)	(0.014)	(0.010)	(0.018)	(0.008)	(0.014)	(0.009)
Housing r_{t+1}:							
Dividend-price ratio$_t$	0.001	0.011	-0.002	-0.054***	0.004	0.017	-0.001
	(0.004)	(0.009)	(0.004)	(0.005)	(0.005)	(0.012)	(0.005)
Credit spread$_t$	-0.002	0.004	-0.004	-0.035***	-0.004	-0.009*	-0.001
	(0.002)	(0.004)	(0.003)	(0.009)	(0.002)	(0.005)	(0.003)
Corporate bond r_{t+1}^{spread}:							
Dividend-price ratio$_t$	0.003	-0.008	0.004*	0.011***	0.003	0.016	0.002
	(0.002)	(0.007)	(0.002)	(0.003)	(0.003)	(0.014)	(0.002)
Rent-price ratio$_t$	0.000	-0.004	0.002	0.028***	-0.001	0.003	-0.001
	(0.001)	(0.006)	(0.002)	(0.005)	(0.002)	(0.006)	(0.002)

Notes: OLS regressions with country fixed effects. The table shows predictive coefficients of regressing log real total returns on one asset class at $t+1$ on the yields of other asset classes at t. Coefficients are standardized to a 1 standard deviation increase in the asset yield (in the full sample). Predictor (x) variables in rows, specifications in columns. Baseline is the unconditional specification in columns 1, 3, and 5 of Table 4. Recessions and expansions are dated using the Bry and Boschan (1971) algorithm. Wars cover the two world wars only. Crises cover the 3 years after the start of a systemic banking crisis dated using the chronology of Jordà et al. (2016). Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Different business cycle phases & countries Previous studies have documented stronger return predictability in recessions (Fama and French, 1989; Golez and Koudijs, 2018), and large bond and equity discount rate movements around banking crises (Muir, 2017). Table 6 tests whether cross-asset-class return predictability varies across different phases of the business cycle (columns 2 and 3), during or outside of World Wars (columns 4 and 5), and in the aftermath of banking crises (columns 6 and 7). The ability of credit spreads to forecast future stock returns is stronger during recessions (Table 6 column 2), consistent with Fama and French (1989), and the ability of rent-price ratios to forecast stock returns improves during wars. However, taken together, there is still very little evidence of cross-asset-class return predictability regardless of the business cycle phase. Appendix Table A.8 shows that results are similar if we adjust the predictors for structural breaks.

Appendix Tables A.10 and A.11 show the cross-asset predictability results within individual countries, respectively, with and without adjusting the predictor variables for structural breaks. There is very little cross-asset predictability at country level. For a number of countries and asset class pairs, the predictability goes in the wrong direction (i.e., negative rather than positive). The cross-asset-class predictability in the US is somewhat stronger than in other countries, but it remains weak compared to the within-asset-class regressions in Table A.3.

Government bonds The focus of this study is on risky asset classes with uncertain and time-varying cashflows. However, much of the existing literature has studied the correlations between (mostly realized) returns on relatively riskier and safer assets, in particular equities and government bonds. These studies have generally found that these correlations are time-varying, and can be linked to differential risks affecting these two asset classes (Baele et al., 2010; Laarits, 2020; Campbell et al., 2020). To link to this existing literature, Appendix Figure A.3 shows the correlations between the discount rates on risky assets in my study and the term premium, a proxy for the discount rate on government bonds. Consistent with the findings for the US, these correlations are time varying (and for equities, switched from positive to negative in the 1980s and 1990s), and they are also generally low or in the case of corporate bonds, mostly negative.[5]

Appendix Table A.9 shows the within- and cross-asset class predictability regressions for government bond returns, and finds that (especially excess) returns on government bonds are positively predictable by their own asset yield, but not by yields on other risky asset classes. This suggests that the low co-movement of discount rates between the three risky asset classes in this study also extends to government bonds.

Long-horizon regressions From equation (4), we can see that asset price movements are primarily driven by changes in *long-horizon* expected returns. To get a better handle on what type of discount rate movements matter for asset prices, I now predict cumulative real returns for horizons from $h = 1$ to $h = 10$ years ahead, first using the own asset yields (mirroring the within-asset-class regressions in Section 3), and second, using the yields on other risky asset classes. To give the cross-asset predictors the best chance of succeeding, I do not condition on the own asset yield in those regressions, and adjust the predictors for structural breaks (though the results become stronger if I don't adjust for breaks, or condition on the own asset yield). I plot the resulted standardized coefficients and R^2 statistics in Figure 2

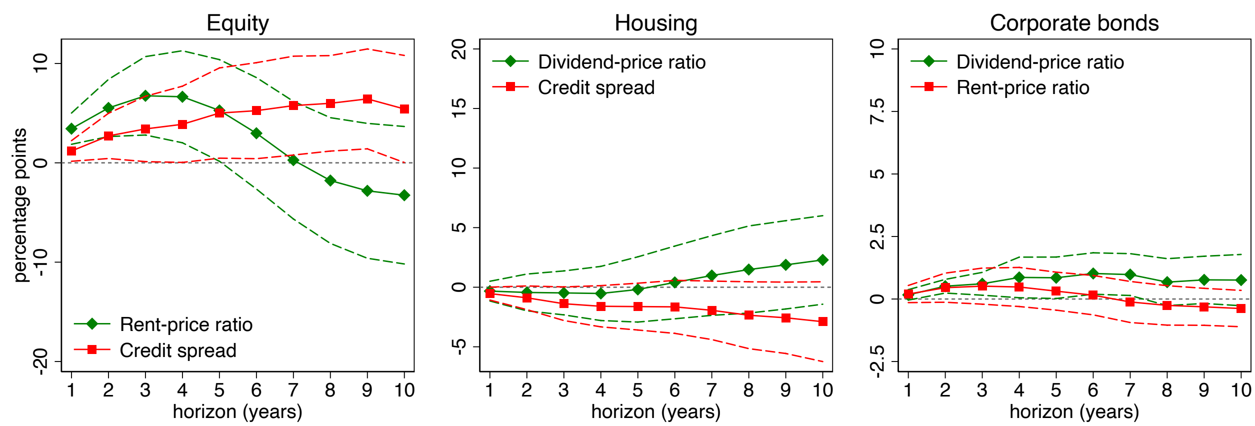
Starting with Figure 2a, the within-asset-class predictive coefficients are economically large and statistically significant, with a one standard deviation increase in the own asset yield predicting 3–5 ppts higher returns 1 year ahead, and 8–15 percentage points higher cumulative returns 5–10 years ahead. The impact is persistent, with all the coefficients significant at all horizons at the 5% level. Turning to the cross-asset predictors in Figure 2b, these are small in magnitude and mostly statistically insignificant. The break-adjusted credit spreads and rent-price ratios carry some predictive power for future equity returns, but the magnitudes are small compared to those for the

[5]This negative correlation can arise due to factors which push the government and corporate bond risk premia in opposite directions, or from changes in government bond yields which do not affect the corporate yield: e.g., an increase in sovereign risk or a reduction in the convenience yield would push up government bond yields, increasing the term premium and reducing the corporate-government bond spread. Evidence in Section 5.1, indeed, suggests that sovereign risk and liquidity are important drivers of bond premia.

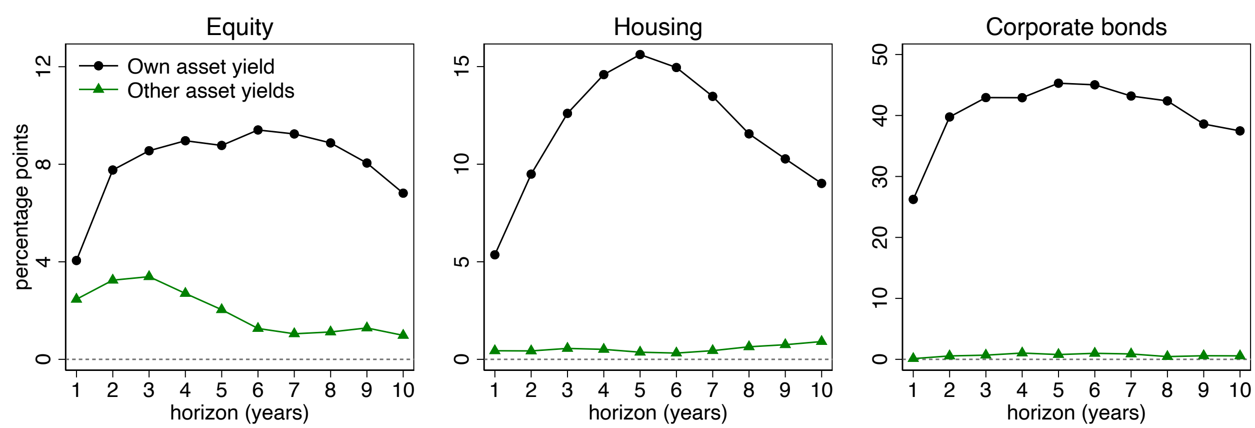
Figure 2: *Within- and cross-asset-class predictability at long horizons (adjusting for structural breaks)*

(a) *Within-asset-class predictability:*

(b) *Cross-asset-class predictability:*



(c) *Predictive R^2:*



Note: Predictable cumulative return change after a one standard deviation increase in the asset yield. All predictors are adjusted for structural breaks. Cumulative return impact estimated using the beta from regressing h-year ahead returns on either own asset yield, or yields of other asset classes. Corporate bond (excess) returns are estimated as -10 times the change in the spread. All regressions are run on a consistent sample across asset classes, predictors and horizons. Standard errors are clustered by country and year, and adjusted for autocorrelation. Dashed lines show 95% confidence bands.

Table 7: *Variance decomposition: asset-class-specific and cross-asset-class discount rate news*

	(1) Equity	(2) Housing	(3) Corporate bonds
Asset-class-specific DR news	43%	58%	85%
Cross-asset-class DR news	-0%	-1%	-4%
CF news	51%	39%	
Residual	6%	4%	

Notes: The shares are obtained by, first, decomposing realized returns on each asset class into the component that is correlated with other risky asset classes r^{other} and one that is not, $r^{\text{asset-spec}}$, and then regressing 15-year ahead cumulative changes in these two return components and cashflow growth (discounted at ρ_i) on the asset yield dp_i as in equations (13)–(15). The residual corresponds to changes in discount rates and cashflows beyond the horizon of 15 years, and any approximation error from the log linearization in equation (11).

dividend yield in Figure 2a, and mostly statistically insignificant. Figure 2c shows that the predictive R^2s are much larger for within-asset-class than for cross-asset-class predictive regressions.

Previous studies have shown that long-horizon predictive regressions suffer from overlap bias, leading to potentially too-small standard errors at longer predictive horizons (Valkanov, 2003; Boudoukh, Richardson, and Whitelaw, 2008). To check for this, Appendix Figure A.4 shows the exact same regressions as in Figure 2, but run on a non-overlapping return sample where I only keep one from every 5 consecutive years of observations (so horizons $h = 1$ to 5 are non-overlapping, and horizons $h = 6$ to 10 overlap only with one other return observation; results also hold for keeping one in every 10 observations). The difference between within- and cross-asset-class predictive regressions is, if anything, more stark than that shown in Figure 2. The within-asset-class coefficients are similar in size to Figure 2, and remain statistically significant at all horizons. The cross-asset-class coefficients, however, are very close to zero and not statistically significant for any combination of predictors and returns. Appendix Figure A.5 repeats these exercises for real (net-of-inflation) rather than excess (net-of-government-bond) returns on corporate bonds, with similar results.[6]

Variance decomposition The final part of the analysis in this section decomposes the variation in asset yield dp for each asset class into cross-asset-class discount rate news, asset-class-specific discount rate news, and cashflow news in line with equation (12) (see Section 2.2 and Appendix A.1). To do this, I first decompose the realized returns on each asset class into the part that is correlated with other asset classes and one that is not, by estimating equation (10) in the cross-country panel. I then forecast 15-year-ahead realized returns, broken down into the cross-asset-class and asset-specific components, and 15-year-ahead cashflows using the asset yield dp_i, with the corresponding regression coefficients giving me the variance decomposition shares in equation (12), subject to a small residual corresponding to discount rate and cashflow news beyond 15 years, and

[6]The dividend-price ratio does have somewhat stronger power for forecasting future real as opposed to excess corporate bond returns, suggesting that the dividend-price ratio has predictive power for future inflation, which forms a large component of the realized real bond return (Campbell and Ammer, 1993).

any approximation errors from the log linearization:

$$\sum_{s=0}^{s=14} \rho_i^s r_{i,j,t+1+s}^{\text{asset-spec}} = \alpha_1 + \beta^{\text{asset-class-specific DR news}} dp_{i,j,t} + \epsilon_{res,i,t} \tag{13}$$

$$\sum_{s=0}^{s=14} \rho_i^s r_{i,j,t+1+s}^{\text{other}} = \alpha_1 + \beta^{\text{cross-asset-class DR news}} dp_{i,j,t} + \epsilon_{other,i,t} \tag{14}$$

$$-\sum_{s=0}^{s=14} \rho_i^s dg_{i,j,t+1+s} = \alpha_1 + \beta^{\text{CF news}} dp_{i,j,t} + \epsilon_{dg,i,t}, \tag{15}$$

where $r^{\text{asset-spec}}$ and r^{other} are estimated by regressing realized returns of one asset class (e.g., equities) on realized returns of the other two asset classes (e.g., housing and corporate bonds), with the predicted values giving me the cross-asset-class component r^{other}, and the residuals the asset-specific component $r^{\text{asset-spec}}$. Note that because the cross-asset-class regression coefficient often change sign at longer horizons (see Figure 2b), I estimate these variance shares by running direct long-horizon regressions instead of estimating a VAR.

Table 7 shows the corresponding variance decompositions for each of the risky asset classes in my study. The consensus for the US stock market is that all the variation in dividend-price ratios is driven by discount rate news corresponding to time variation in the macroeconomic discount factor (e.g., Cochrane, 2011). The results in Table 7 are rather different: consistent with the other findings in this Section, the common discount rate component labelled as "cross-asset-class DR news" explains none of the variation in risky asset prices. Instead, the bulk of variation is explained by asset-specific discount rate movements, and a considerable part by cashflows. This means that to understand the drivers of risky asset prices, we need to understand the drivers of this asset-class-specific discount rate variation.

5. Drivers of asset price fluctuations

What do these findings tell us about the underlying drivers of asset price volatility? The consensus in the literature, mostly motivated by evidence from the US equity market, is that almost all of the (market-wide) asset price movements are driven by time-varying discount rates, which are in turn driven by time variation in the cross-asset discount factor (Cochrane, 2011). My findings present a rather different picture. Almost none of the variation in asset yields corresponds to time variation in cross-asset-class discount rates. Instead, asset-specific discount rate movements are key, and cashflows are also important.

But what ultimately drives these asset-class-specific discount rate movements? This type of asset price variation is difficult to reconcile with many standard risk-based models in macro-finance, which link the discount factor movements to changes in risk aversion (either through time-varying preferences γ_t or through habit formation as in Campbell and Cochrane, 1999), macroeconomic risk in the form of consumption growth Δc_{t+1} (as in the standard C-CAPM), or a different cross-asset-class risk factor Y_{t+1} related, for example, to long-run risk (Bansal and Yaron, 2004), disaster risk (Wachter, 2013), or time-varying consumption composition (Piazzesi, Schneider, and Tuzel, 2007).[7]:

$$1 = \mathbb{E}(\underbrace{\Delta c_{t+1}^{-\gamma_t} Y_{t+1}}_{m_{t+1}} R_{i,t+1}) \tag{16}$$

Even risk factors relating to heterogeneity or different groups of investors such as cross-sectional consumption risk (Constantinides and Duffie, 1996), differences in preferences (Gârleanu and Panageas, 2015), and intermediary risk appetite (He and Krishnamurthy, 2013) tend to generate movements in the macroeconomic discount factor that influence the prices of multiple risky asset classes.

In order to explain the time variation in prices on multiple major risky asset classes, the economic mechanisms need to work through a channel that is altogether different to the time variation in a cross-asset-class risk factor. This can be achieved either by modifying the standard risk-based approach to generate asset-class-specific variation in risk compensation, or moving towards an alternative approach where the volatility in asset prices and implied discount rates is driven by expectation biases applied to asset-class specific information.

5.1. Risk-based mechanisms

The risk-based mechanisms keep the premise that variation in discount rates reflects time-varying compensation for exposure to some form of risk, but move away from the notion that this compensation is driven by changes in a cross-asset macroeconomic risk factor.

1. Time-varying risk exposures Instead of being driven by the volatility of the macroeconomic risk factor σ_m^2, changes in discount rates can be driven by a time-varying exposure to this macroeconomic risk, $\beta_{i,-m}$:

$$\mathbb{E}_t\left(R_{i,t+1}\right) = R_{t+1}^f + R_{t+1}^f \beta_{i,-m,t} \sigma_m^2 \tag{17}$$

Intuitively, house prices would be high (and future housing returns predictably low, reflecting low levels of risk compensation) when housing is a good hedge for macroeconomic risk (low $\beta_{i,-m,t}$). For example, the model in Gabaix (2012) generates discount rate movements through time-varying asset-class-specific exposures to disaster risk.

2. Segmented markets If markets are segmented, the expected returns on each asset class i will correspond to the risk bearing capacity of the marginal investor in that market, m_i:

[7] For example, Chen et al. (2008) show that both dividend yield and credit spread dynamics in a Campbell and Cochrane (1999) habit model are driven by the surplus consumption ratio, and Piazzesi et al. (2007) show that the prices of equity and housing are driven by a common cross-asset discount factor M applied to asset-specific cashflows.

$$\mathbb{E}_t\left(R_{i,t+1}\right) = R^f_{t+1} + R^f_{t+1}\beta_{i,-m}\sigma^2_{m,i,t} \tag{18}$$

Time-variation in this market-specific risk bearing capacity $\sigma^2_{m,i}$ will then produce asset-class-specific movements in discount rates. For example, Haddad and Muir (2021) show that market segmentation between household and intermediary investors can produce asset-class-specific discount rate movements in theory, and proxies for intermediary and household risk aversion have different predictive power for returns on different asset classes in recent US data.

3. Market-specific risk factors Even if markets are integrated, different asset classes can be exposed to different risks. If these risks are uncorrelated, and risk exposures are highly asset-class-specific, this can produce asset-class-specific variation in risk compensation and asset prices. For example, suppose that the stochastic discount factor is composed of three uncorrelated risk factors $m = m_A + m_B + m_C$. Then, rewriting equation (3) gives:

$$\mathbb{E}(R_{i,t+1}) = R^f_{t+1} + R^f_{t+1}\left(\beta_{i,-m_A}\sigma^2_{m_A,t} + \beta_{i,-m_B}\sigma^2_{m_B,t} + \beta_{i,-m_C}\sigma^2_{m_C,t}\right) \tag{19}$$

If movements in the three risk factors m_A, m_B and m_C are uncorrelated and exposures to these movements are asset-class-specific (e.g., $\beta_{i,-m_A} > 0$ and $\beta_{i,-m_B} = \beta_{i,-m_C} = 0$ and so on), the variation in these risk factors can produce discount rate movements which are uncorrelated across different classes of risky assets. Examples of such risk factors in the literature include nominal and real risks (Campbell et al., 2020; Fang et al., 2022), downside risk (Lettau et al., 2014), and liquidity risk (Bao et al., 2011).

Empirical evidence It is difficult to test the mechanism 1. ($\beta_i, -m, t$) above because it is hard to estimate the time-varying risk exposures in the data. That being said, Appendix Table A.12 shows that changes in exposures to common macroeconomic risk factors such as consumption, and downside consumption risk, tend to be strongly positively correlated across asset classes. Regarding the other two risk-based mechanisms, they basically amount to the existence of some asset-class-specific uncorrelated risk factors, either corresponding to different macroeconomic risks (in either integrated or segmented markets) or marginal risk capacities of different investors in segmented markets.

To explain the observed patterns in the data, these risk factors have to have substantial predictive power for future returns, and this predictive power has to be asset class specific. To test for this in the data, I construct proxies for the risk factors prominent in major macro-finance theories, test whether they predict future returns, and perform a variance decomposition exercise to assess their relative contribution to time variation in prices (or yields) of different risky asset classes. These factors correspond to various real-economy risks, measured by surplus consumption (a proxy for habit in Campbell and Cochrane, 1999), the consumption-wealth ratio (Lettau and Ludvigson, 2002), investment/GDP growth to proxy for investment frictions prominent in production-based asset

Table 8: *Predictive power of macro-financial risk factors*

	Equity $\sum_{s=0}^{14} \rho^s r_{t+1+s}$	Housing $\sum_{s=0}^{14} \rho^s r_{t+1+s}$	Corp. bond $\sum_{s=0}^{14} \rho^s r_{t+1+s}^{\text{spread}}$
Dividend-price ratio (resid.)	0.38***		
	(0.11)		
Rent-price ratio (resid.)		0.53***	
		(0.07)	
Credit (price) spread (resid.)			0.79***
			(0.11)
Real activity:			
Surplus consumption (-)	-0.23	0.25***	0.09
	(0.17)	(0.10)	(0.08)
Consumption-wealth ratio (+)	0.19*	-0.01	-0.00
	(0.10)	(0.06)	(0.06)
Investment/GDP growth (-)	-0.08	-0.07	0.02
	(0.09)	(0.05)	(0.03)
Rent expenditure/GDP (+)	0.02	0.11	-0.11
	(0.05)	(0.09)	(0.11)
Leverage & intermediary balance sheets:			
Loans/GDP growth (-)	0.09	-0.24***	0.05
	(0.08)	(0.04)	(0.07)
Bank leverage growth (-)	-0.04	-0.02	0.08
	(0.05)	(0.06)	(0.06)
Bank asset growth (-)	-0.03	0.06	-0.14*
	(0.08)	(0.05)	(0.08)
Liquidity & sovereign risk:			
Government debt/GDP ($\pm$)	0.19***	0.16***	-0.15*
	(0.07)	(0.06)	(0.08)
Broad money/GDP (+)	-0.14**	-0.18***	0.21**
	(0.07)	(0.06)	(0.09)
Nominal & duration risks:			
Inflation (-)	0.20	0.12*	-0.07
	(0.18)	(0.07)	(0.07)
Term premium (+)	-0.00	0.00	-0.41***
	(0.07)	(0.05)	(0.05)
R^2	0.20	0.32	0.40
Observations	1169	1165	878

Notes: OLS regressions with country fixed effects. Predictor (x) variables in rows, dependent (y) variables in columns. All predictors are standardized to a 1 standard deviation increase (signs in brackets show the coefficient sign would expect from theory). Asset yields (log dividend- and rent-price ratios, and log price spread for corporate bonds) are residualized by regressing them on the macro-financial risk factors. r is real total return and r^{spread} is the spread-implied excess return on corporate bonds. Coefficients are standardized to a 1 standard deviation increase in the asset yield. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

pricing models (e.g. Cochrane, 1991), and rent-to-GDP ratio to proxy for time varying consumption composition as in Piazzesi et al. (2007), as well as intermediary risks in the form of bank asset, bank leverage, and real-economy leverage (loans/GDP) growth (Baron and Muir, 2021; Haddad and Muir, 2021). I also include factors related to liquidity and sovereign risk, in the form of the government debt and broad money, nominal and duration risks in the form of inflation and the term premium. Appendix C.1 describes how these factors are constructed.

Table 8 shows the predictive power of these factors (standardized to 1 standard deviation) for future returns on different asset classes, alongside the asset yields used in previous analysis. To ease the interpretation, I residualize the asset yields by regressing them on the macro risk factors, and standardize their changes to 1 standard deviation. I also focus on predicting long-run returns (15-year-ahead cumulative returns discounted by ρ_i) since the movements in long-run returns are more informative for asset prices, with the predictive regressions for 1-year-ahead returns shown in the Appendix Table A.13. The predictive power of factors related to real activity is limited, though, the consumption-wealth ratio predicts future stock returns, in line with the US results of Lettau and Ludvigson (2002). Intermediary factors have some predictive power for housing and bonds but not for stocks, consistent with Haddad and Muir (2021).

Factors related to liquidity and sovereign risk are associated with opposite movements in future returns on equity and housing on the one hand, and corporate bonds on the other. The directions are in line with economic intuition. For example, high levels of government debt to GDP are associated with higher discount rates for equity and housing, presumably reflecting higher macroeconomic risks, but lower discount rates for corporate bonds, with investors potentially moving from the relatively riskier government to corporate bonds when sovereign risks are high. High levels of sovereign risk would also push up the term premium (the difference between 10-year government bond yields and the short-term interest rate), and are again associated with lower future returns on corporate bonds. High levels of broad money are, in turn, associated with low future returns on instruments which are less money-like (stocks and housing), and higher returns on corporate bonds, which are perhaps a closer substitute to money than the other two asset classes.

Overall, there is some evidence for asset-specific movements in expected returns induced by variation in different macro-financial risk factors. But does such variation account for a large proportion of movements in asset prices? To gauge this, I decompose the variation in asset yields into four components: predictable return movements which are correlated with macro-financial risk factors, other predictable return movements, as well as predictable cashflow movements correlated, and uncorrelated with macro-financial risk factors. To do this, I first decompose the asset yield into a part that is correlated, and that which is uncorrelated with macro-financial risk factors, and then use these two components of the asset yield to predict long-run returns and cashflow growth, with the predictive beta coefficients corresponding to the variance decomposition shares (details are provided in Appendix A.1).

The results of this decomposition are provided in Table 9. Predictable return movements associated with macro-financial risk factors account for just under a quarter of variation in credit

Table 9: *Macro-financial risk factors: variance decomposition of asset yields*

	(1) Equity	(2) Housing	(3) Corporate bonds
Macro DR news	-5%	7%	23%
Other DR news	32%	41%	73%
Macro CF news	20%	31%	
Other CF news	45%	12%	
Residual	8%	9%	

Notes: The shares are obtained by, first, decomposing asset yields into the component that is correlated with macro-financial risk factors, dp^{factor}, and the residual dp^{other}, and then predicting 15-year-ahead returns and cashflow growth (discounted by ρ_i) using these two components of the yield, with the predictive coefficients in the regression rescaled by the ratio of $Var(dp^{factor})/Var(dp)$ for macro DR news, and $Var(dp^{res})/Var(dp)$ for other DR news corresponding to the above variance shares (see also equations (A.12)–(A.13) and Appendix A.1). The residual corresponds to changes in discount rates and cashflows beyond the horizon of 15 years, and any approximation error from the log linearization.

spreads, but a relatively small share of variation in equity and house prices. Differently, macro-financial factors account for a considerable share of the expected cashflow movements, especially for housing. Overall, this suggests that there may be other forces, not related to risk compensation per se, which drive the asset-specific variation in "other discount rate news" in Table 9.

5.2. Behavioral mechanisms

A substantial part of asset-class-specific discount rate movements seems to be unrelated to variation in macro-financial risk factors that I can measure in my data. One potential explanation for these price movements is that they relate to non-rational, or subjective expectations. Importantly, these subjective expectations have to be uncorrelated across different classes of risky assets. This suggests that they are not related to factors such as macroeconomic and economy-wide sentiment, and instead relate to asset-specific perceptions of cashflows, risk, and return. To fix ideas, I apply the framework of De la O and Myers (2021, 2022) to the context of multiple risky asset classes to study how changes in subjective expectations can result in asset-class-specific price movements, and then test the predictions of this framework in the data.

De la O and Myers (2021, 2022) show that because the Campbell and Shiller (1988) decomposition in equation (4) is an accounting identity, it applies to both subjective expectations $\mathbb{E}^*$ and realized cashflows and returns. By rearranging the subjective-expectation and realized-return versions of equation (4), they show that the variation in realized returns can reflect both ex-ante subjective risk compensation $\mathbb{E}^* r$, and an ex-post cashflow forecast error fe^{dg} (see Appendix C.2 for details):

$$\sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s} = \sum_{s=0}^{\infty} \rho_i^s \mathbb{E}^* r_{i,t+1+s} + \sum_{s=0}^{\infty} \rho_i^s \underbrace{(dg_{i,t+1+s} - \mathbb{E}^* dg_{i,t+1+s})}_{\mathrm{fe}^{dg}_{i,t+1+s}} \tag{20}$$

Table 10: *Correlations between investment prospects of different asset classes, National Housing Survey*

	(1)	(2)	(3)	(4)	(5)	(6)
	Perceived potential (low/high)			Perceived risk (low/high)		
	Equity	Housing	Bonds	Equity	Housing	Bonds
Equity	1.00	.	.	1.00	.	.
Housing	0.09	1.00	.	0.17	1.00	.
Bonds	0.01	0.15	1.00	0.09	0.15	1.00

Notes: Pairwise Spearman rank correlation coefficients using microdata for the Fannie Mae National Housing Survey, repeated cross-sections, six 2013 survey waves. All variables are residualized controlling for survey wave fixed effects, age, gender, income, education, expectations about the economy and household finances, employment status, and past income growth.

Intuitively, returns on an asset class i can be low today both because investors correctly anticipated this low return in the past ($\mathbb{E}^*r$), or because they over- or under-estimated future cashflows, leading to a price correction via correspondingly low or high returns today. Crucially for my analysis, both of these sources of variation (subjective risk perceptions, and cashflow forecast errors) can be asset class specific. As long as these risk perceptions or cashflow errors are uncorrelated across asset classes, and are predictable by past asset yields (i.e., they help explain asset price variation in a variance-decomposition sense), their variation can generate the return predictability and observed discount rate movements in the data:

$$Cov\left(dp_i, \sum_{s=0}^{\infty} \rho_i^s \mathbb{E}^* r_{i,t+1+s}\right) + Cov\left(dp_i, \sum_{s=0}^{\infty} \rho_i^s \mathrm{fe}^{dg}_{i,t+1+s}\right) > 0 \text{ within any asset class } i, \text{ and} \tag{21}$$

$$Cov\left(dp_i, \sum_{s=0}^{\infty} \rho_k^s \mathbb{E}^* r_{k,t+1+s}\right) + Cov\left(dp_i, \sum_{s=0}^{\infty} \rho_k^s \mathrm{fe}^{dg}_{k,t+1+s}\right) = 0 \text{ across asset classes } k \neq i \tag{22}$$

Intuitively, this type of argument relies on subjective variation in optimism and pessimism about risk or cashflows for a specific asset class: for example, investors may (incorrectly) believe that stocks have high future cashflow growth prospects, or are relatively well-hedged from macro risk, which pushes up the stock price today, and leads to predictably low returns in the future when these incorrect cashflow expectations are realized, or as compensation for a subjectively low perception of risk.

Survey evidence Do perceptions of risk and cashflows vary in a predictable and asset-class-specific manner? Very few surveys contain data on perceptions of returns and cashflows for multiple asset classes, so I focus my attention on the few recent surveys that do, and then move on to more indirect evidence in long-run data. Table 10 reports the Spearman rank correlations between perceived risk and potential (with the latter a proxy for long-run cashflow growth) of equities, housing, and bonds in the cross-section of households in the Fannie Mae National Housing Survey (NHS) (see Appendix C.2 for the data description). These correlations are conditional on a range of household characteristics and time and geographical fixed effects, but unconditional correlations

Table 11: *Past capital gains and perceived investment prospects, National Housing Survey*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Expected capital gain on own house		Perceived potential (low=0; high=1)			Perceived risk (low=0; high=1)		
	1-year	5-year	Equity	Housing	Bonds	Equity	Housing	Bonds
Past capital gain on own house	0.168*** (0.023)	0.169** (0.056)	-0.001 (0.010)	0.017* (0.010)	0.001 (0.010)	-0.000 (0.010)	-0.022*** (0.008)	-0.018* (0.011)
State FE	✓	✓	✓	✓	✓	✓	✓	✓
Survey wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.26	0.16	0.08	0.08	0.13	0.08	0.13	0.14
Observations	1808	1689	1820	1876	1750	1805	1834	1760

Notes: Regressions using microdata for the Fannie Mae National Housing Survey, repeated cross-sections, six 2013 survey waves. Controls are age, gender, income, education, expectations about economy and household finances, employment status, and past income growth. Columns 1 and 2 report OLS estimates of the percentage point change in per-year future house price growth expectations for each 1 ppt increase in past house price growth. Columns 3–8 report logit estimates of the marginal effects of a 1 standard deviation increase in past capital gain on the likelihood of housing, equity and bond investments being perceived as "high potential" (columns 3–5) and "risky" (columns 6–8). All regressions use survey weights. Standard errors are dually clustered by survey wave and state. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

shown in Appendix Table A.14 are similar. Correlations are low, meaning that the same households who perceive equity as risky generally don't perceive housing as risky, and so on.

Table 11 further shows that these perceptions of risk and potential vary over time in a predictable manner that is consistent with theories of biased expectation formation and equations (21) and (22). It shows that a positive past outcome for one asset class – a high reported capital gain on the respondent's own home – is correlated with higher expected future capital gains on own property (columns 1–2), as well as generally higher perceived potential and lower risk for the housing market as a whole (columns 4 and 7). However, there is little change in the perceived potential and risks of equity and bond investments, so these changes in subjective beliefs are largely asset class specific.[8]

Appendix C.2 shows that similar types of mechanisms seem to be present in other surveys. In the Survey of Professional forecasters, proxies for expected excess returns on equities and different bonds are uncorrelated (Appendix Table A.15), and display asset-class-specific overreaction (i.e., positive forecast revisions predict negative future forecast errors suggesting that the forecast revision was too large see Appendix Table A.16).[9] Asset-class-specific return expectations of public pension funds (sourced from Andonov and Rauh, 2021) are weakly correlated with each other (Appendix Table A.17), but display patterns of asset-class-specific biases. Appendix Table A.18 shows that

[8] To interpret the marginal effects, a one standard deviation increase in past housing capital gain (about 7 percentage points) makes households 2 percentage points more likely to perceive investing in housing as having high return and low risk, compared to the sample means of 62% (high return) and 27% (low risk).

[9] See Coibion and Gorodnichenko (2012), Bordalo, Gennaioli, Ma, and Shleifer (2020b), and Appendix C.2 for details.

Table 12: *Return predictability using experienced returns*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity r_{t+1}		Housing r_{t+1}		Corporate bond r^{spread}_{t+1}	
Experienced stock return	-0.047***	-0.037**		0.003		-0.006***
	(0.011)	(0.015)		(0.007)		(0.002)
Experienced housing return		0.002	-0.012**	-0.014**		0.003*
		(0.016)	(0.005)	(0.007)		(0.002)
Experienced corporate bond return		-0.000		0.004	-0.016***	-0.015***
		(0.012)		(0.004)	(0.003)	(0.003)
R^2	0.02	0.02	0.01	0.02	0.04	0.04
Observations	1565	895	1108	864	1053	815

Notes: OLS regressions with country fixed effects. Dependent (y) variables in columns. r is the log real total return, and r^{spread} is the spread-implied corporate bond return. Predictor (x) variables in rows. Experienced return is the exponentially weighted average of past real returns, using a smoothing parameter of 0.04. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

pension funds who experienced a high return on a specific asset class (e.g., equities) in the past expect a high return on this asset class in the future even after controlling for overall portfolio performance (replicating the broad findings of Andonov and Rauh, 2021).

Evidence in long-run data Survey evidence suggests that subjective perceptions of risk and cashflows vary in an asset-class-specific manner. But is this variation important in explaining the time series price volatility at the level of entire asset classes? Existing evidence suggests that these subjective expectations, and the corresponding biases, are often related to past asset-specific outcomes such as past realized returns (Adam and Nagel, 2022). This finding is also consistent with theory: for example, Nagel and Xu (2021) show a model of learning with limited memory generates return predictability via time-varying subjective expectations of future cashflows, and implies that past realized market outcomes (e.g., equity payouts or returns) should negatively predict future returns.

To test this proposition in my data, I follow Nagel and Xu (2021) and construct a measure of experienced returns as the exponentially weighted average of past real returns for a specific asset class.[10] I then use these experienced returns to predict future realized returns on the same asset class, and on other asset classes. Table 12 shows the results for 1-year ahead returns, with long-run predictability of 15-year-ahead return shown in Appendix Table A.19.[11] Consistent with the findings

[10]This measure is constructed as $\mu_{r,t+1} = \mu_{r,t} + \nu(r_{t+1} - \mu_{r,t})$, where μ is the experienced return, r is the realized real return, and ν is a smoothing parameter set to 0.04, which gives me weights close to the baseline in Malmendier and Nagel (2011). Appendix Table A.21 shows robustness to alternative smoothing parameters.

[11]The long-horizon regressions have a relatively short sample, because each non-missing observation requires both a history of returns for the experienced return calculation, and 15 years of future returns for the predictability, hence I focus on the 1-year horizon in the main text.

Table 13: *Experienced returns and macro-financial risk factors: variance decomposition of asset yields*

	(1) Equity	(2) Housing	(3) Corporate bonds
Experienced-return DR news	11%	23%	16%
Macro DR news	-2%	17%	20%
Other DR news	24%	19%	59%
CF news	64%	17%	
Residual	3%	24%	

Notes: The shares are obtained by, first, decomposing asset yields into the components that are correlated with macro-financial risk factors, dp^{factor}, experienced returns, $dp^{exp-rtn}$, and the residual dp^{other}, and then predicting 15-year-ahead returns and cashflow growth (discounted by ρ_i) using these three components of the yield, with the predictive coefficients in the regression rescaled by the ratio of $Var(dp^{factor})/Var(dp)$ for macro DR news, $Var(dp^{exp-rtn})/Var(dp)$ for experienced-return DR news, and $Var(dp^{res})/Var(dp)$ for other DR news corresponding to the above variance shares (see also equations (A.14)–(A.17) and Appendix A.1). The residual corresponds to changes in discount rates and cashflows beyond the horizon of 15 years, and any approximation error from the log linearization.

of Nagel and Xu (2021) for US equities, high past experienced returns on each asset class predict low returns on the same asset class in the future. The magnitudes and R^2s are similar to the baseline predictive regressions in Table 1. A 1 standard deviation increase in experienced returns predicts 1–5 percentage points lower future realized returns 1 year ahead, depending on the asset class. However, this predictive power is largely asset class specific, with high experienced housing returns not predicting future low returns for equities or corporate bonds, and so on.

Importantly, Appendix Table A.20 shows that different to asset yields, experienced returns do not predict future cashflow growth, consistent with these variables measuring latent subjective discount rates and errors in cashflow forecasts. Appendix Table A.21 shows that results hold under alternative smoothing assumptions for experienced returns. Appendix Table A.22 shows that return predictability using experienced cashflow growth is weak, especially for housing, which may reflect the fact that homeowners do not observe imputed market rents and hence may be more prone to base their decisions on experienced price (as opposed to rent) growth.

How important is the discount rate variation associated with changes in experienced returns? To get a rough idea of this, I decompose the variation in asset yields into i). macro-factor-related discount rate news (as in Table 9), ii). experienced-return-related discount rate news, iii). other discount rate news, and iv). cashflow news. To do this, I first regress asset yields on macro factors, and regress the residual from this first regression on experienced returns, allowing me to decompose asset yield movements into those correlated with macro-risk-factor and experienced-return movements, and the residual. I then use each of these three components of the asset yield to predict future long-run returns and cashflows, with the βs on the return predictive regressions giving me the corresponding variance shares (see Appendix A.1 for details).

Table 13 shows the results of this decomposition exercise. Experienced-return-related discount rate news (i.e., predictable variation in future returns associated with past experienced returns on a given asset class) account for 11%–23% of variation in asset yields, with numbers in a similar ballpark to the macro-factor-related discount rate movements. However, a substantial part of discount rate movements ("other DR news") remains unexplained: i.e., between 19% and 59% of asset yield variation is accounted for by discount rate movements which are not correlated with either experienced returns or macroeconomic risk factors. These other discount rate news could be driven by other macroeconomic risk factors and behavioral biases which I cannot measure in my data. Alternatively, they could correspond to demand-based price movements in inelastic markets (Gabaix and Koijen, 2020), which have been showed to exhibit some asset-class-specific variation in recent work by Gabaix, Koijen, Mainardi, Oh, and Yogo (2022). Better understanding the driving forces behind this unexplained asset-class-specific discount rate variation offers a potentially fruitful avenue for future research.

6. Conclusion

In this paper, I used long-run data spanning 17 countries, 150 years and three major risky asset classes to study the underlying drivers of asset price variation. This analysis has confirmed the ubiquity of Shiller (1981)'s volatility puzzle: for all three asset classes, prices vary more than future cashflows, and returns are predictable. However, the reasons for this excess volatility are different to those proposed in much previous research. Instead of being driven by a cross-asset macroeconomic risk factor related to consumption or risk aversion, the bulk of asset price variation is attributable to asset-class-specific discount rate movements, and a smaller but still considerable part to cashflows. Together, my findings suggest that asset-class-specific factors related to future cashflows, asset-specific risks, and subjective perceptions of these risks and cashflows, are a key driver of asset prices.

My findings have several implications for future work. First, a discount rate estimate from one asset class (e.g., equities) does not necessarily give us a good idea of discount rates in other asset classes (e.g., real estate). This puts some caution against commonly used practices of using expected equity returns to discount cashflows across a wide range of investments, and using option markets to obtain estimates of economy-wide risk appetite. Second, my findings imply an additional cross-validation for future theories of asset price volatility, in that they ought to be able to generate asset-class-specific price movements that go beyond variation in observed cashflows. Finally, while I offer an initial assessment of the implications of my findings for the drivers of asset price fluctuations, much work remains to be done, with better data and further research on these asset-specific factors hopefully bringing us closer to understanding the underlying drivers of asset prices.

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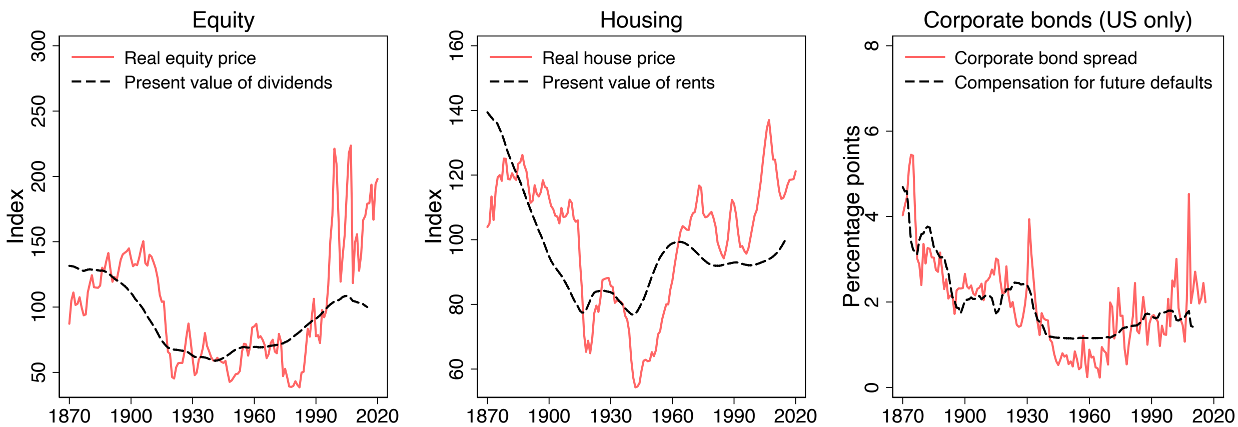
Internet Appendix

The Co-Movement Puzzle

A. Excess volatility within asset classes: additional results

Figure A.1: *Risky asset prices and discounted future cashflows*



Notes: 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.

Table A.1: *Corporate bond default predictability in the US*

	(1)	(2)
	Default rate, t+1	Δ Default rate, t+1
spread_t	1.485***	
	(0.274)	
$\Delta\ \text{spread}_t$		0.195
		(0.331)
R^2	0.430	0.002
Observations	142	141

Notes: Dependent (y) variables are the one-year ahead level and change in the corporate bond default rate. The default rate is calculated as the par value of bonds in default relative to total outstanding, from Giesecke et al. (2011). Data are for US only. Predictor (x) variables are the level and the change in the credit spread. OLS regressions with heteroskedasticity-robust standard errors in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A.2: *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}	r^{spread}_{t+1}
Australia	0.032**	-0.021*	0.011*	-0.003	0.025**	0.036***
	(0.013)	(0.011)	(0.007)	(0.006)	(0.010)	(0.008)
Belgium	0.034	-0.026	-0.021*	-0.038***	0.018*	0.042***
	(0.025)	(0.043)	(0.012)	(0.011)	(0.009)	(0.008)
Canada	0.025*	-0.057***			0.027***	0.014*
	(0.014)	(0.018)			(0.008)	(0.008)
Denmark	-0.006	-0.050**	0.024***	-0.001		
	(0.018)	(0.024)	(0.006)	(0.003)		
Finland	0.035	-0.068*	0.045***	-0.015	0.018	0.057**
	(0.032)	(0.040)	(0.013)	(0.013)	(0.013)	(0.028)
France	0.092***	0.027	0.031***	0.017***	0.036***	0.030
	(0.019)	(0.029)	(0.007)	(0.005)	(0.008)	(0.019)
Germany	-0.027	-0.153***	0.036***	0.003	0.028***	0.017**
	(0.023)	(0.027)	(0.008)	(0.004)	(0.010)	(0.007)
Italy	0.028	-0.064*	0.029***	-0.020	-0.011	0.020***
	(0.035)	(0.038)	(0.008)	(0.015)	(0.015)	(0.006)
Japan	0.029	-0.052**	0.019***	-0.007*	0.014	0.034***
	(0.023)	(0.021)	(0.007)	(0.004)	(0.013)	(0.013)
Netherlands	0.015	-0.062**	0.021***	-0.008	0.030***	0.017*
	(0.021)	(0.025)	(0.007)	(0.005)	(0.008)	(0.010)
Norway	0.006	-0.056**	0.023***	0.004	0.034***	0.025***
	(0.020)	(0.023)	(0.007)	(0.005)	(0.008)	(0.005)
Portugal	0.027	-0.028	0.001	-0.024**	-0.007	0.050**
	(0.031)	(0.062)	(0.012)	(0.010)	(0.021)	(0.024)
Spain	0.053***	-0.055**	0.024**	-0.006	-0.035***	0.013
	(0.020)	(0.026)	(0.011)	(0.006)	(0.008)	(0.012)
Sweden	0.001	-0.098***	0.015**	-0.004	0.032***	0.018***
	(0.019)	(0.017)	(0.006)	(0.003)	(0.007)	(0.004)
Switzerland	0.007	-0.059***	0.007	-0.007*	0.022**	0.021**
	(0.018)	(0.019)	(0.005)	(0.004)	(0.009)	(0.009)
UK	0.046**	-0.022***	0.021***	0.001	0.009	0.022***
	(0.019)	(0.006)	(0.006)	(0.005)	(0.008)	(0.006)
USA	0.020	-0.040***	0.022**	-0.007	0.035***	0.016***
	(0.015)	(0.012)	(0.009)	(0.005)	(0.005)	(0.006)
Significant/Total	5/17	14/17	14/16	5/16	11/16	14/16

Notes: OLS regressions at country level. Coefficients are standardized to a 1 standard deviation increase in the predictor variable. Predictor (x) variables are the log dividend-price ratio, log rent-price ratio, and the corporate bond spread. Dependent (y) variables in columns. r is the log real total return, dg is log real dividend or rental growth, and r^{spread} is the spread-implied excess corporate bond return, calculated as $-10 * \Delta spread$. Danish corporate bond regression omitted due to the low number of observations (the bond series start in 1991). Heteroskedasticity-robust standard errors in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A.3: *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}	r^{spread}_{t+1}
Australia	0.028**	-0.040***	0.018***	-0.016*	0.032***	0.043***
	(0.014)	(0.012)	(0.007)	(0.009)	(0.008)	(0.006)
Belgium	0.029	-0.038	-0.038**	-0.055***	0.014*	0.042***
	(0.024)	(0.041)	(0.017)	(0.012)	(0.008)	(0.007)
Canada	0.038***	-0.072***			0.026***	0.017**
	(0.011)	(0.017)			(0.008)	(0.008)
Denmark	0.031*	-0.037	0.021***	-0.004		
	(0.016)	(0.025)	(0.006)	(0.006)		
Finland	0.063**	-0.114***	0.050***	0.002	-0.004	0.081***
	(0.032)	(0.036)	(0.016)	(0.014)	(0.010)	(0.024)
France	0.103***	0.018	0.023***	0.001	0.038***	0.051***
	(0.020)	(0.024)	(0.008)	(0.007)	(0.008)	(0.017)
Germany	-0.035	-0.183***	0.023*	-0.005	0.040***	0.027***
	(0.025)	(0.022)	(0.013)	(0.004)	(0.009)	(0.006)
Italy	0.034	-0.070*	0.005	-0.021	-0.002	0.022***
	(0.036)	(0.042)	(0.005)	(0.015)	(0.014)	(0.005)
Japan	0.034	-0.077**	0.018*	0.003	0.024***	0.039***
	(0.029)	(0.032)	(0.009)	(0.008)	(0.009)	(0.010)
Netherlands	0.046**	-0.098***	0.023***	-0.009	0.022***	0.024***
	(0.021)	(0.025)	(0.006)	(0.006)	(0.008)	(0.009)
Norway	0.021	-0.048**	0.036***	0.009**	0.024***	0.027***
	(0.019)	(0.021)	(0.006)	(0.004)	(0.008)	(0.004)
Portugal	0.053	-0.038	0.004	-0.019*	-0.001	0.071***
	(0.034)	(0.055)	(0.007)	(0.010)	(0.025)	(0.019)
Spain	0.054***	-0.072***	0.030***	-0.011	-0.018*	0.027**
	(0.018)	(0.024)	(0.011)	(0.007)	(0.011)	(0.012)
Sweden	0.032	-0.104***	0.030***	-0.001	0.022***	0.023***
	(0.020)	(0.017)	(0.005)	(0.004)	(0.009)	(0.004)
Switzerland	0.019	-0.065***	0.010**	-0.002	0.019**	0.027***
	(0.018)	(0.018)	(0.005)	(0.003)	(0.009)	(0.008)
UK	0.061***	-0.024**	0.031***	-0.001	0.013	0.027***
	(0.017)	(0.010)	(0.007)	(0.005)	(0.008)	(0.005)
USA	0.038***	-0.062***	0.025***	-0.005	0.018***	0.024***
	(0.014)	(0.012)	(0.009)	(0.004)	(0.007)	(0.006)
Significant/Total	9/17	13/17	14/16	4/16	12/16	16/16

Notes: OLS regressions at country level. Predictor (x) variables are the log dividend-price ratio, log rent-price ratio, and the corporate bond spread, all adjusted for structural breaks and standardized 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, and r^{spread} is the spread-implied excess corporate bond return. Danish corporate bond regression omitted due to the low number of observations (the bond series start in 1991). Heteroskedasticity-robust standard errors in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A.4: *Equity return and dividend growth predictability, United States and cross-country panel*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	US post-1950		US full sample		Panel post-1950		Panel full sample	
	r^{eq}_{t+1}	dg^{eq}_{t+1}	r^{eq}_{t+1}	dg^{eq}_{t+1}	r^{eq}_{t+1}	dg^{eq}_{t+1}	r^{eq}_{t+1}	dg^{eq}_{t+1}
Dividend-price ratio$_t$	0.039**	-0.014	0.020	-0.040***	0.030***	-0.054***	0.023***	-0.049***
	(0.020)	(0.009)	(0.015)	(0.012)	(0.009)	(0.010)	(0.008)	(0.009)
R^2	0.053	0.045	0.012	0.113	0.016	0.044	0.012	0.043
Observations	70	70	149	149	1186	1186	2355	2355

Notes: OLS regressions of year-ahead log total real equity returns and log real dividend growth on log dividend-price ratio. Panel includes country fixed effects, and uses data for all 17 countries. Coefficients are standardized to a 1 standard deviation increase in the log dividend-price ratio in the respective subsample. Standard errors in parentheses. For the panel, standard errors are clustered by country and year, and adjusted for autocorrelation. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

A.1 Variance decompositions

Within asset classes From the Campbell and Shiller (1988) decomposition in equation (4), the variance of the asset yield dp is the sum of the covariance between the yield and long-run cumulative returns and cashflow growth (discounted at ρ_i):

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

These co-variances can be estimated directly by regressing long-run discounted sums of future returns and cashflows on today's asset yield, or indirectly by running a VAR. For the within-asset-class regressions I use the VAR approach, though all approaches give similar results. For this I follow Golez and Koudijs (2017) and estimate the following VAR in real total returns, cashflow growth, an yields $[r_{i,t}, dg_{i,t}, dp_{i,t}]' \equiv z_{i,t}$:

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

$$\text{subject to } (e1' - e2' + \rho e3')A = e3' \tag{A.3}$$

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

where the moment constraints in (A.3) reflect the period-by-period version of the Campbell-Shiller identity $dp_{i,t} = r_{i,t+1} - dg_{i,t+1} + \rho_i dp_{i,t+1}$. The variance shares are then estimated as follows:

$$\text{Var}(dp_{i,t}) = e3'\Gamma e3 = \underbrace{e1'A(I - \rho A)^{-1}\Gamma e3}_{\text{DR news}} - \underbrace{e2'A(I - \rho A)^{-1}\Gamma e3}_{\text{CF news}} \tag{A.4}$$

I also compute an estimate of discount rate and cashflow news for each country and year in my sample by decomposing the unexpected return in each country and year, $r_{i,t+1} - \mathbb{E}_t r_{i,t+1}$, into changes in the long-run forecast of future returns and cashflows, following Campbell (1991), as follows:

$$\underbrace{r_{i,t+1} - \mathbb{E}_t r_{i,t+1}}_{\text{Unexpected return}} = \underbrace{-e1'\rho_i A(I - \rho_i A)^{-1} u_{i,t+1}}_{\text{DR news}} + \underbrace{(e1 + e1'\rho_i A(I - \rho_i A)^{-1}) u_{i,t+1}}_{\text{CF news}} \tag{A.5}$$

For corporate bonds, I rely on the Nozawa (2017) version of the Campbell and Shiller (1988) identity:

$$s_t^{\text{price}} \approx \mathbb{E} \sum_{s=0}^{T} \rho^s r_{t+1+s}^{ex} - \mathbb{E} \sum_{s=0}^{T} \rho^s l_{t+1+s} \tag{A.6}$$

Above, $s^{\text{price}} = log(\text{P}^{\text{gov}}/\text{P}^{\text{corp}})$ is the log price spread, i.e., log of the ratio of government to corporate bond prices, r^{ex} is the log corporate bond return in excess of the government bond with the same maturity, l is the credit loss, and T is the maturity of the bond. Since the average maturity of bonds in my sample is close to 15 years, I estimate the variance share directly by regressing 15-year-ahead cumulative future excess bond returns (discounted at $\rho^{\text{bond}} = 0.99$ from Nozawa, 2017) on today's price spread:

$$\sum_{s=0}^{14} \rho_{\text{bond}}^s r_{j,t+1+s}^{ex} = \alpha_j + \beta^{\text{DR share}} s_{j,t}^{\text{price}} + \epsilon_{j,t+15} \tag{A.7}$$

Above, j is country, t is year, and $\beta^{\text{DR share}}$ is the discount rate news share for bonds. Since I do not observe defaults, the cashflow news share is simply 1 minus the discount rate news share.

Across asset classes Realized returns on one asset class i can be decomposed into the part that is correlated with other asset classes $k1$ and $k2$, r^{other}, and one that is not, i.e., the asset-class-specific component r^{res}:

$$r_{i,t} = \underbrace{\alpha + \beta_1 r_{k1,t} + \beta_2 r_{k2,t}}_{r^{\text{other}}} + r_{i,t}^{\text{res}} \tag{A.8}$$

I estimate the regression (A.8) by running OLS with country fixed effects (βs are positive and statistically significant). By replacing r_i with $r^{\text{other}} + r^{\text{res}}$ in the Campbell-Shiller identity in (4), the variance in the asset yields can then be decomposed into i). The covariance between the yield and future returns which are asset-class-specific, r^{res}, ii). The covariance with future returns on asset class i that are correlated with returns on other risky asset classes r^{other}, and iii). The covariance with cashflows:

$$Var(dp_{i,t}) \approx \underbrace{Cov(dp_{i,t}, \sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s}^{\text{res}})}_{\text{Asset-class-specific DR news}} + \underbrace{Cov(dp_{i,t}, \sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s}^{\text{other}})}_{\text{Cross-asset-class DR news}} + \underbrace{Cov(dp_{i,t}, -\sum_{s=0}^{\infty} \rho_i^s dg_{i,t+1+s})}_{\text{CF news}} \tag{A.9}$$

To estimate these variance shares directly, I regress future long-run returns r^{res}, r^{other}, and cashflows dg (cumulated for 15 years) on today's asset yield dp, as shown in equations (13)–(15), and report the resulting coefficients in Table 7. The basic result of this analysis is that variation in, for example, the price-dividend ratio is associated with future predictable movements in returns that are specific to equities, and not in movements in equity returns that are correlated with those on housing and corporate bonds.

Macro-financial risk factors and experienced returns I start with an observation that asset yields include a part that is correlated with macro-financial risk factors F (e.g., reflecting that yields may be high in recessions), $dp^{factors}$, and a part that is not, dp^{res}:

$$dp_{i,t} = \underbrace{\alpha + \Gamma_f F_t}_{dp_{i,t}^{factors}} + dp_{i,t}^{res} \tag{A.10}$$

I estimate equation (A.10) by regressing dp on the factors F from Table 8 and a country fixed effect. The variance of asset yield dp can then be decomposed into the covariance of $dp^{factors}$ and future returns (the macro-financial factor discount rate news component), the covariance of dp^{res} and future returns (the other discount rate news component), and the covariance between dp and future cashflows (cashflow news, which can also be broken down into the part that is correlated with dp^{res} and $dp^{factors}$):

$$
\begin{aligned}
Var(dp_{i,t}) = & \underbrace{Cov(dp_{i,t}^{factors}, \sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s})}_{\text{Macro-factor DR news}} + \underbrace{Cov(dp_{i,t}^{res}, \sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s})}_{\text{Other DR news}} + \\
& \underbrace{Cov(dp_{i,t}^{factors}, -\sum_{s=0}^{\infty} \rho_i^s dg_{i,t+1+s})}_{\text{Macro-factor CF news}} + \underbrace{Cov(dp_{i,t}^{res}, -\sum_{s=0}^{\infty} \rho_i^s dg_{i,t+1+s})}_{\text{Other CF news}}
\end{aligned} \tag{A.11}
$$

I estimate the corresponding shares by regressing long-run returns and cashflows $\sum r$ and $\sum dg$ on the two different components of the asset yield, $dp^{factors}$ and dp^{res}, and rescaling the βs by the ratio of the variance in the asset yield and the corresponding component, for example:

$$\sum_{s=0}^{s=14} \rho_i^s r_{i,j,t+1+s} = \alpha_j + \beta^{factors} dp_{i,j,t}^{factors} + \epsilon_{i,j,t+15} \tag{A.12}$$

$$\text{Macro DR news share} = \beta^{factors} * Var(dp_{i,j,t}^{factors}) / Var(dp_{i,j,t}) \tag{A.13}$$

The decomposition in Section 5.2 works analogously, only in the first step I decompose dp into three rather than two components, the part that is correlated with the factors $dp^{factors}$, the part that is correlated with experienced returns $dp^{exp-rtn}$, and the residual:

$$dp_{i,t} = \underbrace{\alpha + \Gamma_f F_t}_{dp_{i,t}^{factors}} + dp_{i,t}^{not\ factors} \tag{A.14}$$

$$dp_{i,t}^{not\ factors} = \underbrace{\zeta + \psi \text{Experienced return}_{i,t}}_{dp^{exp-rtn}} + dp_{i,t}^{res} \tag{A.15}$$

The macro discount rate news are then calculated as in equations (A.12)–(A.13), and the experienced-return discount rate news analogously:

$$\sum_{s=0}^{s=14} \rho_i^s r_{i,j,t+1+s} = \alpha_j + \beta^{exp-rtn} dp_{i,j,t}^{exp-rtn} + \epsilon_{i,j,t+15} \tag{A.16}$$

$$\text{Experienced returns DR news share} = \beta^{exp-rtn} * Var(dp_{i,j,t}^{exp-rtn}) / Var(dp_{i,j,t}) \tag{A.17}$$

A.2 Persistent regressors

A common concern in the return predictability literature relates to regressor persistence (Stambaugh, 1999). Even though asset yields in my data are panel-stationary, and yields adjusted for structural breaks are stationary within each country as well as in the panel, they are highly persistent, with autocorrelation coefficients around 0.8–0.9, shown in the top row of table A.5. Additionally, innovations in the asset yield dp are correlated with returns and cashflow growth, as shown in the

Table A.5: *Regressor persistence and the Stambaugh (1999) bias*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity		Housing		Corporate bonds	
	r_{t+1}	dg_{t+1}	r_{t+1}	dg_{t+1}	r^{ex}_{t+1}	r^{spread}_{t+1}
Autocorrelation of dp	0.88		0.96		0.80	
Correlation with errors in dp_{t+1}	-0.41	0.59	-0.61	0.37	-0.60	-0.96
p-values for predicting the variable with dp_t:						
Driscoll-Kraay	0.01	0.00	0.00	0.03	0.00	0.00
Monte Carlo	0.00	0.00	0.00	0.00	0.00	0.00
Wild bootstrap	0.05	0.00	0.00	0.05	0.00	0.00

Notes: r is log real total return, dg is log real dividend or rent growth, r^{ex} is the return on corporate bonds in excess of long government bonds, r^{spread} is the spread-implied excess corporate bond return, calculated as -10 times the change in the spread. dp is the dividend-price ratio for equities, the rent-price ratio for housing, and the log price spread for corporate bonds. Correlation with errors in dp_{t+1} shows the correlation in residuals from two predictive regressions: one predicting $t+1$ returns or cashflows with the current asset yield dp_t, and another predicting $t+1$ asset yield with the current yield dp_t. Driscoll-Kraay p value is obtained by clustering standard errors by country and year, and allowing for autocorrelation of up to 10 lags. Monte Carlo p values are obtained from generating 10,000 predictive regressions assuming the true predictive coefficient is zero but allowing for Stambaugh (1999) bias through correlated regression residuals. Wild bootstrap standard errors are clustered by country and year.

second row of Table A.5. As shown by Stambaugh (1999), this means that the predictive relationships in my data may be driven by autocorrelated innovations in the asset yield.

To guard against this, I follow Cochrane (2008) and Golez and Koudijs (2018), and run Monte Carlo simulations which assume that returns are not predictable by the dividend-price ratio, but errors in dp, returns, and cashflows are correlated, and assess the bias in the resulting regression coefficients. More precisely, I simulate 10,000 panel datasets of the following structure, and test whether in these simulated data returns or cashflow growth are spuriously predictable due to the persistence of regressors:

$$\begin{aligned} dp_{i,j,t} &= \rho_i \beta^{dp} dp_{i,j,t-1} + \epsilon^{dp}_{i,j,t} \\ dg_{i,j,t} &= (\rho_i - 1) dp_{i,j,t-1} + \epsilon^{dg}_{i,j,t} \\ r_{i,j,t} &= \epsilon^{dg}_{i,j,t} - \rho_i \epsilon^{dp}_{i,j,t} \end{aligned}$$

For the simulations, I keep the same covariances across variables, countries, and time, as in my actual data. The simulations show that the biases from persistent regressors in my data are very small, with (spurious) simulated predictive betas close to zero. The "Monte Carlo" row of Table A.5 shows that the probability of (spuriously) observing a predictive coefficient on returns or dividend growth in my actual data, reported in Table 1, in these Monte Carlo simulations, is roughly zero, and the bottom row of Table A.5 additionally shows that the significance of the predictive coefficients in my data is also robust to using an alternative wild bootstrap method. This is largely because the cross-country panel includes roughly 2,000 observations of annual data, so the probability of observing some correlations for spurious reasons is small, a similar result to that found by Golez and Koudijs (2018).

Table A.6: *Out of sample R^2 of different predictive models*

	(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^{spread}_{t+1}	$\overline{r^{\text{spread}}_{t+1,t+5}}$
Own dp vs average past return	0.026	0.059	0.029	0.173	0.135	0.224
Other assets' dp vs average past return	0.009	0.016	0.008	0.038	0.036	0.067
Other assets' & own dp vs own dp only	-0.013	-0.053	-0.019	-0.046	-0.010	-0.014
Observations	1370	1288	1367	1272	1361	1243

Notes: Out of sample R^2 is computed as $1 - \mathrm{SSE}^{\text{full}}/\mathrm{SSE}^{\text{simple}}$, where $\mathrm{SSE}^{\text{full}}$ is the sum of square forecast errors from the full predictive model and $\mathrm{SSE}^{\text{simple}}$ is the sum of square forecast errors for the simple predictive model. In the top row, the full model is the own asset yield and the country fixed effect, and the simple model is the country fixed effect only. In the second row, the full model is the other assets' yields plus fixed effect, and the simple model is the fixed effect only. In the bottom row, the full model is all three asset yields plus fixed effect, and the simple model is the own asset yield plus fixed effect. Out of sample forecasts for $t+1$ and $t+1$ to $t+5$ average are computed using the sample of 1870 to t, with the first forecast produced for the 1901 using the 1870–1900 sample (for 5-year return, the first forecast is for the 1897–1901 average return using data for 1870–1896). In the top two rows, all differences between forecasts are statistically significant at 5% level based on the Clark and West (2007) test, and in the bottom row none of the differences are statistically significant at 5%.

A.3 Out of sample predictability

Goyal and Welch (2008) showed that many of the variables able to predict future stock returns in sample perform poorly out of sample. To see if this is the case in my data, I compute the out of sample R^2 statistics used in Goyal and Welch (2008) for each of my predictive regressions. More specifically, I use data from 1870 to t to compute a return forecast for $t+1$, and compare the performance of two alternative models by computing the out of sample R^2 as follows:

$$\mathrm{ROOS}_i = 1 - \frac{\sum_{t=1901}^{2015} \sum_{j=1}^{17} (y_{i,j,t} - \hat{y}^{full}_{i,j,t})^2}{\sum_{t=1901}^{2015} \sum_{j=1}^{17} (y_{i,j,t} - \hat{y}^{simple}_{i,j,t})^2} \tag{A.18}$$

Above, ROOS is the out of sample R^2; j, i, and t are, respectively, country, asset class, and year indices, with different ROOS statistics computed for different asset classes and competing predictive models. y is return observation, $\hat{y}^{full}$ is the return forecast using the full predictive model, and $\hat{y}^{simple}$ is the return forecast using a nested simpler predictive model. The first forecast is done for 1901 using data for 1870 to 1900, and the last forecast is done for 2015 using data for 1870 to 2014.

The top row of Table A.6 shows that the out-of-sample R^2s within asset classes are positive and large, reaching some 6–22% for 5-year-ahead horizons. All out of sample R^2s are different from zero according to the Clark and West (2007) test, and the magnitude of the year-ahead equity out of sample R^2s is similar to that found by Golez and Koudijs (2018) in long-run data. This means that in my data, returns are predictable not only in but also out of sample. Similarly, cross-asset-class predictability is much weaker than within-asset-class predictability not only in-sample (Section 4), but also out-of-sample. The second and third rows of Table A.6 compare the out of sample predictive power of other asset classes' yields to the historical mean (second row), and own asset yield (third row). The improvement on the historical mean is very small, and compared to the own (within-asset-class) asset yield, the cross-asset-class out of sample R^2 is negative.

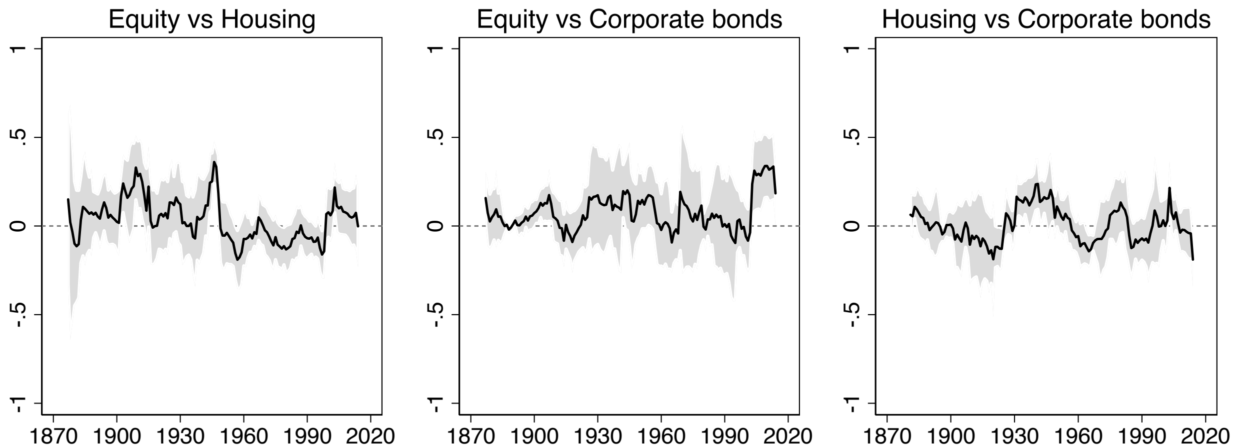
B. Discount rate co-movement: additional results

Table A.7: *Discount rate and cashflow news correlations within each country*

	Discount rate news			Cashflow news
	Equity & housing	Equity & corporate bonds	Housing & corporate bonds	Equity & housing
Australia	0.04	0.05	0.16	0.14
Belgium	0.45***	0.13**	0.24***	0.53***
Canada		0.24***		
Denmark	−0.03	−0.04	0.19	0.06
Finland	0.14*	−0.32	−0.14	0.20**
France	0.15**	0.09	−0.06	0.32***
Germany	0.10	0.09	−0.08	0.06
Italy	0.17	0.08	−0.29**	0.27
Japan	0.06	−0.01	−0.30*	0.19
Netherlands	−0.11	0.19*	0.06	0.01
Norway	−0.08	0.16	0.02	0.14
Portugal	−0.01	−0.02	−0.07	0.24
Spain	−0.26**	−0.21	0.16	0.02
Sweden	0.13	0.23*	0.08	0.10
Switzerland	−0.13	0.05	0.04	0.14
UK	−0.13*	0.29*	0.05	0.23**
USA	0.11	0.35***	0.02	0.29***
Sig. > 0 / Total	3/16	6/17	1/16	5/16
Sig. < 0 / Total	2/16	0/17	2/16	0/16
Not sig. / Total	11/16	11/17	13/16	11/16

Notes: 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 credit spread. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Figure A.2: *Correlations between changes in asset yields on different asset classes*



Notes: Pooled sample of 17 advanced economies, 1870–2020. Solid lines show pairwise correlation coefficients between changes in the dividend-price ratio, rent-price ratio, and corporate bond spread over rolling centered decadal windows (e.g., 1870–1880 for year 1875). All variables are demeaned at country level. Shaded areas show 95% confidence bands using country-clustered standard errors.

Table A.8: *Cross-asset-class predictability across business cycle phases, adjusting for structural breaks*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Recession	Expansion	War	No war	Crisis	No crisis
Equity r_{t+1}:							
Rent-price ratio$_t$	0.029***	0.038**	0.029***	0.016	0.026***	-0.019	0.033***
	(0.007)	(0.018)	(0.008)	(0.017)	(0.008)	(0.014)	(0.008)
Credit spread$_t$	0.009	0.041***	-0.003	0.041***	0.006	0.027*	0.005
	(0.007)	(0.015)	(0.009)	(0.016)	(0.008)	(0.016)	(0.007)
Housing r_{t+1}:							
Dividend-price ratio$_t$	-0.002	-0.001	-0.001	-0.053***	0.000	-0.011	-0.001
	(0.004)	(0.008)	(0.003)	(0.003)	(0.004)	(0.010)	(0.004)
Credit spread$_t$	-0.005**	0.001	-0.007**	0.010**	-0.006***	-0.010**	-0.003
	(0.002)	(0.006)	(0.003)	(0.004)	(0.002)	(0.005)	(0.003)
Corporate bond r_{t+1}^{spread}:							
Dividend-price ratio$_t$	0.002	-0.001	0.002	0.015***	0.001	0.023**	-0.000
	(0.003)	(0.006)	(0.002)	(0.004)	(0.003)	(0.011)	(0.002)
Rent-price ratio$_t$	0.003	0.003	0.003	0.013***	0.001	0.009	0.001
	(0.002)	(0.007)	(0.003)	(0.002)	(0.002)	(0.008)	(0.002)

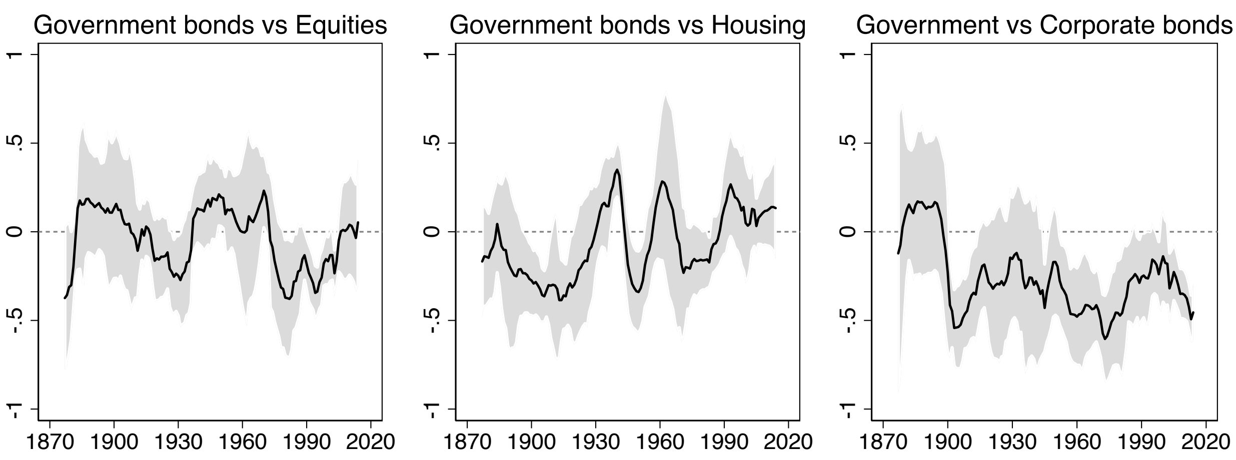
Notes: OLS regressions with country fixed effects. The table shows predictive coefficients of regressing log real total returns on one asset class at $t+1$ on the yields of other asset classes at t. Coefficients are standardized to a 1 standard deviation increase in the asset yield (in the full sample). Predictor (x) variables, all adjusted for structural breaks using the Bai and Perron (2003) procedure, are in rows. Specifications are in columns. Baseline is the unconditional specification in columns 1, 3, and 5 of Table 4. Recessions and expansions are dated using the Bry and Boschan (1971) algorithm. Wars cover the two world wars only. Crises cover the 3 years after the start of a systemic banking crisis dated using the chronology of Jordà et al. (2016). Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A.9: *Government bond return predictability*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Real government bond return				Excess government bond return			
	r_{t+1}		$\overline{r_{t+1,t+5}}$		r_{t+1}		$\overline{r_{t+1,t+5}}$	
Term premium	0.009**		0.006		0.022***		0.013***	
	(0.005)		(0.004)		(0.003)		(0.002)	
Dividend-price ratio		0.010		0.007		0.002		0.002
		(0.008)		(0.008)		(0.005)		(0.004)
Rent-price ratio		-0.001		-0.009*		-0.003		-0.009**
		(0.006)		(0.005)		(0.005)		(0.004)
Corporate bond spread		-0.006		-0.004		-0.005		-0.003
		(0.006)		(0.005)		(0.004)		(0.003)
R^2	0.01	0.01	0.01	0.02	0.08	0.01	0.12	0.04
Observations	2372	1507	2285	1479	2366	1496	2268	1457

Notes: OLS regressions with country fixed effects. The table shows predictive coefficients of regressing log government bond returns on the term premium (difference between the long-term government bond, and short-term bill rate), and the yields on other asset classes (term premium and corporate bond spreads in levels, dividend-price and rent-price ratios in logs). Coefficients are standardized to a 1 standard deviation increase in the asset yield (in the full sample). Returns are in excess of inflation (columns 1–4) and the short-term bill rate (columns 5–8). Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Figure A.3: *Co-movement between term premia on government bonds, and yields on risky asset classes*



Notes: Pooled sample of 17 advanced economies, 1870–2020. Solid lines show pairwise correlation coefficients between the term premium for government bonds (long-term bond yield minus the bill rate), dividend-price ratio for equities, rent-price ratio for housing, and corporate bond spread (long-term corporate minus government bond yield) over rolling centered decadal windows (e.g., 1870–1880 for year 1875). All variables are demeaned at country level. Shaded areas show 95% confidence bands using country-clustered standard errors.

Table A.10: *Cross-asset-class predictability in individual countries*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity r_{t+1}		Housing r_{t+1}		Corporate bond r_{t+1}^{spread}	
	Rent-price ratio	Credit spread	Dividend-price ratio	Credit spread	Dividend-price ratio	Rent-price ratio
Australia	0.015	0.003	-0.046***	-0.013	-0.013	0.003
	(0.025)	(0.023)	(0.016)	(0.009)	(0.023)	(0.012)
Belgium	0.013	0.020	-0.022*	-0.021	0.002	0.007
	(0.027)	(0.031)	(0.013)	(0.020)	(0.006)	(0.011)
Finland	0.051	0.034	0.022	-0.001	-0.027	0.004
	(0.031)	(0.032)	(0.015)	(0.010)	(0.022)	(0.019)
France	0.027	0.005	-0.003	0.006	0.006	0.002
	(0.033)	(0.010)	(0.015)	(0.004)	(0.006)	(0.010)
Germany	0.014	-0.017	0.029***	-0.026	0.000	0.004
	(0.013)	(0.026)	(0.010)	(0.016)	(0.008)	(0.006)
Italy	-0.017	0.023	-0.021	0.023**	0.004	0.003
	(0.019)	(0.033)	(0.015)	(0.010)	(0.012)	(0.006)
Japan	0.012	-0.056*	0.018***	0.012	0.008	-0.017
	(0.029)	(0.030)	(0.005)	(0.011)	(0.018)	(0.027)
Netherlands	0.030	0.013	-0.022*	-0.039***	0.007	0.005
	(0.021)	(0.015)	(0.012)	(0.012)	(0.009)	(0.010)
Norway	0.046	0.097***	-0.003	-0.006	0.002	0.004
	(0.035)	(0.036)	(0.010)	(0.015)	(0.006)	(0.013)
Portugal	0.022	0.052	0.012	0.003	-0.003	-0.010
	(0.059)	(0.032)	(0.015)	(0.007)	(0.014)	(0.028)
Spain	0.014	-0.022	-0.009	0.004	0.005	-0.006
	(0.018)	(0.014)	(0.008)	(0.005)	(0.012)	(0.008)
Sweden	0.010	0.035	-0.009	-0.021*	0.003	0.006
	(0.024)	(0.028)	(0.010)	(0.011)	(0.010)	(0.007)
Switzerland	-0.033	0.011	0.006	0.004	0.001	-0.005
	(0.037)	(0.036)	(0.007)	(0.007)	(0.009)	(0.010)
UK	0.038	0.050	-0.048***	-0.019	0.007	0.004
	(0.029)	(0.041)	(0.014)	(0.014)	(0.009)	(0.012)
USA	0.059	-0.009	-0.004	-0.007	0.008	0.009
	(0.039)	(0.025)	(0.006)	(0.008)	(0.006)	(0.010)
Sig. > 0 / Total	0/15	1/15	2/15	1/15	0/15	0/15
Sig. < 0 / Total	0/15	1/15	4/15	2/15	0/15	0/15

Notes: OLS regressions at country level. Coefficients are standardized to a 1 standard deviation increase in the predictor variable (logs for dividend- and rent-price ratios; percentage points for the spread). Dependent (y) variables in the top row. r is the log real total return, and r^{spread} is the spread-implied excess corporate bond return, calculated as $-10 * \Delta spread$. Predictor (x) variables in the second row. Results for Canada and Denmark omitted due to lack of, respectively, rental yield and credit spread data. Heteroskedasticity-robust standard errors in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A.11: *Cross-asset-class predictability in individual countries, adjusted for structural breaks*

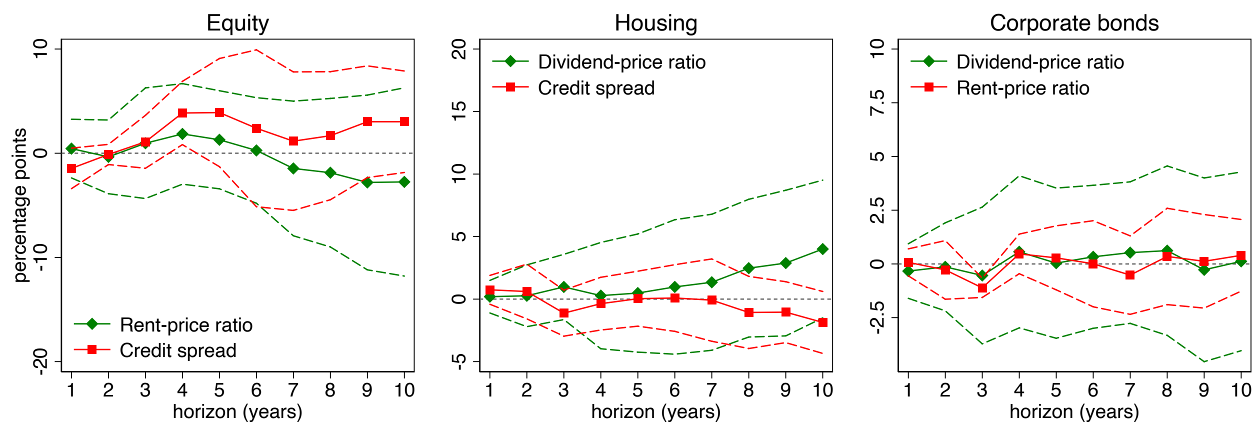
	(1)	(2)	(3)	(4)	(5)	(6)
	Equity r_{t+1}		Housing r_{t+1}		Corporate bond r^{spread}_{t+1}	
	Rent-price ratio	Credit spread	Dividend-price ratio	Credit spread	Dividend-price ratio	Rent-price ratio
Australia	0.020	0.006	-0.027***	-0.016*	-0.004	0.015
	(0.025)	(0.021)	(0.009)	(0.009)	(0.019)	(0.011)
Belgium	0.009	0.008	-0.020*	-0.011	-0.000	0.003
	(0.018)	(0.025)	(0.012)	(0.013)	(0.007)	(0.008)
Finland	0.045**	0.060	0.026	0.031**	-0.059**	0.001
	(0.021)	(0.038)	(0.020)	(0.015)	(0.026)	(0.010)
France	0.059**	0.009	0.018*	-0.003	0.008*	0.001
	(0.023)	(0.010)	(0.010)	(0.005)	(0.004)	(0.006)
Germany	0.023	-0.007	0.022*	-0.030*	0.001	0.011*
	(0.018)	(0.019)	(0.012)	(0.017)	(0.007)	(0.007)
Italy	0.005	0.025	-0.007	0.009	0.002	-0.007
	(0.019)	(0.027)	(0.009)	(0.007)	(0.008)	(0.009)
Japan	0.118***	-0.028	-0.003	-0.010	0.001	-0.011
	(0.039)	(0.037)	(0.006)	(0.012)	(0.006)	(0.027)
Netherlands	0.039**	0.032**	-0.035***	-0.026**	0.013	0.005
	(0.015)	(0.013)	(0.011)	(0.010)	(0.010)	(0.005)
Norway	0.032	0.066**	-0.003	-0.009	0.000	0.003
	(0.024)	(0.030)	(0.008)	(0.012)	(0.007)	(0.010)
Portugal	0.016	0.042*	0.010	0.003	-0.002	-0.012
	(0.032)	(0.023)	(0.011)	(0.005)	(0.014)	(0.019)
Spain	0.012	-0.011	-0.018**	-0.006	-0.001	0.000
	(0.024)	(0.017)	(0.008)	(0.007)	(0.008)	(0.010)
Sweden	0.031	0.043	-0.007	-0.020*	0.008	0.008
	(0.020)	(0.029)	(0.008)	(0.012)	(0.008)	(0.007)
Switzerland	-0.026	0.007	0.011**	0.004	0.001	-0.004
	(0.027)	(0.030)	(0.005)	(0.005)	(0.006)	(0.009)
UK	0.015	0.035	-0.037***	-0.020**	0.014	0.008
	(0.025)	(0.038)	(0.013)	(0.010)	(0.009)	(0.007)
USA	0.074**	0.013	-0.009	-0.003	0.016**	0.017*
	(0.035)	(0.026)	(0.010)	(0.008)	(0.008)	(0.009)
Sig. >0 / Total	5/15	3/15	3/15	1/15	2/15	2/15
Sig. <0 / Total	0/15	0/15	5/15	5/15	1/15	0/15

Notes: OLS regressions at country level. Coefficients are standardized to a 1 standard deviation increase in the predictor variable (logs for dividend- and rent-price ratios; percentage points for the spread). Dependent (y) variables in the top row. r is the log real total return, and r^{spread} is the spread-implied excess corporate bond return, calculated as $-10 * \Delta spread$. Predictor (x) variables in the second row are adjusted for structural breaks, with break dates identified using the Bai and Perron (2003) method. Results for Canada and Denmark omitted due to lack of, respectively, rental yield and credit spread data. Heteroskedasticity-robust standard errors in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

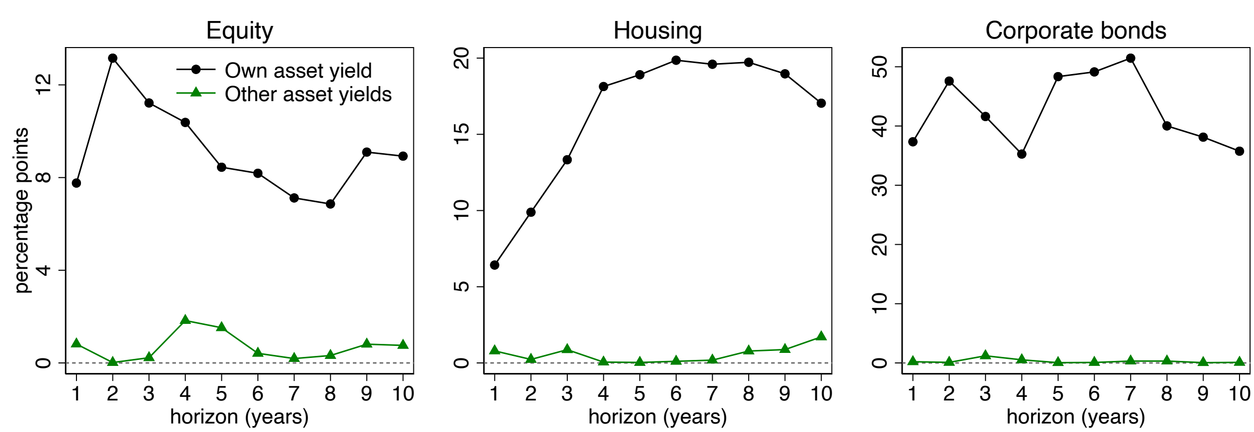
Figure A.4: *Within-and cross-asset-class predictability at different horizons: non-overlapping windows*

(a) *Within-asset-class predictability:*

(b) *Cross-asset-class predictability:*



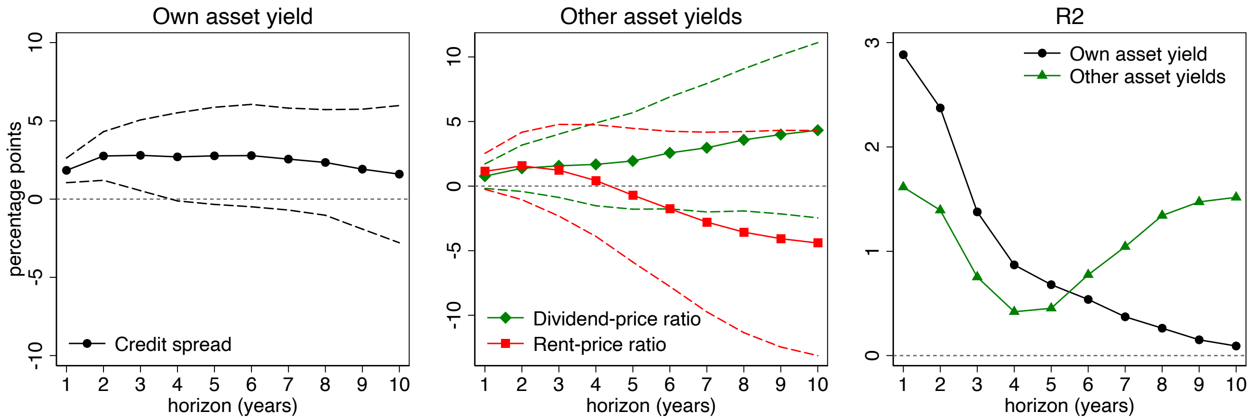
(c) *Predictive R^2:*



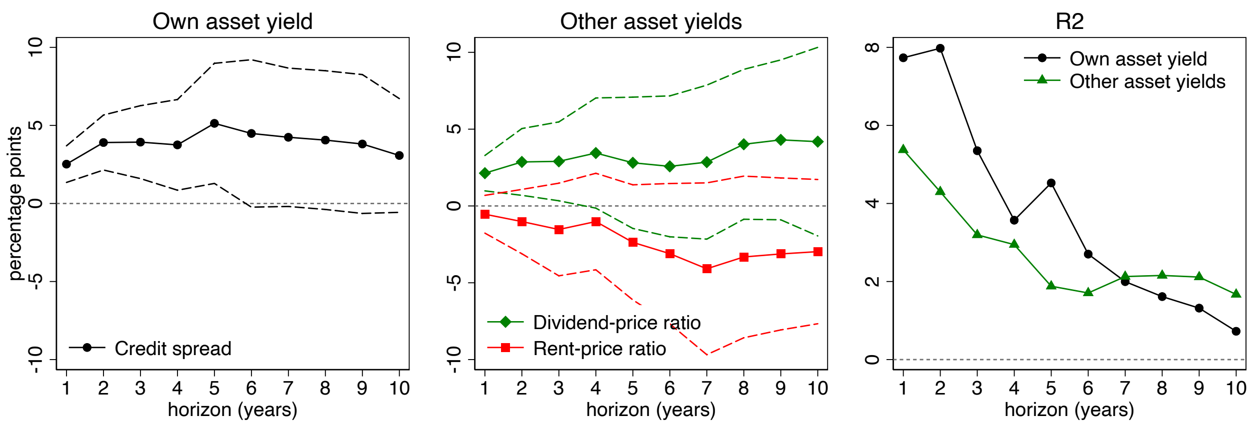
Note: Predictable cumulative return change after a one standard deviation increase in the asset yield. The sample includes 1 in every 5 years of consecutive observations (so horizons $h = 1$ to $h = 5$ are non-overlapping, and $h = 6$ to $h = 10$ overlap with one other observation). Standard errors are clustered by country and time (at 5-year intervals). All predictors are adjusted for structural breaks. Cumulative return impact estimated using the beta from regressing h-year ahead returns on either own asset yield, or yields of other asset classes. Corporate bond (excess) returns are estimated as -10 times the change in the spread. All regressions are run on a consistent sample across asset classes, predictors and horizons. Dashed lines show 95% confidence bands.

Figure A.5: *Total corporate bond return predictability within and across asset classes*

(a) *Full sample:*



(b) *Non-overlapping sample:*



Note: Left and middle panel: predictable cumulative change in total real corporate bond return after a 1 standard deviation higher credit 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. All predictors are adjusted for structural breaks. Cumulative return impact is the beta obtained by regressing h-year ahead return on today's asset yield. All regressions are run on a consistent sample across predictors and horizons. Non-overlapping sample only includes one in 5 years of consecutive observations.

Table A.12: *Correlations between macroeconomic risk exposures of different asset classes*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumption beta			Downside consumption beta			Return volatility		
	Equity	Housing	Corporate Bonds	Equity	Housing	Corporate Bonds	Equity	Housing	Corporate Bonds
Equity	1			1			1		
Housing	0.74	1		0.75	1		0.81	1	
Corporate bonds	0.64	0.60	1	0.64	0.79	1	0.84	0.76	1

Notes: Pairwise correlations between estimates of consumption beta, downside consumption beta, and realized return volatility for different asset classes. Consumption beta is the covariance between log excess return on the specific asset class and log real consumption growth. Downside consumption beta is the 0.25th quantile regression coefficient from regressing log excess returns on log consumption growth. Volatility is the annual standard deviation of log excess return. All 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.

C. Drivers of asset price fluctuations: additional results

C.1 Risk-based explanations

Construction of macro-financial risk factors The consumption-based factors include the deviation of log real consumption from the backward-looking 10-year moving average of real consumption, a proxy for surplus consumption. For the consumption-wealth ratio, I proxy total non-human wealth as the sum of stock market capitalization and housing wealth, and use real wages as a proxy for real income.[12] I then follow Lettau and Ludvigson (2002) and estimate the cointegrating relationship between consumption, non-human wealth, and labour income, and compute the consumption-wealth ratio as the deviation of consumption from this long-run cointegrating relationship.[13] The consumption and wage data are sourced from the Jordà-Schularick-Taylor (JST) macrohistory database (Jordà et al., 2016), stock market capitalization data come from Kuvshinov and Zimmermann (2022), and housing wealth data are from Jordà et al. (2019).

Investment/GDP (3-year growth) and rent expenditure data are, respectively, from the JST database and Jordà et al. (2019). Variables proxying for intermediary risk appetite include bank asset growth, which has been shown to predict returns in Baron and Muir (2021), as well as measures of economy-wide leverage in the form of loan/GDP and bank leverage 3-year growth, from Jordà et al. (2021) and JST database. Government debt, broad money, and inflation data are from the JST database, and the term premium is the difference between the 10-year government bond yield and the short-term bill rate.

[12]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.

[13]I use two leads and lags of annual data in the estimation, in line with Lettau and Ludvigson (2002) who use 8 lags of quarterly data.

Table A.13: *Predictive power of macro-financial risk factors at 1-year horizon*

	Equity r_{t+1}	Housing r_{t+1}	Corp. bond r^{spread}_{t+1}
Dividend-price ratio (resid.)	0.07***		
	(0.03)		
Rent-price ratio (resid.)		0.06***	
		(0.02)	
Credit (price) spread (resid.)			0.29***
			(0.07)
Real activity:			
Surplus consumption (-)	-0.05	0.04**	0.02
	(0.03)	(0.01)	(0.02)
Consumption-wealth ratio (+)	0.02	0.01	-0.06**
	(0.01)	(0.01)	(0.03)
Investment/GDP growth (-)	-0.02	0.01	-0.01
	(0.02)	(0.01)	(0.02)
Rent expenditure/GDP (+)	0.00	0.02**	0.02
	(0.02)	(0.01)	(0.03)
Leverage & intermediary balance sheets:			
Loans/GDP growth (-)	-0.01	-0.02	-0.03
	(0.02)	(0.02)	(0.03)
Bank leverage growth (-)	0.02	-0.01	0.03
	(0.02)	(0.01)	(0.02)
Bank asset growth (-)	-0.01	0.02**	-0.08**
	(0.01)	(0.01)	(0.04)
Liquidity & sovereign risk:			
Government debt/GDP ($\pm$)	0.04**	0.00	0.04
	(0.02)	(0.01)	(0.03)
Broad money/GDP (+)	-0.01	-0.01	-0.04
	(0.02)	(0.01)	(0.04)
Nominal & duration risks:			
Inflation (-)	-0.08***	-0.05***	-0.01
	(0.03)	(0.01)	(0.04)
Term premium (+)	0.01	0.02***	-0.18***
	(0.02)	(0.01)	(0.04)
R^2	0.09	0.10	0.15
Observations	1169	1165	878

Notes: OLS regressions with country fixed effects. Predictor (x) variables in rows, dependent (y) variables in columns. All predictors are standardized to a 1 standard deviation increase (signs in brackets show the coefficient sign would expect from theory). Asset yields (log dividend- and rent-price ratios, and log price spread for corporate bonds) are residualized by regressing them on the macro-financial risk factors. r is real total return and r^{spread} is the spread-implied excess return on corporate bonds. Coefficients are standardized to a 1 standard deviation increase in the asset yield. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

C.2 Behavioral explanations

Return predictability under subjective expectations As shown by De la O and Myers (2021, 2022), return predictability can arise both because i). Subjective expectations of returns vary over time, and ii). Incorrect subjective expectations of *cashflows* (forecast errors) vary over time. Here, I apply the De la O and Myers (2021, 2022) framework to multiple asset class context. First, consider that the Campbell and Shiller (1988) decomposition in equation (4) is derived from an accounting identity, which means that it holds for any arbitrary expectation operator $\mathbb{E}^*$, and also for realized (rather than expected) returns:

$$dp_{i,t} \approx \mathbb{E}^* \sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s} - \mathbb{E}^* \sum_{s=0}^{\infty} \rho_i^s dg_{i,t+1+s} \tag{A.19}$$

$$\approx \sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s} - \sum_{s=0}^{\infty} \rho_i^s dg_{i,t+1+s}. \tag{A.20}$$

Taking the difference (A.20)-(A.19) yields equation (20) in the main text, reproduced below:

$$\sum_{s=0}^{\infty} \rho_i^s r_{i,t+1+s} = \sum_{s=0}^{\infty} \rho_i^s \mathbb{E}^* r_{i,t+1+s} + \sum_{s=0}^{\infty} \rho_i^s \underbrace{\left(dg_{i,t+1+s} - \mathbb{E}^* dg_{i,t+1+s}\right)}_{\mathrm{fe}_{i,t+1+s}^{dg}} \tag{A.21}$$

Taking the covariance of dp_i and the right-hand-side of equation (A.21) gives

$$Cov\left(dp_{i,t}, \sum_{s=0}^{\infty} \rho_k^s r_{k,t+1+s}\right) = Cov\left(dp_{i,t}, \sum_{s=0}^{\infty} \rho_k^s \mathbb{E}^* r_{k,t+1+s}\right) + Cov\left(dp_{i,t}, \sum_{s=0}^{\infty} \rho_k^s \mathrm{fe}_{k,t+1+s}^{dg}\right). \tag{A.22}$$

Equation (A.22) holds both within ($k = i$) and across ($k \neq i$) asset classes. It shows that the (within- or across-asset-class) return predictability in the data can be driven by both the correlation between asset yields dp and subjective return expectations, and correlations between yields and cashflow forecast errors. The presence of within-asset-class predictability and the absence of cross-asset-class predictability then leads to conditions in equations (21) and (22) in the main text.

National Housing Survey data The Fannie Mae National Housing Survey is a nationally representative live telephone survey of approximately 1000 individuals per month. The survey contains information on the responder characteristics (income, age, employment etc), experienced capital gains, and expected future capital gains on own house. It also asks respondents about

Table A.14: *Correlations between investment prospects of different asset classes, National Housing Survey, raw data*

	(1)	(2)	(3)	(4)	(5)	(6)
	Perceived potential (low/high)			Perceived risk (low/high)		
	Equity	Housing	Bonds	Equity	Housing	Bonds
Equity	1.00	.	.	1.00	.	.
Housing	0.09	1.00	.	0.10	1.00	.
Bonds	0.04	0.12	1.00	0.08	0.17	1.00

Notes: Pairwise Spearman rank correlation coefficients using microdata for the Fannie Mae National Housing Survey, repeated cross-sections, six 2013 survey waves.

general prospects for investing in housing, equity and bond markets. I would like to thank Rachel Zimmerman and Yang Hu for help accessing the survey data. For the purpose of my analysis, I use the following variables:

- Perceived risk and potential (0/1 dummy). Q75-77: "Do you think buying a home/buying stocks/buying government or corporate bonds is an investment with low potential/high potential; low risk/high risk?"
- Experienced capital gains (percentage points). Q99B: "By about what percent do you think your home's value has gone up/down over the last 12 months?"
- Expected future capital gains (percentage points). Q99C: "By about what percent do you think your home's value will go up/down over the next 12 months/5 years?"
- Controls: survey wave, state, gender, age bracket (Q122B), income bracket (Q142), education bracket (Q121), employment status (Q132), past income growth (Q116), economy on right track or not (Q10), expected household financial situation (Q11).

The data on all these variables are available for six survey waves in 2013.

Survey of Professional Forecasters The SPF provides quarterly forecasts for a range of real-economy and financial variables, at the level of individual forecaster. 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 return 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 change in the long-term yield forecast minus the bill forecast; both at the 10-year horizon. I also compute shorter-horizon proxies for the excess returns on Treasuries (a negative of the spread growth forecast 5 quarters ahead), the excess return of AAA bonds over Treasuries and BAA bonds over AAA bonds (the reason for using spread growth is that the bond return is approximately equal to minus the change in spread times duration).

As well as the forecasts, I compute forecast errors and revisions as in Coibion and Gorodnichenko (2012) and Bordalo et al. (2020). Forecast errors are the difference between the forecast and the eventual realization (eg the 10-year ahead equity return forecast in 2000 to the average return over 2000–2010). Forecast revisions are the changes in the forecast for a given horizon between the current and previous quarter. For 5-quarter ahead forecasts (Treasuries, AAA, BAA), I use the difference between the 6-quarter ahead forecast in quarter t-1, and the 5-quarter ahead forecast in quarter t. For 10-year ahead forecasts (Stocks, Treasuries), I use the difference between the 10-year ahead forecasts in year t and t-1.

Table A.15 shows that forecasts of equity and (yield-implied) bond return forecasts and forecast errors are generally uncorrelated. Table A.16 shows the results of the following regression:

$$\underbrace{x^{i}_{t+h} - x^{i,n}_{t+h|t}}_{FE^{i,n}_{t+h}} = \beta^n_0 + \beta^n_{own}\underbrace{(x^{i,n}_{t+h|t} - x^{i,n}_{t+h|t-1})}_{FR^{own,i,n}_{t+h}} + \beta^n_{cross}\underbrace{(x^{j,n}_{t+h|t} - x^{j,n}_{t+h|t-1})}_{FR^{cross,i,n}_{t+h}} + u^n_{t,t+h}, \tag{A.23}$$

where $FE^{i,n}$ is the forecast error on asset i – e.g., equities – made by forecaster n, FR^{own} is the within-asset-class (e.g. equity forecast) revision, and FR^{cross} are forecast revisions for other asset classes. An upward forecast revision is generally followed by a negative forecast error, suggesting that forecaster-level forecasts are prone to overreaction as in Bordalo et al. (2020). However, a forecast revision for equities is not followed by a negative forecast error on bonds, suggesting that this overreaction is *asset class specific*. he only exception is forecasts on BAA bonds overreacting to revisions on AAA bonds, suggesting that there may be some common overreaction within asset classes (in this case, for different types of corporate bonds), but not across asset classes.

Table A.15: *Correlations between forecasts for different asset classes in the SPF*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Return forecasts				Return forecast errors			
	Equity	Treasuries	AAA bonds	BAA bonds	Equity	Treasuries	AAA bonds	BAA bonds
Equity	1.00	.	.	.	1.00	.	.	.
Treasuries	-0.11	1.00	.	.	0.08	1.00	.	.
AAA bonds	0.03	-0.16	1.00	.	0.16	0.17	1.00	.
BAA bonds	0.01	-0.01	0.03	1.00	.	-0.59	0.26	1.00

Notes: Pairwise Spearman rank correlation coefficients, Survey of Professional Forecasters data. The observations are at individual forecaster level, and net out forecaster fixed effects. All forecasts are proxies for excess returns. The bond return forecast is the negative of the change in the spread (approximately the excess return divided by duration). For spreads, Treasuries are in excess of t-bills, AAA bonds are in excess of Treasuries, and BAA bonds are in excess of AAA bonds. Equity return is the stock return forecast minus the bill rate. Equity forecasts are for 10 years ahead, AAA and BAA forecasts are for 5 quarters ahead, Treasuries forecasts are for 10 years ahead when correlated with equities and for 5 quarters ahead when correlated with other bonds. Forecast error is the future realized return (or minus spread growth) minus the forecast. BAA forecast data start in 2010, so there are not enough observations to correlate them with equity forecast errors. All data are winsorized at the 1% level.

Table A.16: *Asset-class-specific overreaction in SPF forecasts*

	(1)	(2)	(3)	(4)
	Equities forecast error	Treasuries forecast error	AAA bonds forecast error	BAA bonds forecast error
Equities forecast revision	-0.50***	0.05	-0.00	-0.02
	(0.13)	(0.04)	(0.02)	(0.04)
Treasuries forecast revision	0.32**	-0.31**	0.03	0.00
	(0.16)	(0.12)	(0.09)	(0.07)
AAA bonds forecast revision	0.25	-0.15	-0.40***	-0.35**
	(0.59)	(0.30)	(0.11)	(0.18)
BAA bonds forecast revision				-0.98***
				(0.20)
R^2	0.07	0.07	0.09	0.37
Observations	164	113	263	68

Notes: Forecast revision is the change in the forecast for quarter $t+h$ between quarter $t-1$ and t for bonds, and year $t-1$ and t for equities. Forecast error is the realized value at $t+h$ minus the forecast for $t+h$ made at t. In columns (1) and (2), forecast horizons h are 10 years for equities and Treasuries, and 5 quarters for AAA and BAA bonds. In columns (3) and (4), forecast horizons are 5 quarters for Treasuries, AAA and BAA bonds, and 10 years for equities. All regressions include individual forecaster fixed effects. All forecasts are for excess returns, computed directly for equities and estimated as minus the change in the spread for bonds. Since BAA spread forecast data start in 2010, I do not include them in regressions 1–3 to maintain a sufficiently large sample. All data are winsorized at the 1% level. Standard errors in parentheses are clustered by forecaster and quarter. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A.17: *Correlations between expected returns on different investments reported by US pension funds*

	(1) Equity	(2) Real assets	(3) Fixed income	(4) Hedge funds	(5) Private equity
Equity	1.00	.	.	.	.
Real assets	0.39	1.00	.	.	.
Fixed income	0.28	0.47	1.00	.	.
Hedge funds	0.07	0.40	0.37	1.00	.
Private equity	0.64	0.34	0.32	0.01	1.00

Notes: Pairwise Spearman rank correlation coefficients between expected returns on different asset classes reported by US public pension funds in their GASB disclosures. Data are from Andonov and Rauh (2021), and cover 228 US state and local government pension plans over the period 2014 to 2017. Expected returns are residualized using pension fund balance sheet characteristics (size and target portfolio weights in different asset classes) and dummies for year-month reporting period, state, and pension system type.

Table A.18: *Extrapolation in US pension fund return expectations*

	(1) Equity expected return	(2) Real assets expected return	(3) Private equity expected return
Portfolio past return	0.163**	0.357***	0.296*
	(0.082)	(0.103)	(0.171)
Equity past return	0.038		
	(0.127)		
Real assets past return		0.093***	
		(0.031)	
Private equity past return			0.158***
			(0.038)
Year × Reporing month FE	✓	✓	✓
Controls	✓	✓	✓
Adjusted R^2	0.264	0.309	0.366
Observations	786	531	463

Notes: Regressions using microdata on expected returns on different asset classes reported by US public pension funds in their GASB disclosures. Data are from Andonov and Rauh (2021), and cover 228 US state and local government pension plans over the period 2014 to 2017. Controls are the same as in Andonov and Rauh (2021) Table 4 (past standard deviation, unfunded liability over gross state product (GSP), GSP per capita, log pension fund size, and year-reporting month dummies. Standard errors are clustered at pension fund level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Pension fund GASB disclosures Andonov and Rauh (2021) provide a dataset of return expectations and target allocations of US public pension funds. The data come from the Comprehensive Annual Financial Reports (CAFRs) or in separate GASB 67 statements, and cover 228 US state and local government pension plans over the period 2014 to 2017 (at annual frequency). The pension funds report the expected returns on a range of assets. Andonov and Rauh (2021) aggregate these expected returns into more comparable broad asset class categories using allocation weights.

Table A.17 shows the Spearman rank correlations between pension fund level return expectations for five broad asset classes: equity, real assets (including real estate), fixed income, hedge funds, and private equity. I focus on the cross-section and residualize these return expectations using year-reporting month fixed effects and data on pension fund balance sheet characteristics. The return expectations of pension funds are more correlated than those of households or professional forecasters, but there is still some asset-specificity, with return expectations on more similar asset classes (e.g., equity and private equity) more correlated than others (e.g., equity and fixed income). Table A.18 replicates one of the findings in Andonov and Rauh (2021), that high past experienced returns on a specific asset class result in higher asset-specific return expectations, but using nominal returns rather than real or excess returns as the analysis in Andonov and Rauh (2021), to be consistent with the data in Table A.17 (though the results for real and excess returns are similar).

Table A.19: *Long-run return predictability using experienced returns*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity $\sum_{s=0}^{14} \rho^s r_{t+1+s}$		Housing $\sum_{s=0}^{14} \rho^s r_{t+1+s}$		Corp. bond $\sum_{s=0}^{14} \rho^s r^{\text{spread}}_{t+1+s}$	
Experienced stock return	-0.249***	-0.293***		-0.044		-0.025**
	(0.080)	(0.088)		(0.051)		(0.011)
Experienced housing return		0.154*	-0.106**	-0.122**		0.026***
		(0.080)	(0.047)	(0.053)		(0.005)
Experienced corporate bond return		0.097**		-0.020	-0.046***	-0.037**
		(0.041)		(0.029)	(0.014)	(0.018)
R^2	0.11	0.18	0.09	0.15	0.11	0.13
Observations	1272	677	862	639	801	613

Notes: OLS regressions with country fixed effects. Dependent (y) variables in columns. r is the log real total return, and r^{spread} is the spread-implied corporate bond return. Predictor (x) variables in rows. Experienced return is the exponentially weighted average of past real returns, using a smoothing parameter of 0.04. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A.20: *Cashflow predictability using experienced returns*

	(1)	(2)	(3)	(4)
	Equity		Housing	
	dg_{t+1}	$\sum_{s=0}^{14} \rho^s dg_{t+1+s}$	dg_{t+1}	$\sum_{s=0}^{14} \rho^s dg_{t+1+s}$
Experienced stock return	-0.001	-0.006		
	(0.012)	(0.092)		
Experienced housing return			-0.007	-0.092*
			(0.005)	(0.050)
R^2	0.00	0.00	0.01	0.08
Observations	1562	1269	1107	861

Notes: OLS regressions with country fixed effects. Dependent (y) variables in columns. dg is the log real dividend and rent growth (for equities and housing, respectively). Predictor (x) variables in rows. Experienced return is the exponentially weighted average of past real returns, using a smoothing parameter of 0.04. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A.21: *Predictability using experienced returns: alternative smoothing parameters*

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity r_{t+1}		Housing r_{t+1}		Corporate bond r_{t+1}^{spread}	
	More smooth	Less smooth	More smooth	Less smooth	More smooth	Less smooth
Exper. stock r	-0.053**	-0.031**	0.001	0.005	-0.009***	-0.005**
	(0.021)	(0.013)	(0.009)	(0.006)	(0.002)	(0.002)
Exper. housing r	0.011	-0.007	-0.020**	-0.009	0.005*	0.002
	(0.019)	(0.014)	(0.010)	(0.006)	(0.003)	(0.002)
Exper. corp. bond r	-0.005	0.002	0.003	0.005	-0.020***	-0.014***
	(0.017)	(0.011)	(0.005)	(0.004)	(0.004)	(0.003)
R^2	0.02	0.02	0.02	0.02	0.04	0.04
Observations	895	895	864	864	815	815

Notes: OLS regressions with country fixed effects. Dependent (y) variables and specifications in columns. r is the log real total return, and r^{spread} is the spread-implied corporate bond return. Predictor (x) variables in rows. Experienced return is the exponentially weighted average of past real returns, using a smoothing parameter of 0.02 (more smooth), 0.08 (less smooth), or the Malmendier and Nagel (2011) smoothing algorithm with $\lambda = 1.5$, the baseline in their data. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table A.22: *Return predictability using experienced cashflow growth*

	(1)	(2)	(3)	(4)
	Equity		Housing	
	r_{t+1}	$\sum_{s=0}^{14} \rho^s r_{t+1+s}$	r_{t+1}	$\sum_{s=0}^{14} \rho^s r_{t+1+s}$
Experienced dividend growth	-0.010	-0.177***	-0.008	-0.103**
	(0.016)	(0.066)	(0.005)	(0.046)
Experienced rent growth	0.001	0.062	0.002	-0.032
	(0.015)	(0.078)	(0.003)	(0.029)
R^2	0.00	0.04	0.01	0.07
Observations	994	784	963	745

Notes: OLS regressions with country fixed effects. Dependent (y) variables in columns. r is the log real total return, and r^{spread} is the spread-implied corporate bond return. Predictor (x) variables in rows. Experienced cashflow growth is the exponentially weighted average of past real cashflow growth rates, using a smoothing parameter of 0.04. Driscoll-Kraay standard errors clustered by country and year, and adjusted for autocorrelation in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

D. Data coverage

Table D.1: *Data coverage*

Country	Equity	Housing	Corporate Bonds
Australia	1870–2020	1901–2020	1915–2016
Belgium	1870–2020	1890–2020	1870–2016
Canada	1870–2020		1905–2017
Denmark	1872–2020	1875–2020	1991–2016
Finland	1912–2020	1920–2020	1922–2015
France	1870–2020	1870–2020	1870–2017
Germany	1870–2020	1870–2020	1870–2018
Italy	1870–2020	1927–2020	1873–2016
Japan	1886–2020	1931–2020	1900–2016
Netherlands	1900–2020	1870–2020	1885–2016
Norway	1880–2020	1871–2020	1903–2016
Portugal	1870–2019	1948–2019	1905–2016
Spain	1899–2020	1900–2020	1884–2016
Sweden	1871–2020	1883–2020	1871–2016
Switzerland	1875–2020	1901–2020	1925–2016
UK	1870–2020	1895–2020	1870–2017
USA	1871–2020	1890–2020	1870–2016

Table D.2: *Statistical summary of the data*

	(1)	(2)	(3)
	Real equity return	Real housing return	Real corporate bond return
Mean	7.0	7.0	3.2
Standard deviation	21.6	9.8	9.7
	Real dividend growth	Real rent growth	Corporate default rate
Mean	3.2	1.2	1.0
Standard deviation	27.0	7.4	1.5
	Dividend-price ratio	Rent-price ratio	Credit spread
Mean	3.8	5.1	1.2
Standard deviation	1.7	1.8	1.1
Observations	1538	1538	1538

Notes: Pooled sample of 17 countries, 1870–2020. All figures are in percentage points. Credit spread is the yield to maturity difference between long-term corporate and government bonds. The corporate default rate is for the US only, and measures the par value of bonds in default relative to total, from Giesecke et al. (2014). The number of default rate observations is 143.

E. Corporate bond data description

E.1 Measurement

Corporate bond data include yields, spreads, and returns on bonds issued by private sector creditors, targeting 10–15 year maturity. The corporate bond discount rate proxy is the spread, equal to the yield to maturity differential between corporate and government bonds:

$$\text{spread}_t = YTM_{\text{corporate},t} - YTM_{\text{government},t} \tag{A.24}$$

Note that because I take the differential with respect to long-term government bonds, the spread measure does not include the term premium.

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:

$$r^{holding}_{bond,t+1} = (C_{bond,t+1} + P_{bond,t+1} - P_{bond,t})/P_{bond,t} \tag{A.25}$$

For about half of the sample, the capital gain data are directly observed, and for the other half, I estimate it as minus the change in the bond yield times duration. The second bond return measure is the excess return implied by the spread movements:

$$r^{spread}_{bond,t+1} = -10 * (\text{spread}_{t+1} - \text{spread}_t) \tag{A.26}$$

Since the maturity of the bonds in my sample is around 10–15 years, the duration is close to 10, and I estimate the excess return as minus the spread change times duration. Even though this measure does not rely on observed capital gains on corporate bonds, it has two advantages relative to the holding period return measure. First, it treats all observations in the sample consistently, whereas the holding period return measure mixes up directly observed and duration-approximated capital gains. Second, by looking at excess returns, it abstracts from variation in expected inflation which forms a key part of changes in total returns on bonds (Campbell and Ammer, 1993). This makes it more comparable to (either total or excess) return movements for the other two assets in my study, equity and housing, which are both real assets. This means that, as in many other studies in the literature (e.g., Greenwood and Hanson, 2013; Nozawa, 2017; López-Salido et al., 2017), the spread-implied excess return is my preferred measure.

Most of the corporate bond data were hand collected from primary sources, by aggregating yields and returns on individual bonds listed on the domestic stock exchange. The bulk of the data come from domestic stock exchange listings, complemented with bonds listed on major foreign exchanges (e.g. London and New York), and bonds traded over the counter. 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 organizations, 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.[14] For some historical

[14] Mortgage bonds issued by financial companies were typically considered safe assets, so I exclude them

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. (2019). Section E.3 documents the detailed sources for the corporate bond series for each country. The government bond dataset also excludes foreign currency bonds and targets a maturity of 10–15 years.

E.2 Data quality

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, while later on railway bonds became less, and bank and industrial 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. Third, it may be difficult to maintain a consistent maturity of corporate bonds, both over time and relative to government bonds.

Since my analysis is focussed on the short to medium run variation in risk premia, it is important that the sample composition and bond credit quality does not change at these short to medium term horizons. This is likely to be the case: since much of the series are constructed from microdata, I ensure that the sample coverage is broad enough so that bonds don't drop in and out of the sample over the space of a few years. I also limit the coverage of the microdata to bonds issued by risky private entities, excluding mortgage bonds and government-guaranteed bonds. The sectoral coverage of the data is broad: for example, the microdata-based series include both financials and non-financials, and non-financial non-railway bonds even for the early historical period. When the number of bonds traded on the exchange was low, I sought to supplement the exchange-traded data with bonds traded over the counter, and issue yields on bonds placed both publicly and privately.

Of course, it is still likely that the underlying credit quality of the representative bond has changed across long periods of time and across different countries. When it comes to the underlying microdata, differences across countries are more apparent than differences over time. Some countries, such as UK, US, and Germany, 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. The composition of the bond market within countries has also varied over long time periods, but here it is more difficult to detect systematic changes from the underlying microdata. For example, a series of financial deregulations in the 1980s may have improved market access and led to higher credit risk bonds entering the market, but we actually see bond yields decline until the early 1990s in the data before increasing again in the 1990s and 2000s in line with other measures of market risk premia (Kuvshinov and Zimmermann, 2020). In general, the credit spread is much less persistent than the dividend- and rent-price ratios (Table A.5). To make sure these long-run trends do not

from the sample which focuses on risky bonds. I do, however, include private non-financial company bonds backed by mortgages or property, which have higher yields than financial-issued mortgage bonds, and were generally considered risky.

affect my estimates of short and medium run response of future returns to changes in the yield, I conduct the predictability tests for series adjusted for structural breaks using the Bai and Perron (2003), as well as the raw spread data. In light of the evidence above, the remaining influences of time-varying bond credit quality on my results are likely to be minor.

Finally, accurate maturity data are difficult to find 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 call 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 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. Even thought the average corporate bond maturity in my sample ends up being closer to 15 than 10 years, the same is true for government bonds, leaving the spread calculation relatively unaffected. Whenever possible, I ensure that the spread is calculated as the difference between the corporate bond yield, and that on the government bonds of similar maturity. Over the whole sample, the biases arising from uncertainty around maturity dates are likely to be small.

E.3 Country-level sources

Tables D.3–D.19 specify the data sources used for the corporate bond yield in each country. Bond returns are taken form the same sources when available (with the exception of the UK, see text below Table D.18). All data are for end of the year, but changing to yearly averages does not affect the results (since equity data are end-of-year, changing to yearly average bond yields slightly reduces the correlation between equity and bond discount rates). The data exclude bonds denominated in foreign currency, issued by foreign companies, bonds with explicit government guarantees, and mortgage bonds issued by credit institutions or special purpose vehicles.

Australia

Table D.3: *Corporate bond data sources: Australia*

Year	Data source
1915–1979	Value-weighted average of yields at issue, bonds issued on Sydney stock exchange by private non-financial corporations and financial institutions. For years where few private sector bonds were issued (1923–24, 1933–34 and 1938–49), I fill the gaps using changes in yields on bonds issued by public corporations and utilities. The underlying microdata on bond issues are from the Reserve Bank of Australia, kindly shared by Anna Nitschke. A description of the sources can be found in Black, Kirkwood, Williams, and Rai (2013).
1980–1988	Yields on 5-year debentures of financial companies, from the OECD *Financial Statistics*, various years (these are close to the preceding issue yield microdata for overlapping periods).
1989–1996	Yield to maturity on long-term Australian corporate bonds, value-weighted, computed from bond-level microdata in Datastream
1997–2016	Corporate bond yield, bonds of 5–10 year maturity, from various Datastream series (Macquarie, BoAML, S & P).

The historical data for Australia are based on the series of yields at issue helpfully shared with me by Anna Nitschke of RBA. These data document each bond issue on the public Australian exchanges, collated from the Sydney and Melbourne Stock Exchange gazettes. More details on the data can be found in Black et al. (2013). I have aggregated these data into an annual issue yield series, weighting the individual bond issues by the amount of issuance. During some years in the 1920s, 1930s and the period around World War II, there few private sector bond issues on the market, but a large number of bond issues by public corporations and utility companies. I fill the gaps using the issue yields for these companies which effectively assumes a stable spread between private and utility bonds – something that is the case for the adjacent overlapping data where I have statistics on both private sector bonds and utilities.

For the 1980s, I use data on issue yields of bonds issued by financial corporations from the OECD *Financial Statistics* publications, which are very close to the microdata-based private company issue yield series for overlapping years. For the more recent period, I rely on series computed from microdata on yields to maturity on individual long-term Australian corporate bonds, and other Australian corporate bond data in Datastream.

I am grateful to Anna Nitschke for sharing the bond level microdata for Australia.

Belgium

Table D.4: *Corporate bond data sources: Belgium*

Year	Data source
1870–1913	Current yield on industrial bonds from Drappier (1937).
1913–1938	Value-weighted yield to maturity on a basket of corporate bonds of 5+ year maturity, selection of bonds listed on the Brussels Stock Exchange, microdata provided by Frans Buelens.
1939–1979	Yield to maturity on private sector bonds, 5–20 year maturity, from the National Bank of Belgium *Economic Summaries*, *10-year statistics*, and *Statistical Yearbooks*, various years. A data gap for 1957–59 is filled using corporate bond microdata provided by Frans Buelens.
1980–1982	Yield to maturity on bonds of financial intermediaries, scaled to match the all-corporate bond yield data from the National Bank of Belgium publications (pre-1980) and Datastream (post-1982).
1983–1998	Long-term corporate bond yield from Datastream.
1999–2002	Business lending rate from Zimmermann (2019), scaled to match the corporate bond yield data in 1998 and 2003
2003–2016	Value-weighted yield to maturity on long-term corporate bonds, aggregated from individual bond microdata in Datastream.

Most of the series for Belgium rely on private sector bond yields published in the various issues of the statistical yearbooks and statistical summaries of the National Bank of Belgium, complemented by a ready-made industrial bond yields series in Drappier (1937). I combine the series in various yearbooks into one consistent long-run series. The gap between the Drappier (1937) and statistical yearbook series, and a short 2-year gap in the 1950s are bridged by using microdata on the major corporate bonds traded on the Brussels stock exchange from the SCOB database, which were helpfully shared by Frans Buelens. Series for the recent period are based on corporate bond yield statistics and bond-level microdata in Datastream. A 3-year gap in the late 1990s is bridged using statistics on business lending rates.

I am grateful to Frans Buelens for sharing the historical bond level microdata for Belgium, and Kaspar Zimmermann for sharing the lending rate data.

Canada

Table D.5: *Corporate bond data sources: Canada*

Year	Data source
1905–1948	Corporate bond yields compiled by Wood, Gundy and Co., from Buckley and Urquhart (1993).
1949–1978	Industrial bond yields compiled by Moss, Lawson and Co., from Buckley and Urquhart (1993).
1979–2007	Long-term corporate bond yield from Bank of Canada historical interest rate statistics.
2008–2016	Yield to maturity on 10+ year corporate bonds, various Datastream series

The historical data for Canada are based on ready-made measures of the long-term corporate and industrial bond yields in various issues of the historical statistics published by Buckley and Urquhart (1993) and the Bank of Canada.

Denmark

Table D.6: *Corporate bond data sources: Denmark*

Year	Data source
1991–2016	Value-weighted average yield to maturity on Danish corporate bonds, aggregated from bond-level microdata in Datastream.

The case of Denmark is somewhat special in that the non-mortgage corporate bond market was more or less non-existent before the 1990s. There was a large private bond market in operation going back to the 19th century, but the bonds traded were almost exclusively mortgage bonds which were considered safe assets, with yields almost identical to those of government bonds (Abildgren, 2014), making these unsuitable for the analysis in this paper. For the private non-mortgage bonds, I rely on series constructed from bond-level microdata on bonds traded on the Danish exchanges.

Finland

Table D.7: *Corporate bond data sources: Finland*

Year	Data source
1922–1929	Average yield to maturity on corporate bonds traded on the Helsinki stock exchange, from listings in the *Kauppalehti* newspaper.
1969–1995	Yields on taxable bonds issued by non-government issuers. Issue yield before 1986 and secondary market yield afterwards (the two series are close to each other). Source: OECD *Financial Statistics*, various issues.
1998–2015	Average issue yield of private sector bonds issued by Finnish companies with remaining maturity of at least 5 years, from the Bank of Finland *Statistical Bulletin*, various years. Series are not value-weighted to ensure representativeness.

Most of the data from Finland come from the *OECD Financial Statistics* publications, which provide data on issue and secondary market yields of Finnish private sector bonds. The OECD *Financial Statistics* publication stopped in 1998, so for the recent period I use bond issuance statistics in the Bank of Finland *Statistical Bulletins*, aggregating up the issue yields on individual bonds. For the OECD series I take the spread over taxable government bonds from the same publication, with government bond maturity of 5 years since that most closely matches the maturity of corporate bonds. For the earlier period, I make use of the historical data on Finnish secondary market bond yields published in the stock listings in the *Kauppalehti* newspaper for years with sufficiently broad coverage.

I am grateful to Mika Vaihekoski for assisting with numerous queries regarding the Finnish bond market data.

France

Table D.8: *Corporate bond data sources: France*

Year	Data source
1870–1913	Arithmetic average yield on bonds traded on the Paris stock exchange, from listings in various newspapers (*L'Univers*, *Le Gaulois*) in Ward (2018).
1914–1970	Yield on private sector bonds from CEPII, series TXOB, sourced from Villa (1994).
1971–1989	Secondary market yield on private sector bonds, from the OECD *Financial Statistics*, various issues.
1990–2016	Value-weighted yield to maturity on long-term corporate bonds, aggregated from individual bond microdata in Datastream.

The pre World War I data are aggregated up from statistics on yields and prices of individual bonds, based on data reported in the contemporary French newspapers, with the microdata sourced from Ward (2018). For the later period, a ready-made private sector bond yield series are available from CEPII (constructed by Villa, 1994) and various issues of the OECD *Financial Statistics*. For the recent period, I construct a series of private sector bond yields to maturity from bond-level data in Datastream. All the series are consistent with each other across overlapping periods.

I am grateful to Felix Ward for sharing the bond-level microdata for the pre-1914 period.

Germany

Table D.9: *Corporate bond data sources: Germany*

Year	Data source
1870–1925	Average yield on private sector German bonds traded on the Berlin Stock Exchange, from listings in the *Berliner Börsenzeitung* newspaper.
1927–1956	Industrial bond yield series from the Deutsche Bundesbank (1976), with gaps filled using industrial bond yield data from Papadia and Schioppa (2020), *Statistisches Jahrbuch für das Deutsche Reich*, and Morawietz (1994).
1957–2016	Yield to maturity on German corporate bonds from the Bundesbank database, series BBK01.WU0022. Since the maturity of the series for later years is close to 5 years, I take the spread over the 5-year bund when detailed maturity data on government bonds become available (1976 onwards).

For the early German bond market data, I rely on individual bond quotations on the Berlin Stock Exchange reported in the *Berliner Börsenzeitung* newspaper. For these, I exclude mortgage bonds, raw material bonds (common during the years around hyperinflation), and pre-hyperinflation nominal bonds which were traded at close to zero after the change of currency in 1924. I also exclude the hyperinflation years from the sample, since these mix up paper and raw material bonds, and there is a lot of noise in the data. To calculate the spread for the period before WW1, I use the difference between yields on government and corporate bonds. For the spreads during the 1919–1925 period of high political uncertainty and sovereign default risk, I use the difference between 75th and 25th percentiles of the bond distribution as proxy for the credit spread.

After 1925, I switch to the industrial bond series published by Deutsche Bundesbank (1976), which are close to the *Börsenzeitung* series for overlapping years. To fill gaps in these series, I use data on the prices of 6% industrial bonds traded on the Berlin Stock Exchange from Papadia and Schioppa (2020), and the bond yield series in Morawietz (1994). The Morawietz (1994) series is a mixture of private and public bonds, so I scale these up to match the levels of the industrial bond series for overlapping years. For the post-1957 period, a high-quality ready-made corporate bond series are available from the online database of the Bundesbank.

Italy

Table D.10: *Corporate bond data sources: Italy*

Year	Data source
1873–1914	Arithmetic average current yield on private sector bonds from listings in the *La Stampa* newspaper covering the Milan Stock Exchange, and Italian bonds traded on the Amsterdam Stock Exchange (ASE listings in the OPC Database by Stichting Capital Amsterdam).
1949–1979	Yield to maturity on corporate bonds with remaining maturity of 5–20 years, calculated from bond-level data in the Mediobanca *Indici e Dati*.
1980–2002	Yield on bank bonds from Mediobanca's *Indice i Dati* and OECD *Financial Statistics*.
2003–2016	Value-weighted yield to maturity on private sector bonds, calculated from bond-level data in Mediobanca's *Indice i Dati*.

The early Italian data are based on trades reported in the *La Stampa* newspaper covering the Milan stock exchange, and of Italian bonds traded on the Amsterdam stock exchange. The Amsterdam-listed bonds were mostly issued by Italian tramway companies, and only comprise a small part of the data. For the period from 1949 onwards, detailed bond-level data are available in the *Indice i Dati* publication by Mediobanca. To abstract from fluctuations in the riskiness of government bonds during this period, I use the difference between the 75th and 25th percentiles of the individual bond yield distribution in the microdata as proxy for the credit spread. For the more recent years, I use long-term corporate bond yields in the *Indici e Dati* publication and microdata, and the OECD *Financial Statistics*.

I am grateful to Stichting Capital Amsterdam and Siebert Weitenberg for granting me access to the Amsterdam stock listings database.

Japan

Table D.11: *Corporate bond data sources: Japan*

Year	Data source
1900–1940	Current yield on corporate bonds (industry and banks) from Fujino and Akiyama (1977).
1956–1959	Current yield on industrial bonds from Fujino and Akiyama (1977).
1960–1991	Secondary market yield on industrial bonds from OECD *Financial Statistics*, various issues.
1992–1997	Secondary market yield on 12-year corporate bonds from OECD *Financial Statistics*, various issues (the series are very close to industrial bonds).
1998–2004	Business lending rate from Zimmermann (2019), scaled to match the corporate bond yield in 1997 and 2005
2005–2016	Redemption yield on 10-year corporate bonds from Datastream.

Long-run historical series of corporate bond yields are available from Fujino and Akiyama (1977). For the more recent period, detailed series are available from the various issues of the OECD *Financial Statistics*. I choose the OECD series which most closely match the target maturity and sector (10-year corporate bonds), which are very close to the corresponding Fujino and Akiyama (1977) series for the overlapping years. More recent data are based on corporate bond yields in Datastream, with a gap filled using statistics on business lending rates.

I would like to thank Kaspar Zimmermann for sharing the lending rate data.

Netherlands

Table D.12: *Corporate bond data sources: Netherlands*

Year	Data source
1885–1962	Average yield to maturity on long-term bonds of Dutch companies traded on the Amsterdam Stock Exchange, calculated from stock exchange listings in the OPC Database by Stichting Capital Amsterdam. Bond maturity estimated based on first and last trading dates. Unweighted averages. Microdata winsorized at the top 0.5%.
1963–1974	Secondary market yield on private sector bonds from the OECD *Financial Statistics*, various issues (very close to the pre-1963 microdata-based series for overlapping years).
1975–2016	Value-weighted yield to maturity on long-term corporate bonds, aggregated from bond-level microdata in Datastream.

The early period series are constructed from individual bond microdata in the OPC Database by Stichting Capital Amsterdam, which contains daily stock listing data summarizing the properties and prices of each bond listed on the exchange. There is little maturity data in the listing, so I estimate these based on the date on which the bond stops being traded, and censor the sample to include estimated maturities of between 5 and 35 years. I exclude colonial bonds (mostly referring to territories in Indonesia), even if the company is registered in the Netherlands, and exclude foreign currency and mortgage bonds. Bonds of several companies continue to be traded at very low prices (1–5% of par value) even after the price drop presumably corresponding to the company liquidation. To avoid the high yields on these bonds from biasing the aggregate series, I winsorize the underlying microdata at the top 0.5% of observations. For the recent period, I use the series in the OECD *Financial Statistics*, and construct a new aggregate series from bond-level microdata in Datastream. The OECD series for 1960–1962 are very close to the series constructed from microdata.

I am grateful to Stichting Capital Amsterdam and Siebert Weitenberg for granting me access to the OPC listings database, and helping with historical data queries.

Norway

Table D.13: *Corporate bond data sources: Norway*

Year	Data source
1903–1963	Arithmetic average yield to maturity on long-term bonds issued by Norwegian companies, from the Kierulf Handbook (*Haandbog over Norske obligationer og aktier*, various years), listings of the Oslo stock exchange (*Kursliste over Vaerdipapier*) and the *Farmand* magazine.
1964–2002	Yield to maturity on 10-year corporate bonds from Klovland (2004) (spliced with listings microdata in 1963).
2003–2016	Value-weighted yield to maturity on long-term corporate bonds issued by Norwegian companies, aggregated from bond-level microdata in Datastream.

For the early period, I construct a series of secondary market yields based on bond-level data in the Kierulf Handbook, listings of the Oslo stock exchange and the *Farmand* magazine. The official listings do not contain detail on quantities so I use arithmetic averages, but the series are close to existing series constructed by Norwegian financial historians (Klovland, 2004) for the overlapping years. The data include both exchange-traded bonds and some bonds traded over-the-counter whose prices are reported in the Kierulf Handbook, but as time progresses the share of exchange traded bonds in the sample grows larger and throughout the series, exchange traded bonds account for the majority of the sample.

For the recent period, I switch to the existing 10-year corporate bond yield series constructed by Klovland (2004) whose data start in the 1960s, and an aggregate series constructed using individual bond microdata in Datastream for the last decade of the sample.

I am grateful to Jan Tore Klovland for answering numerous queries and helpful advice, and to the staff at the Oslo Nasjonalbiblioteket for help in locating the historical data sources.

Portugal

Table D.14: *Corporate bond data sources: Portugal*

Year	Data source
1905–1974; 1986–1998	Value-weighted average yield to maturity on long-term corporate bonds listed on the Lisbon stock exchange, constructed from listings in the *Diario do Governo* and *Boletim da Bolsa*.
2010–2016	Value-weighted yield to maturity on long-term corporate bonds issued by Portuguese companies aggregated up from bond-level microdata in Datastream.

Most of the Portuguese series are based on microdata for listings of the Lisbon stock exchange, and cover the long-term domestic currency denominated corporate bonds issued by Portuguese companies which were traded in Lisbon. From 1926 onwards, I am able to value-weight the series by amount outstanding, but before then the data are equally weighted (the equally weighted and value weighted yield series are close to each other during the 1920s). To ensure sufficient coverage, I include a number of longer-maturity bonds bringing the average maturity closer to 15 years than 10 years, but this is similar to the maturity of government bonds in the sample so the bond spread should be relatively unaffected by the inclusion of these longer maturity bonds. I omit the years 1975–76 during which the stock exchange was closed, and the post-revolution period of 1977–1985 during which the credit spread cannot be calculated reliably. The data for the end of the sample are constructed from bond-level yields in Datastream.

I am grateful to Jose Rodrigues da Costa and Maria Eugenia Mata for help and advice in finding and interpreting the data sources for the historical Portuguese data; and to staff at the Banco do Portugal archive for helpful advice and sharing data.

Spain

Table D.15: *Corporate bond data sources: Spain*

Year	Data source
1884–1912	Current yield on long-term corporate bonds listed on the Barcelona and Madrid stock exchanges, constructed from microdata in newspaper listings in *La Vanguardia*, *La Correspondencia de España*, *El Liberal* and *Diario Oficial de Avisos de Madrid*, sourced from Ward (2018); equally-weighted averages.
1913–1963	Value-weighted yield to maturity on long-term corporate bonds listed on the Barcelona and Madrid stock exchanges, constructed from microdata in the *Boletin de Cotization Oficial* (Madrid stock exchange) and the *La Vanguardia* newspaper (Barcelona stock exchange).
1964–1979	Corporate bond issue yield from the OECD *Financial Statistics*, various issues.
1980–1991	Equally-weighted average yield to maturity on long-term corporate bonds, constructed from bond-level microdata in the *Boletin de Cotization Oficial* of the Madrid Stock Exchange.
1992–1995	Corporate bond secondary yields from the OECD *Financial Statistics*, various issues.
1996–2016	Value-weighted yield to maturity on long-term corporate bonds issued by Spanish companies, aggregated from bond-level microdata in Datastream.

For the majority of the historical period, Spain had two major exchanges operating in Barcelona and Madrid. For ordinary shares, the majority of trading was conducted on the Madrid Stock Exchange (see the Data Appendix in Kuvshinov and Zimmermann, 2022). But for corporate bonds, the Barcelona exchange often saw more trading than Madrid during the earlier period. Therefore, for the microdata underlying the historical Spanish series I seek to combine statistics from the Madrid and Barcelona exchanges using the trades reported in the *Boletin de Cotization Oficial* (Madrid) and *La Vanguardia* newspaper (Barcelona). The pre World War I microdata were helpfully shared with me by Felix Ward (see Ward, 2018, for details).

For the 1960s and 1970s, I am able to switch to corporate bond yield data in the OECD *Financial Statistics* which are close to the secondary yields constructed from the listings microdata during the early 1960s. Because of gaps in the OECD data during the 1980s I switch back to the listings microdata for these years, and for the 1990s I use the yields in the OECD publication as well as a series constructed from bond-level data in Datastream (which are close to OECD data for overlapping years).

I am grateful to Felix Ward for sharing the bond-level microdata for the pre-1914 period.

Sweden

Table D.16: *Corporate bond data sources: Sweden*

Year	Data source
1870–1913	Yield to maturity on all private sector bonds traded on the secondary market, targeting 10-year maturity, constructed as an equally weighted average of bond-level microdata. Bond-level microdata come from the following sources: listings of stock brokers, helpfully shared with us by Kristian Rydkvist, the "red book" *Svenska Aktiebolag och Enskilda Banker*, listings and market summaries in *Ekonomiska Meddelanden från Svenska Bankföreningen*, and Aurell (1892).
1914–1926	Average yield on new issues of long-term private sector bonds, aggregated up from bond-level issuance data in *Ekonomiska Meddelanden*.
1927–1964	Arithmetic-average yield to maturity on long-term bonds traded on the Stockholm Stock Exchange, aggregated up from bond-level microdata in *Ekonomiska Meddelanden* and the red book, various issues.
1965–1987	Issue yield of industrial bonds, OECD *Financial Statistics*, various issues.
1988–2000	Industrial bond issue yield from the Riksbank *Statistical Yearbooks*, various years
2001–2005	Handelsbanken market corporate bond yield
2006–2016	Value-weighted yield to maturity on long-term corporate bonds issued by Swedish companies, aggregated from individual bond microdata in Datastream.

The Swedish bond yield series draws on a variety of sources, many of these consisting of newly digitized bond-level microdata. For the period before World War I, I rely on stock listings data – published as either biweekly bulletins or monthly summaries of brokers' listings in the *Ekonomiska Meddelanden* publication, Aurell (1892), and the "red book" documenting each listed stock and bond issued by Swedish companies, *Svenska Aktiebolag och Enskilda Banker*. After World War I, bond trading on the stock exchange dried up considerably but there were still large numbers of bonds issued, majority of them private placings. Therefore I switch to these issuance data for the decade after 1914, and switch bank to secondary-market yields once trading picks up again in late 1920s. The issue and secondary market yield series are close to each other for overlapping years.

In the 1960s, the detail of the bond trading data reported in the *Ekonomiska Meddelanden* reduces considerably, so I switch to the aggregated series of issue yields on industrial bonds reported in the OECD *Financial Statistics*, which are close to the *Ekonomiska Meddelanden* data (e.g., an issue yield constructed from the *Ekonomiska Meddelanden* statistics matches both the secondary yield and the OECD data for overlapping years). In the late 1980s, I switch to the official Riksbank industrial yield series reported in statistical yearbooks, which again closely matches the other series. For the recent years, I use the Handelsbanken corporate bond yield series, and construct an aggregate series of corporate bond yields from bond-level microdata available in Datastream.

I am grateful to Daniel Waldenström for providing guidance on the historical data for Sweden, to Kristian Rydkvist for providing guidance and sharing data, and to staff at the Lund University archives for helping me access the underlying publications.

Switzerland

Table D.17: *Corporate bond data sources: Switzerland*

Year	Data source
1925–1971	Value-weighted average yield to maturity on long-term bonds issued by Swiss corporations, aggregated up from bond-level data in the Zurich stock exchange listings, *Kursblatt der Züricher Effektenbörse*. To fill the gap in year 1947, I use the change in the bank bond yield series published in the historical statistics by the Swiss National Bank.
1972–1997	Yields on private sector bonds in the OECD *Financial Statistics*, various issues, and the Swiss National Bank historical statistics.
1998–2003	Average of the Pictet & Cie bank and non-bank corporate bond yields.
2004–2006	Changes in yields extrapolated using changes in the yield on all Swiss non-government bonds from Datastream.
2007–2016	Swiss corporate bond yield on A–BBB rated bonds constructed from various series in Datastream.

For the early period, I am able to construct a value-weighted series of long-term corporate bond yields from the microdata on bonds traded on the Zurich stock exchange, with individual bond data digitized from the listings (*Kursblatt*) of the exchange. For the late 20th century, I rely on series published by the OECD *Financial Statistics*, the Swiss National Bank, and Datastream. These consist of interest rates on bank debentures published in the SNB historical statistics, secondary market yields on Swiss corporate bonds in the OECD data, and series provided by Pictet & Cie and the private sector bond data in Datastream. I start with the OECD issue yields in the early 1970s, and switch to the secondary market yields in the 1980s, filling a 1976–1979 gap where issue yield series in OECD is different to other sources with data from the SNB Historical Statistics on bank debenture yields. Once the OECD data series stop in the late 1990s, I switch to the various private bond yield proxies available from Datastream, choosing those proxies that are most similar to the OECD data for overlapping years, and maintain a consistent bond definition over time. For years 2004–2006, I rely on changes in yields on all Swiss non-government bonds – which are systematically lower than the other corporate bond yield series – to link across the estimates of Swiss private corporate bond yields before 2004 and after 2006.

United Kingdom

Table D.18: *Corporate bond data sources: United Kingdom*

Year	Data source
1870–2016	Corporate bond yield from the Bank of England "Three centuries of macroeconomic data" dataset; see Thomas, Hills, and Dimsdale (2010) for more information.

For the UK, a long-run series of corporate bond yields have been compiled by the Bank of England (Thomas et al., 2010). For corporate bond returns – unlike for the other countries – I use a different source, consisting of long-dated corporate bond (debenture) return estimates in Coyle and Turner (2013). The Bank of England series do not include returns and the Coyle and Turner (2013) series do not include yields, but the two series are consistent with each other (the changes in yields and total returns have a correlation of -0.74).

United States

Table D.19: *Corporate bond data sources: United States*

Year	Data source
1870–1918	Yields on risky railroad bonds from Macaulay (1938). To match the BAA-AAA yield average, I take the 95th percentile of the distribution of yields on individual railroad bonds and scale it up by a factor of about 1.1 This results in a yield roughly 1 percentage point above the mean railroad yield, which matches up well with the BAA-AAA yield for overlapping years.
1919–2017	The average of Moody's BAA and AAA yields.

Long-run corporate bond yield data for the US are available in the form of Moody's BAA and AAA yields. To be consistent with other countries, I take the average of these two yields as a proxy for the overall yield on private sector bonds. For the period before 1919, I rely on data on individual railroad bonds published in Macaulay (1938). The railroad bonds are generally less risky and offer a lower mean yield than the average of the BAA and AAA series. But taking the 5th percentile of the railroad bond yield distribution and scaling it up by 1.1 results in a very good match to the Moody's series for years 1919–1927, so I use this slightly scaled upper percentile of the railroad bond yield distribution as the measure of the pre-1918 bond yield. In practice, this adjustment gives a similar result to scaling up the mean Macaulay (1938) yield up by about 1 percentage point. The number of bonds in the Macaulay (1938) sample is about 40 per year, and – since the bonds are of relatively high quality – the average difference between the 5th and 95th percentiles of the yield distribution is slightly less than 1 percentage point, which means that the potential for measurement error from using different parts of the yield distribution to proxy for the mean BAA-AAA yield is small.

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