Implied Volatility Duration and the Early Resolution Premium

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Abstract

We introduce *Implied Volatility Duration* (IVD) as a new measure for the timing of uncertainty resolution, with a high IVD corresponding to late resolution. Portfolio sorts on a large cross-section of stocks indicate that investors demand on average about seven percent return per year as a compensation for a late resolution of uncertainty. This premium is higher in times of low market returns and cannot be explained by standard factor models. In a general equilibrium model, we show that the expected excess return differential between 'late' and 'early' stocks can only be positive, if the investor's relative risk aversion exceeds the inverse of her elasticity of intertemporal substitution, i.e., if she exhibits a preference for early resolution of uncertainty in the spirit of Epstein and Zin (1989). Our empirical analysis thus provides a purely market-based assessment of the relation between two preference parameters, which are notoriously hard to estimate.

Keywords: Preference for early resolution of uncertainty, implied volatility, cross-section of expected stock returns, asset pricing

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1 Introduction

The supreme challenge in asset pricing research is to explain how risk and attitudes towards risk translate into market prices. For example, if riskier stocks have higher average returns than safer stocks, one would conclude that the marginal investor is risk averse. In this paper we focus on the timing of uncertainty resolution, that is *when* uncertainty is resolved, rather than *how much* of *what* type of uncertainty the investor is exposed to.[1] Dynamic choice theory implies that if investors have non-neutral preferences concerning the timing of uncertainty resolution, specific uncertainty resolution profiles are favorable, which must then be reflected in asset prices. By characterizing stocks as exhibiting early or late resolution of uncertainty we find empirical support for investors actually having a preference for early resolution of uncertainty (PERU), which manifests itself in a return differential between 'late' and 'early' stocks of around seven percent per year on average. This premium is not due to different exposures of late and early resolution stocks to standard risk factors.

Whether the marginal investor indeed exhibits PERU is of major importance in many asset pricing models. For example, in the long-run risk model pioneered by Bansal and Yaron (2004) as well as its subsequent extensions, PERU is necessary to reproduce key stylized facts from the data such as the high and countercyclical equity risk premium. Technically, the representative agent exhibits PERU when the coefficient of relative risk aversion is greater than the inverse of the elasticity of intertemporal substitution. It is, however, notoriously difficult to obtain reliable empirical estimates for these two preference parameters (see Havránek (2015) and Thimme (2016)). Consequently, there is an intense debate about whether recursive preferences that distinguish between risk aversion and the inverse of the intertemporal elasticity of substitution (as opposed to, e.g., time-additive constant relative risk aversion (CRRA)) are relevant at all.

Our contribution to this debate is that we offer model-free evidence concerning timing preferences. We do so by measuring the return differential between stocks featuring late and early resolution of uncertainty and interpret this difference as the premium investors require as

[1]We do not investigate issues related to ambiguity, so we use the terms uncertainty and risk interchangeably.

a compensation for a later rather than an earlier resolution.

We illustrate the basic idea behind our empirical exercise via a simple example in the spirit of Epstein and Zin (1989) presented graphically in Figure 1. There are two claims E and L, which, as seen from time $t = 0$, both pay off one dollar with probability p at time $t = 2$. The difference between the claims is that, for claim E, all uncertainty about the outcome is resolved at $t = 1$, whereas uncertainty about the payoff of claim L is resolved only at $t = 2$. Put differently, the variance for the payoff of claim E narrows down from its initial value $p(1 - p)$ at $t = 0$ to zero at $t = 1$, whereas the variance of claim L stays at $p(1 - p)$ until $t = 2$. An agent exhibiting PERU will prefer claim E over claim L and will therefore be willing to pay a higher price for E than for L. Thus, the expected return on E must be less than that on L.

[FIGURE 1 HERE]

We provide an empirical measure to identify type E and type L stocks in the cross-section. To identify pairs of stocks with the above properties we suggest to make use of option-implied volatilities (IVs).[2] More precisely, we consider two stocks whose IVs over a long horizon from t to T are close to each other, and since the variances over the long horizon are almost the same, the two stocks exhibit basically the same amount of long-term uncertainty. Among all pairs, we only consider those where the IVs over a shorter horizon from t to $T_0 < T$ are markedly different. This in turn means that the remaining variance from T_0 to T must be smaller for the stock with the higher short-horizon IV, so that a greater share of overall uncertainty is resolved early. In accordance with our motivating example in Figure 1 we label the stock with the higher short-horizon IV among the two stocks in the pair a type E ('early') claim, while the other one is of type L ('late').

The average return difference between L and E stocks in the respective pairs in our sample is 5.2 percent per year with a t-statistic of 3.1. As we show in regression analyses, this

[2] We are aware that an IV is a quantity given under the risk-neutral measure $\mathbb{Q}$, while our theoretical argument refers to the physical probability measure $\mathbb{P}$. We later on show that IVs are closely related to physical volatilites, and that our empirical results are not driven by variance risk premia, i.e., by differences between variances under the physical and the risk-neutral measure.

return difference cannot be explained by the exposures to the usual set of factors proposed by Fama and French (1996, 2015). We call the return difference between L and E stocks the *early resolution premium*.

The above investment strategy is a direct way of bringing the notion of early resolution of uncertainty to the data. As a more convenient absolute measure for the timing of uncertainty resolution, which can be computed for any stock with traded options, we introduce the concept of *Implied Volatility Duration* (IVD). Perfectly analogous to the well-known Macaulay duration in the area of fixed income, it represents a time-weighted average of the IVs for different subperiods of a total period from 0 to T. So, ceteris paribus, the higher the IVD, the larger the share of the total IV, i.e., of total uncertainty, which is resolved later.

We then perform a double sort of the stocks in our sample into quintiles for 365-day IV and IVD. We call the extreme portfolios with the highest and the lowest-IVD stocks 'late' and 'early', respectively. Within the stocks with high IV, we find a significantly positive average return of around seven percent on the 'late-minus-early' (LME) portfolio, we we take as evidence in favor of the representative investor exhibiting PERU. The fact that we find a significant LME return only in the group of stocks with high IV is not surprising: When the overall level of uncertainty is low, its resolution over time naturally is less relevant to the investor.

The excess return on the LME portfolio varies over time and is higher in times of high economic uncertainty and in periods with negative returns on the aggregate stock market. Similar to the investment strategy based on pairs of stocks with matching 365-day IV and strongly differing 30-day IV, the loadings of the LME portfolio on the factors are small, so that the alpha is basically of the same magnitude as the portfolio return itself.

To investigate the explanatory power of IVD for the cross-section of expected returns we include an interaction term of (squared) 365-day IV and IVD as a characteristic in second-stage Fama-MacBeth regressions. We find that it explains some cross-sectional variation in pricing errors relative to a variety of popular factor models. Moreover, we construct an LME factor that is long in late and short in early resolution stocks. It can be thought of as a proxy for the representative investor's (time-varying) desire to have uncertainty resolved early. Once we add this factor to the regressions, the significance of the characteristic vanishes, such that a risk-based explanation of the early resolution premium appears likely.

We rationalize our empirical findings in a general equilibrium model in the spirit of Bansal and Yaron (2004). In this model we price type E and L dividend claims. The key result of our analysis is that in order to generate a pronounced spread between expected returns on the L stock and the E stock, the investor's degree of relative risk aversion must exceed the inverse of her elasticity of intertemporal substitution by a considerable amount, i.e., the investor must exhibit PERU. Our model also gives rise to a linear factor structure, which includes the market factor accounting for the overall *level of uncertainty* and a late-minus-early factor related to the *timing of uncertainty resolution*.

The rest of the paper is structured as follows. In Section 2, we review the related literature. In Section 3, we present the investment strategy based on pairs. Motivated by the results from this exercise, we introduce the concept of IVD in Section 4 and perform a variety of tests to assess its explanatory power in the cross-section. Our general equilibrium model is presented in Section 5. Section 6 concludes. The appendix contains additional information about the investment strategy, details about the solution of the model and additional tables.

2 Related Literature

Our paper is related to several strands of the literature. As stated above, the issue of whether the representative agent exhibits PERU is of key importance in asset pricing models with recursive preferences, since only under PERU the sign of the market price of risk for key state variables is such that the model can match the data. Prominent examples for models of this type are Bansal and Yaron (2004) and Drechsler and Yaron (2011). Epstein et al. (2014) criticize these long-run risk models because they would imply an immense discount for early resolution of uncertainty. For example, the dynamics of Bansal and Yaron (2004) imply that the investor would be willing to forgo 31 percent of lifetime wealth to eliminate all uncertainty about future consumption. Note that while our results support an important assumption of long-run risk models regarding investors' preferences, our results do not require the existence of a long-run risk component in consumption growth.

Formally, an agent exhibits PERU if the degree of relative risk aversion exceeds the inverse of the elasticity of intertemporal substitution (EIS). So, all one would basically need is estimates of these two preference parameters. In the literature, special attention has been devoted to the EIS. Hall (1988) estimates the EIS from the consumption Euler equation in a time-additive CRRA model. He concludes that it is most likely very small and not much greater than zero, if at all. Epstein and Zin (1991) estimate the EIS in a recursive utility model where the relation $\gamma = \frac{1}{\psi}$ need not hold. They find estimates of γ around one and the EIS to be roughly in the range of 0.2 to 0.9. These results would imply that the representative agent has a preference for late resolution of uncertainty. But also the opposite result has been found in empirical studies. For example, Attanasio and Weber (1989) find a γ of about five and an EIS around two, which is in favor of a preference for early resolution of uncertainty.

Other authors estimate preference parameters using survey data, where the socio-economic background of survey respondents is crucial. In an asset pricing context, this means that it is of key importance whether the survey respondents could at least potentially represent the marginal investor. Vissing-Jørgensen and Attanasio (2003) provide evidence that, among stockholders, the EIS is well above one, which together with the usually assumed values for risk aversion greater than one would imply PERU. There is also some experimental evidence in favor of PERU provided by, e.g., Brown and Kim (2014) and Meissner and Pfeiffer (2015). In an earlier study, Ahlbrecht and Weber (1996) find that some participants prefer early and others late resolution of uncertainty.

Somewhat related to our paper, Jagannathan and Liu (2015) provide evidence in favor of PERU based on a model with learning. Depending on the preferences for early or late resolution of uncertainty, new information about the persistence of dividend growth results in either an increase or a decrease of the price-dividend ratio. However, while also using market prices, their approach requires a much more elaborate model. In contrast, our analysis is model-free.

Our paper also relates to the literature on option-implied information about the cross-section of stock returns, represented by papers such as An et al. (2014) and much of the work cited there. The work by Johnson (2016) and Xie (2014) is in a certain sense similar to ours, because they consider the asset pricing implications of implied volatility across maturities. However, they consider the term structure of the VIX volatility index, i.e., in a characteristic of market-wide implied volatility, whereas we focus on the timing pattern of uncertainty resolution in individual stocks and its implication for expected returns.

3 An investment strategy

3.1 Pairs of stocks

Our main idea in this paper is to compare returns on stocks that provide late and early resolution of uncertainty. To take this idea to the data, we take option implied volatilities (IVs) for different maturities as a representation of the uncertainty associated with the returns on this stock over different horizons. Using end-of-month data on the IV surface provided by OptionMetrics IvyDB for the period from January 1996 to August 2015, we identify pairs of stocks with similar 365-day implied volatility (IV_{365}) but rather different 30 day-IV (IV_{30}). In particular, we look for stocks for which the IV_{365} values differ by at most 1 percentage point (e.g. , 30% vs. 31%), while the difference between the respective (annualized) IV_{30} values is at least 25 percentage points.[3] In the spirit of the motivating example in Figure 1, we go the stocks with lower IV_{30} long and the other ones short.[4] At every point in time we compute the equally-weighted average of the returns of the stocks in the long and the short portfolio, respectively.

When we hold the long and the short portfolio over twelve months, the return differential

[3]For liquidity reasons, we only use the IVs for at-the-money (ATM) calls.

[4]For a discussion of the robustness of this procedure and the associated summary statistics see Appendix A.

between the two amounts to highly significant 5.17 percentage points, as shown in Table 1. Table C.2 shows that this return difference increases in the required distance between IV_{30}. Moreover, it becomes insignificant when not matching IV_{365}. Thus, the effect is not driven by the mere difference in short-term IVs.

[TABLE 1 HERE]

As further indicated by Table 2 the returns on this trading strategy cannot be explained by standard risk factors. As a matter of fact, it exhibits substantial alpha relative to the factor models. Furthermore, the loadings on the factors are not very pronounced. Only for the market factor we obtain a significant coefficient, but it is negative, i.e., if anything, the strategy represents a hedge against market risk. Appendix A contains a more elaborate analysis and robustness checks for trading strategies based on pairs.

[TABLE 2 HERE]

These results represent the starting point for our further investigation of the early resolution premium. In terms of data for the following analyses, we take monthly return and market capitalization data for actively traded common shares from the Center for Research in Security Prices (CRSP) database. Stocks with a market price of $1 or less are excluded. Delisting returns are included wherever available. Over the entire sample period we consider 7.148 stocks (and their respective volatility surfaces). On average, we consider 2331 stocks in a given month. Data on the monthly risk-free rate are taken from Kenneth French's website, and accounting-related data are taken from the CRSP-Compustat merged database.

3.2 Discussion

We argue that there is a strong economic argument behind the profitability of the investment strategy described above, namely that the return difference is a premium for early resolution of uncertainty. Consider two stocks with the same return variance over the total horizon T. If one of the stocks has a higher variance over a short horizon $T_0 < T$, it must have lower variance over the period from T_0 to T. In terms of the timing of uncertainty resolution, this means that the stock with the higher short term variance exhibits early resolution of uncertainty relative to the stock with the lower variance from t to T_0. As we are going to formally derive in the context of a general equilibrium model in Section 5, if the marginal investor exhibits PERU, the expected return on the stock with the later resolution needs to be higher to compensate the investor for having to wait longer until uncertainty is resolved.

In this spirit, the positive return on the investment strategy described above is in line with a positive premium for stocks with a late resolution of uncertainty. Moreover, the negative estimates of market beta from Table 2 point to another interesting aspect. In times of market downturns, returns on our strategy are particularly high. It thus seems that it is especially in these periods, when investors demand a substantial premium for bearing uncertainty for a longer period. This feature can also be observed in Figure 2, which shows the returns on the market and on the investment strategy. For instance, during the two recessions in our sample (marked gray), the investment strategy described above earned substantial positive returns.

[FIGURE 2 HERE]

An important issue to be discussed is that we use IVs, i.e., volatilities under the risk-neutral measure, as a forward-looking measure of volatilities under the true measure. One might argue that what we pick up is a phenomenon related to the spread between $\mathbb{Q}$ and $\mathbb{P}$ volatility rather than the expectation of volatility evolution and the associated timing of uncertainty resolution. First, the potential issue is mitigated by the fact that we only consider differences in IVs both across maturities for a given stock as well as across stocks. Components of variance risk premia that are common to all stocks and maturities will simply cancel out. Moreover, in line with the literature on the predictive properties of implied volatility (see for example Christensen and Prabhala (1998) and Busch et al. (2011)), we find that there is a strong positive relation between IV and realized volatility in our sample. We perform cross-sectional regressions of the realized variance, estimated from daily returns over 30 and 365 days, on the respective implied variances over those time horizons. The slope coefficients are always positive, with an average coefficient of 0.45 for 30 days and 0.52 for 365 days and average R^2 values of 18 and 31 percent, respectively. Finally, to make sure that our results are not driven by variance risk premia of the individual stocks, i.e. the differences between $\mathbb{P}$- and $\mathbb{Q}$-variances, we control for these premia in our Fama-MacBeth regressions (see Section 4.4).

4 Implied Volatility Duration

4.1 Definition

The trading strategy from the previous section is based on pairs of stocks satisfying the criteria described above with respect to short and long-term IV. The restrictions we impose are rather tight, so that the average number of pairs per month is 110, covering on average about one tenth of the available stocks. While this strategy is a direct way to implement a test for the existence of an early resolution premium, it would nevertheless be preferable to cover a larger share of the overall sample. Moreover, it would be desirable to have a characteristic that directly indicates how early or late uncertainty is expected to be resolved and which can be assigned to every single stock at every point in time.

The characteristic we suggest for this purpose is 'implied volatility duration' (IVD). The IVD of stock i at time t, denoted by IVD_{it}, is defined as follows:

$$\text{IVD}_{it} = \sum_{j=1}^{J} \frac{\Delta IV_{i,t,j}^2}{\sum_{j=1}^{J} \Delta IV_{i,t,j}^2} \cdot \tau_j \tag{1}$$

where $\Delta IV_{t,i,j}^2 = IV_{i,t,t+\tau_j}^2 - IV_{i,t,t+\tau_{j-1}}^2$ is the difference at time t between the non-annualized squared IVs for call options maturing at $t + \tau_j$ and those maturing at day $t + \tau_{j-1}$.[5] We set

[5]OptionMetrics reports annualized values, so we multiply the implied variance for options maturing at date

$\tau_0 = 0$ so that $IV^2_{i,t,t+\tau_0} = IV^2_{i,t,t} \equiv 0$. For our empirical exercise, we use maturities of up to one year available in OptionMetrics, i.e., $J = 8$ and $(\tau_1, \ldots, \tau_8) = (30, 60, 91, 122, 152, 182, 273, 365)$ (days).

The interpretation of IVD is similar to that of the well-known Macaulay duration in the area of fixed income instruments. The denominator of the right-hand side of (1) is simply equal to $IV^2_{i,t,t+\tau_J}$ (analogous to the normalization of the present values of the individual cash flows, i.e., the bond price), so that the increments $\Delta IV^2_{i,t,j}$ are normalized by the implied variance over the total horizon (analogous to the present values of the individual cash flows). We can thus interpret the terms $\frac{\Delta IV^2_{i,t,j}}{\sum_{j=1}^{J} \Delta IV^2_{i,t,j}}$ as weights for the respective horizon τ_j, meaning that IVD is an implied variance-weighted average time over which uncertainty is resolved. Comparing IVD across stocks then tells us for which stock uncertainty is expected to be resolved earlier.

Figure 3 presents two stylized cases for short and long IVD, representing in our interpretation early and late resolution of uncertainty. The larger the area above the piecewise linear function, the more of the total IV_{365} stems from longer term IV, and consequently, our characteristic, IVD, is larger.

[FIGURE 3 HERE]

4.2 Portfolio sorts

To investigate how IVD is related to other quantities such as future returns, implied volatility, and other characteristics, we group the stocks in our sample into portfolios according to their IVD. More precisely, at the end of every month we perform an independent double sort of all stocks into 25 portfolios based on IVD and IV_{365}.

[TABLE 3 HERE]

$t + \tau_j$ by $\tau_j/365$ to undo the annualization.

As shown in Table 3, except for the low IV_{365} group, where the spread is even larger, IVD varies between slightly more than 190 and around 220 days, a sizeable spread of close to one calendar month. Across any given column, however, again with the potential exception of the first, there is hardly any variation in IVD. An analogous picture emerges for IV_{365}. In general, there is a large variation of this characteristic across stocks with values between 22 and 79 percentage points, but across each individual row in Panel B, IV_{365} does not vary much. All in all, this indicates that IVD as a measure of resolution timing is essentially independent of IV as a measure of the level of uncertainty.[6]

We now study the returns on what we call 'late-minus-early' (LME) portfolios, which are formed in every IV_{365}-quintile by going long 'late' (high IVD) and shorting 'early' (low IVD) stocks.

[TABLE 4 HERE]

The different panels of Table 4 show value-weighted and equally-weighted returns for the quintile and the LME portfolios over holding periods of one and twelve months. Our most important finding is that in the quintile of high IV_{365} stocks, returns on the LME portfolio are significantly positive and large for both return horizons and for both weighting schemes. For example, Panel A shows that forming a new value weighted LME portfolio from high IV_{365} stocks every month and holding this portfolio for twelve months results in a statistically significant average return of more than seven percent per year. We interpret this significantly positive average return on the LME portfolio as a premium for the early resolution of uncertainty. The premium becomes even more pronounced when we consider more extreme subsets of stocks with respect to their IV_{365}. The average return on the LME portfolio held for 12 months is about 10 percent in the top IV_{365}-decile, and 13 percent when we consider the five percent of stocks with the highest IV_{365} (not tabulated).

[6] To investigate this more formally, we compute the correlation coefficient between the two measures for each month in our sample. The time-series average of these correlation coefficients is close to zero.

For lower IV_{365}-quintiles, there is no significant difference between returns on late and early stocks for either return horizon or weighting scheme, but the fact that the early resolution premium is more pronounced among the group of high IV_{365} stocks seems very plausible. For stocks with low overall uncertainty the timing of uncertainty resolution is obviously not as relevant, so one would not expect a pronounced premium for early resolution in the first place.

The results in Panels C and D of Table 4 further support the view that it is not the absolute amount of risk, but the timing of its resolution which matters in our sorts. Like in the case of a 12-month holding period, value-weighted and equally-weighted LME returns in the highest IV_{365}-quintile are significantly positive also over a horizon of one month. The standard risk-based intuition, however, would suggest a *negative* sign for this return differential, since the stocks in the long portfolio (long IVD) are those with on average lower risk over the first month, so that, given a short term risk-return tradeoff, they should exhibit lower returns over this horizon.

[TABLE 5 HERE]

As indicated above, the use of $\mathbb{Q}$-volatilities as a forward-looking measure for the uncertainty under physical probabilities is based on the conjecture that these two types of volatilities are closely linked, i.e., that future realized volatilities are indeed close to current IVs.

Table 5 shows the realized return variances for our 25 double-sorted portfolios. Most importantly, IV does indeed predict realized variance, since realized variances increase monotonically in IV_{365}. Furthermore, we expect early resolution stocks to have higher realized variances over the first month than their late resolution counterparts in a given IV group, and this is indeed the case.[7] Over 12 months, on the other hand, realized variances should be roughly the same for the late and early resolution portfolios, and this is also supported by the data.[8]

[7] An F-test rejects the null hypothesis of equal variances of the late and early portfolio in the highest IV quintile for the one month holding period for both equally and value-weighted returns.

[8] The null hypothesis of equal variances cannot be rejected based on Levene's test with p-values of 0.76 and 0.57 for value-weighted and equally weighted returns, respectively. The F-test is not applicable here, since 12-month returns in successive months overlap to a large degree.

Again, as in the case of the trading strategy based on pairs, standard factors are not able to explain the high returns on the LME portfolio in the high IV_{365} quintile. The alphas in the regressions presented in Table 6 are substantial and statistically significant. As before, there are only very few significant loadings across the different specifications. The only exception is the market factor which LME is negatively related to, although with an insignificant coefficient for the Fama and French (2015) five factor model.

[TABLE 6 HERE]

4.3 Portfolio characteristics

Panel A in Table 7 displays a number of descriptive statistics for the five IVD-sorted portfolios in the top IV_{365} quintile. The last column shows the time series average of the cross-sectional median of each characteristic over the entire sample, to see how representative the top IV_{365} stocks are for the full set of stocks in the cross-section. The betas of these portfolios with respect to standard risk factors are shown in Panel B.

[TABLE 7 HERE]

Our first observation is that stocks in the top IV_{365} quintile tend to have a rather low market capitalization, as compared to the sample mean. This raises the question, whether the timing of the resolution of uncertainty is only important for small stocks rather than in a general sense for stocks with uncertain returns, i.e., for high IV_{365} stocks. To address this concern, we perform an independent double sort of the stocks in our sample with respect to market equity and IVD. Table C.4 in the appendix shows that none of the resulting LME portfolios generates a significant average return. This result provides strong indication that the early resolution premium is not a phenomenon limited to small stocks.

Similarly, we find that high IV_{365} stocks are typically value stocks that have low operating profitability, high investments and are less liquid, compared to the sample as a whole. As shown in Tables C.5 to C.7, the corresponding double sorts on IVD and these characteristics do not yield significant returns for the LME portfolios except in the case of investment.

Table 7 shows that overall across the five IVD portfolios in the highest IV quintile, there is hardly any variation nor are there clear patterns in any of the characteristics or factor betas. The lack of marked patterns indicates that the return differential between late and early resolution stocks is not due to other well-known premia. Some features of the stocks in the high IV quintile however merit discussion:

Given that IVD is a duration-based uncertainty measure, it is natural to look at the relation between this characteristic and cash-flow duration (CFD). Table 7 shows that there is no systematic variation in CFD, computed as in Weber (2016), along the IVD dimension. This is not really surprising, given that IVD is based on second moments, while CFD measures first moments, in order to provide an estimate of the average dividend payout date.

High implied volatility stocks also have high idiosyncratic volatility as measured relative to the Fama and French (1992) three factor model. Because short IVD stocks tend to have high IV_{30} which encompasses idiosyncratic volatility, it is not surprising that idiosyncratic volatility decreases in IVD. Table C.9 shows the average idiosyncratic volatility for each of the IV and IVD sorted portfolios. Idiosyncratic volatility differences are much more pronounced across the IV quintiles than within IV quintiles in the IVD dimension. The average spread in idiosyncratic volatility between high and low IV stocks is 2.6 percentage points, between the stocks in the late and early portfolios it is just 0.4 percentage points. In the next subsection, we show that our results are not driven by the well-known low idiosyncratic volatility anomaly.

In Table 7 we also report two versions of the variance risk premium for the five IVD portfolios in the top IV quintile. The ex ante measure is computed as the difference between the realized return variance (estimated from daily returns and scaled appropriately) over the previous month and the squared implied volatility at the end of that month. The realized version uses the same squared implied volatility, but the realized variance is computed over the next instead of the previous month.

Variance risk premia are decreasing in absolute value with increasing IVD. This is not surprising. Among high IV_{365} stocks, those with a higher IV_{30} are typically sorted into the short IVD portfolio. Thus, if the 30-day variance risk premium is high (in absolute terms) for high IV_{30} stocks, then short IVD is related to a more negative variance risk premium. In the next section, we show that variance risk premia do not drive our results.

SIR_{IO} is the ratio of short interest over institutional ownership as computed in Drechsler and Drechsler (2016) and serves as a proxy for shorting fees. We find that stocks in the top IV_{365} quintile tend to have high SIR_{IO}. Drechsler and Drechsler (2016) show that stocks with higher shorting fees have lower average returns. However, just as many other characteristics, the spread in average SIR_{IO} within the high IV_{365} quintile is very small compared to the spread across IV_{365} quintiles. Moreover, there is no monotonic pattern within the top IV_{365} quintile. This is consistent with the finding in Drechsler and Drechsler (2016) that shorting fees are a persistent characteristic of stocks whereas IVD is a rather transitory feature (see below). Importantly, the early portfolio has lower SIR_{IO} (and thus presumably lower shorting fees) than the late portfolio which, given the results in Drechsler and Drechsler (2016), should imply a lower return for the late portfolio. In the upcoming subsection we further address the issue.

In Panel B of Table 7, we report factor betas for the IVD quintile portfolios. Similar to the investment strategy based on pairs, discussed in Section 3, there is a negative relation between IVD and market betas, which makes the high positive returns on the LME portfolio even more striking. The other betas do not exhibit any pronounced pattern across IVD sorted portfolios. This suggests that the return differential between late and early resolution stocks is not due to differences in the exposure to known risk factors.

Table 8 shows the migration of stocks across IVD quintile portfolios for both the entire sample and the stocks in the top IV quintile. The timing of uncertainty resolution is a very transitory characteristic. All relative frequencies in Table 8 are below 0.5 which means that the average stock is more likely to move out of a given portfolio by the end of the month than to remain in the respective portfolio. Unlike other characteristics, which are typically rather persistent, IVD is not a characteristic of a stock throughout time but of a stock at a specific point in time. In line with that, we do not find any relation between IVD and other, more persistent characteristics (see Table 7). An early resolution stock may become a late resolution stock as soon as new information that resolves uncertainty becomes available. Likewise, a late resolution stock may become an early resolution stock as the time at which resolution is expected approaches. If there is an early resolution premium, stocks will only trade at a discount for as long as they exhibit late resolution.

4.4 IVD and the cross section of returns

We now study if the variation in IVD across stocks can explain the variation in the cross-section of pricing errors relative to some commonly used asset pricing models. In particular, we run monthly Fama-MacBeth regressions of single stock excess returns on a number of factors as well as on IVD as a characteristic. To make sure that the estimation of the factor betas is not hampered by idiosyncratic noise, we first estimate all factor betas for 25 portfolios sorted by size and book-to-market ratio. We then assign each individual stock the beta of the portfolio the stock belonged to in the respective month. In Section 4.2 we found that the return differential between late and early resolution stocks is substantial only for high IV_{365} stocks. Furthermore, the average return on the LME portfolio is the higher the more extreme the quantiles we use for the selection of the long and short leg. To take this into account, we consider the interaction term $IVD \times IV_{365}^2$ as a characteristic.

The interaction term is by construction positive for all stocks in the cross-section. To avoid the bias that could result from regressing an on average positive pricing error on a strictly positive characteristic, we demean IVD before calculating the interaction terms for the regression. Since IVD and IV_{365}^2 are virtually independent, the interaction term itself is also on average zero and large in absolute terms for stocks with high IV_{365}^2.

[TABLE 9 HERE]

The results are presented in Table 9. The interaction term is highly significant and explains pricing errors relative to all three standard factor models. For robustness, we show in Table C.16 in the appendix that this result is robust to a large variety of further factor model specifications. The coefficient of the characteristic is very stable across models. Concerning economic significance, multiplying an estimated coefficient for the characteristic of 0.05 percent by the average implied variance in the top IV_{365} quintile of around $0.77^2 \approx 0.6$ (see Table 7) yields a value of 0.03 percent, such that an increase in IVD of one day ceteris paribus leads to a higher abnormal return of three basis points per month. The average IVD-spread between the high and low IVD quintile in our sample is around 30 days (see again Table 7), implying a return difference of around one percent per month between the quintile portfolios, which is well in line with the findings presented in Section 4.2.

The risk premia associated with the factors are barely significant and vary considerably across model specifications. The only minor exception is the market factor, for which the risk premium is positive and stable across specifications. This is probably due to the (empirical) fact that the size and value premia have been less pronounced in the recent past compared to the postwar sample.

Coming back to an issue already discussed above, IVD is based on implied variance, which itself consists of the sum of expected physical variance and a variance risk premium. As seen in Table 7, low IVD stocks have lower variance risk premia. We check if the explanatory power of our characteristic is due to its relation to the variance risk premium, which in turn may be strongly related to expected returns. Because IVD contains information from the term structure of implied volatilities for maturities of up to one year, we include the individual variance risk premia over 30 and 365 days as controls. As can be seen in Table C.10, this does not change our results. The coefficient of the interaction term remains practically unchanged, with respect to both magnitude and significance.

As pointed out in the previous subsection, 30 day idiosyncratic volatility is higher for the early than the late stocks. Although the differences in idiosyncratic volatility are small, we nevertheless controlled for it in our regressions. In Table C.11 in the appendix, we show our results of the Fama-MacBeth regression when controlling for idiosyncratic volatility. In light of the results of Stambaugh et al. (2015), we interact idiosyncratic volatility with (a function of) the authors' mispricing characteristic MISP. As Stambaugh et al. (2015) show, the effect of idiosyncratic volatility on expected return changes sign in mispricing (negative for overvalued stocks and positive for undervalued stocks). In the baseline setting, to maintain our linear framework, we simply demean MISP such that idiosyncratic volatility is interacted with a negative value for undervalued stocks and with a positive value for overvalued stocks.[9] Given the results of Stambaugh et al. (2015), we would expect a negative coefficient of $Ivol \times MISP$. This is indeed the case. However, it leaves our results significant and qualitatively unaltered. As a further robustness check, we repeat the double sort of stocks on IV_{365} and IVD for stocks with a Stambaugh et al. (2015) mispricing measure of or below 20 percent (Stambaugh et al.'s "Most Underpriced" stocks). As shown in Stambaugh et al. (2015), for these stocks, the relation between idiosyncratic volatility and expected returns is positive, i.e. in this subset of stocks, high idiosyncratic volatility is related to higher rather than lower expected returns. As can be seen from Table C.12 in the appendix, our effect still prevails, even though the idiosyncratic volatility effect works against our effect in this subsample.

Stocks with high implied volatility tend to be stocks that are expensive to short as is indicated by the high values of SIR_{IO} throughout the high IV quintile. Drechsler and Drechsler (2016) show that stocks that are expensive to short have on average lower returns to compensate arbitrageurs for the risks involved in shorting stocks, i.e. the low returns of expensive-to-short stocks constitutes a systematic risk premium. With respect to our results, the important point is that – unlike for the anomalies considered in Drechsler and Drechsler (2016) – it is not the case that stocks in the short leg of the anomaly portfolio, i.e. 'early' stocks are substantially more difficult to short than those in the long leg. If anything, the average values of SIR_{IO} would suggest the opposite. In other words, given the characteristics of the stocks in the top

[9]Using piecewise linear functions of the form $f(\text{MISP}) = \mathbb{1}_{\theta_i \leq \text{MISP} \leq \theta_{i+1}}(a_i + b_i \cdot \text{MISP})$ for different sets of cutoffs θ_i, intercepts a_i and slope coefficients b_i calibrated to the results in Stambaugh et al. (2015) yield similar results and leave the coefficient of $\text{IV}^2 \times \text{IVD}$ unaltered.

IV quintile, the ‘shorting premium’ documented in Drechsler and Drechsler (2016) would not imply the return differential between late and early stocks that we observe. As a further test whether our results are driven by the shorting premium, in Table C.13 in the appendix, we control for our sample equivalent of Drechsler and Drechsler’s E-factor that serves as a factor-mimicking portfolio for the shorting premium risk factor. We moreover control for a proxy version of the authors’ cheap-minus-expensive (CME) factor where instead of sorting on the unavailable shorting fee data we sort on the proxy SIR_{IO} (see Table C.14 in the appendix). Both robustness checks leave our results unaltered, suggesting that the return differential we document is not driven by the shorting premium.

4.5 Factor structure in high IV stocks

We now investigate if there is a risk-based explanation of the early resolution premium, i.e., if standard pricing models can be meaningfully augmented to account for the return differential between late and early stocks. In particular, a stock’s high IVD may just be a signal for a strong exposure of its return to a latent factor priced by investors. Given our results so far, the natural candidate for such a new factor is the return on the LME portfolio. To see whether LME is priced, we perform a cross-sectional Generalized Method of Moments regression (see Cochrane (2009)), where we jointly estimate betas and market prices of risks as well as the respective standard errors.

As test assets we use the 25 portfolios sorted independently with respect to IV_{365} and IVD described in Section 4.2. The advantage of this sort is that it generates sufficient variation in LME betas to allow for a proper identification of the market price of risk. As we show in detail in Table C.15 in the appendix, other sorts do not provide such sufficient variation. This is in line with our observation from Table 8, namely that a stock’s IVD changes frequently while other characteristics are very persistent. In a portfolio based on other sorts, we thus find stocks with strongly differing volatility durations. As a consequence, there is hardly any variation in LME betas across portfolios sorted on the usual characteristics.

To construct the proxy for the latent factor, we perform an independent double sort on IV_{365} and IVD into 5×2 portfolios. The LME factor is then given by the difference between the value weighted returns on the above and below median IVD portfolio in the top IV_{365} quintile. Although this sorting procedure is similar to the one described above in Section 4.2 there is one important difference. We do not form 5×5 portfolios, and in particular we do not consider the difference between the extreme IVD-quintile portfolios to avoid mechanical relations between portfolio returns and the factor (which would then be equal to the difference of the returns on two of the test assets).

[TABLE 10 HERE]

Estimates of the market prices of risks are presented in Table 10. The early resolution premium is positive, large, and significant in all specifications. The market price of risk is consistently estimated at around 0.8 percent (or slightly higher for the version with only the market factor), a value close to the average return difference between the late and early portfolios in the top IV_{365} quintile (see Panels C and D in Table 4). Furthermore, we hardly find significant estimates for any of the other factors. In Table C.17 in the appendix, we show that these results are robust to alternative factor model specifications.

The pricing performance of the model for the 25 test portfolios, as measured by the cross-sectional R^2, increases considerably when LME is added. For example, for the Fama and French (2015) five factor model, R^2 increases from 1% to 57%.

[FIGURE 4 HERE]

In Figure 4, we plot model-implied versus realized average returns on the 25 test assets for the different models. The plots in this figure show the main source of the increase in R^2 when LME is added. The pricing performance of the specifications without LME (shown in the left column of graphs) is consistently poor for the five IVD portfolios in the top IV_{365} quintile, and the inclusion of LME substantially reduces the mispricing of exactly this subset of portfolios.

With respect to the pricing of the other twenty portfolios, the augmented models perform only slightly better than the respective benchmark.

The fact that the increase in pricing performance is observed mostly for the portfolios in top IV_{365} quintile again emphasizes that our LME factor explains variation in the expected returns of a specific group of stocks, namely those for which the timing of the resolution of uncertainty is most relevant. Our empirical results indicate that there is a common component in the returns on early and late stocks and that investors claim a compensation for holding stocks with a high exposure to this common source of variation. The model-implied expected returns on other stocks without such an exposure are not affected by the LME factor.

As a litmus test for the pricing performance of the LME factor, we run Fama-MacBeth regressions with single stocks, similar to our analysis in Section 4.4, but include LME betas in the second stage regression. Ultimately, if the model augmented by LME is supposed to explain the early resolution premium, the factor should reduce the explanatory power of the characteristic $IVD \times IV_{365}^2$. As before, to reduce noise in the beta estimation, we assign to each stock in the sample the factor betas of the portfolio the stock is in. To this end, we use the estimated betas on the 25 IV_{365}/IVD sorted portfolios and in each month, assign them to the constituent stocks of the portfolio. This procedure ensures sufficient variation in LME betas. The results of the Fama-MacBeth regressions are shown in Table 11.

[TABLE 11 HERE]

The interaction term becomes insignificant as soon as we include LME for all specifications. We consider this result as strong evidence in favor of a risk-based explanation for the early resolution premium.

5 Rationalizing the early resolution premium

5.1 Model

In the following we present a general equilibrium model in the spirit of Bansal and Yaron (2004) to rationalize the stylized facts established in the previous sections. In particular, we show that a preference for early resolution of uncertainty in the sense of Epstein and Zin (1989) generates a return differential between late and early resolution stocks, and we also suggest an economic interpretation of the LME factor as a driver of expected returns in the cross-section. The model solution is described in detail in Appendix B.

Consider an agent with preferences described by the recursive value function

$$U_t = \left[(1-e^{-\delta})C_t^{1-\frac{1}{\psi}} + e^{-\delta}\left(E_t\left[U_{t+1}^{1-\gamma}\right]\right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right]^{\frac{1}{1-\frac{1}{\psi}}}.$$

Here, γ, ψ and δ denote the agent's coefficient of relative risk aversion, her elasticity of intertemporal substitution, and her time preference parameter, respectively. In the case $\gamma = \frac{1}{\psi}$, the agent has time-additive CRRA preferences. Log consumption growth exhibits the following dynamics:

$$\Delta c_{t+1} = \mu_c + \sum_{i=1}^{n} \phi_{ci}\, x_{i,t} + \sigma_c\, \varepsilon_{t+1}^{c},$$

The processes x_i are state variables that model different *cycles* with dynamics

$$x_{i,t+1} = \rho_i\, x_{i,t} + \sqrt{v_{i,t}}\, \varepsilon_{t+1}^{i}.$$

with time-varying volatilities

$$v_{i,t+1} = \bar{v} + \rho_v\left(v_{i,t} - \bar{v}\right) + \sigma_v\, \varepsilon_{t+1}^{vi}.$$

For simplicity, we assume that all innovations ε are i.i.d. standard Normal. Furthermore, the economic uncertainties of the different cycles have the same long-run mean $\bar{v}$, persistence ρ_v, and volatility σ_v. These assumptions can easily be generalized and would not change our conclusions qualitatively. The difference between the cycles is their persistence, i.e. innovations to a cycle may have a rather transitory or a very long-lasting effect on aggregate consumption, depending on the persistence ρ_i of state variable x_i.

Real life examples of such processes x_i are business cycles in different sectors, political cycles, and innovation waves in different industries. Uncertainty about economic growth triggered by a particular cycle i is time-varying. One may think of the US presidential election cycle as an example. Much of the political uncertainty may be resolved on election day. But there may also be lingering time-varying uncertainty about the political agenda and its impact on growth during a presidential term triggered by statements of political representatives.

Our model is similar to the long-run risk model of Bansal and Yaron (2004). The major difference is that we consider multiple cycles instead of just one. The focus of the long-run risks model is on aggregate consumption and dividend claims, not the cross-section of firms. Our approach to introduce a cross-section in the model is to allow firms' cash flows to depend to different degrees on different cycles. As an example, certain firms may benefit more from innovations in certain production technologies than others. These different exposures impact the prices of the firms' stocks in equilibrium.

We assume that firm j pays dividends d^j with dynamics

$$\Delta d^j_{t+1} = \mu_j + \sum_{i=1}^{n} \phi_{ji}\, x_{i,t} + \sigma_j\, \varepsilon^j_{t+1}. \tag{2}$$

where the local dividend innovations ε^j_{t+1} are mutually independent and independent from the local innovations in consumption and the state variables. For each asset j, representing the claim on dividend d^j, we calculate the conditional term structure of expected excess returns:

$$\mathbb{E}_t\left[r^j_{t\to t+\tau} - r^f_{t\to t+\tau}\right] + \frac{1}{2}Var_t(r^j_{t\to t+\tau}) = \pi^j_{0,\tau} + \sum_{i=1}^{n} \pi^j_{i,\tau}\, v_{i,t}. \tag{3}$$

Here, $r^j_{t\to t+\tau}$ denotes the log return on asset j between time t and time $t+\tau$, and $r^f_{t\to t+\tau}$ is the corresponding risk-free rate. The conditional term structure of return variances is given by

$$Var_t(r^j_{t\to t+\tau}) = \chi^j_{0,\tau} + \sum_{i=1}^{n} \chi^j_{i,\tau}\, v_{i,t}. \tag{4}$$

The coefficients π^j_0 and π^j_i, as well as χ^j_0 and χ^j_i are shown in Appendices B.3 and B.4. Qualitatively, these coefficients are functions of the exposures ϕ_{ji} of asset j's return to innovations in cycle i, and the persistent ρ_i of cycle x_i. Equation (4) allows us to calculate asset j's implied volatility duration and, using Equation (3), we can investigate the relation between IVD and expected returns over different horizons in the cross-section of firms. As opposed to our empirical exercise, we consider $\mathbb{P}$-volatilities instead of implied volatilities, which is negligible because variance risk premia are virtually zero in long-run risk models without jumps.

5.2 Calibration

To exemplify the main mechanism, we choose a parsimonious specification of the model with only two cycles, denoted by x_{tran} and x_{pers}, where the latter is more persistent than the former. Our calibration follows Bansal et al. (2012) and can be found in Table 12. We choose $\phi_{c,tran} = \phi_{c,pers} = \frac{1}{\sqrt{2}}$ to match the unconditional consumption growth variance of Bansal et al. (2012). One notable difference is that the persistence of the variance processes is lower than in their calibration which makes the term structures less rigid. At the same time, the persistence levels of the growth rates are high and vary across cycles with $\rho_{tran} = 0.98$ and $\rho_{pers} = 0.99$. These numbers allow us to match the unconditional equity premium. Qualitatively, it is only important that the cycles differ in terms of their persistence parameters.

[TABLE 12 HERE]

For illustrative purposes, we consider three different generic dividend claims, denoted by m, e, and l. The first is equally exposed to innovations in both cycle variables, i.e. $\phi_{m,tran} = \phi_{m,pers}$, and can be interpreted as a "market portfolio". The other two claims have a particular exposure to either the persistent or the more transitory cycle. In particular, there is one "early" claim e, for which we set $\phi_{e,pers} = \phi_{c,pers}/\psi$. This causes the price dividend ratio of this claim to only depend on shocks to the transitory cycle (for details see Appendix B.2). Analogously, the price of the "late" claim l only moves with innovations in the persistent cycle.

[FIGURE 5 HERE]

The upper panel in Figure 5 shows the term structure of return volatilities for the three claims when the variances of the two cycles are in their steady state, i.e. $v_{tran,t} = v_{pers,t} = \bar{v}$. As a starting point of our analysis, we use the preference parameters chosen by Bansal et al. (2012), i.e. $\gamma = 10$ and $\psi = 1.5$, which imply a preference for early resolution of uncertainty. Due to its exposure to the persistent cycle, the late claim has a slightly higher steady state return variance which could easily be offset by varying the claims' local volatilities or the steady state variance of either cycle. The market portfolio is less volatile than the other two claims due to diversification between the two cycles. We also calculate the steady state IVDs of all three claims in line with Equation (1). The steady state IVDs of all three claims are virtually identical and equal to 121.2 days.

We now assume that the persistent cycle is currently in a rather calm state, in particular $v_{pers,t} = 0.9\,\bar{v}$, and set the time t variance of the transitory cycle to

$$v_{tran,t} = \frac{\chi^{l}_{0,12} - \chi^{e}_{0,12} + (\chi^{l}_{pers,12} - \chi^{e}_{pers,12})\, v_{pers,t}}{\chi^{e}_{tran,12} - \chi^{l}_{tran,12}}$$

making the 12-month return variances of the two claims equal to each other.

The lower panel in Figure 5 shows the time t-conditional term structure of return volatilities. By construction, the volatilities of annual returns on the late and early claim are the same, but for shorter horizons, the return volatility of the early claim is higher. At time t, the two claims are a candidate pair for the investment strategy described in Section 3. Taking a look at the IVDs of the different claims, we find that the IVD of the market portfolio is virtually left unchanged, while the IVD of the early (late) claim decreases (increases). Our model highlights the notion that IVD is a temporary characteristic of a claim and cannot be attributed permanently. Claim e is an early claim at time t because of the currently high uncertainty about the cycle that this claim is exposed to. With more cycles (i.e. when $n \gg 2$), there will always be a number of processes that are currently uncertain, relative to the others.

We now analyze the expected returns on the different claims. We again start the discussion with the above preference specification ($\gamma = 10$ and $\psi = 1.5$). The upper graph in Figure 6 shows steady state term structures of expected returns. Unconditionally, the late claim has a higher expected return than the early claim, due to the higher persistence of the cycle that its cash-flows are exposed to. It is important to keep in mind that this claim is also unconditionally more risky (see Figure 5). As in our empirical analysis in Sections 3 and 4, we have to control for risk to make a sensible statement about the early resolution premium.

[FIGURE 6 HERE]

Expected returns, conditional on $v_{tran,t}$ and $v_{pers,t}$ as constructed above, are shown in the lower panel of Figure 6. We find that expected returns on the late claim clearly exceed expected returns on the early claim. This is true for the 12-month horizon, over which the return volatilities are equal, but also for shorter horizons, over which the return volatility of the early claim is higher than that of the late claim. The spread is between 2 and 3 percentage points per year which is also quantitatively large given the moderate spread in IVDs.

[FIGURE 7 HERE]

We now analyze whether this early resolution premium depends on the timing preferences of the investor. Figure 7 shows the spread between expected returns on the late and the early claim for different values of the risk aversion parameter, keeping the elasticity of intertemporal substitution fixed at 1.5. A risk aversion coefficient of $\gamma = \psi^{-1} = 1/1.5$ means that the agent is neutral with respect to the timing of uncertainty resolution. We find that even for higher values of the risk aversion coefficient, the late-minus-early portfolio has a negative expected return. This is because the early claim is actually riskier than the late claim over short horizons. In light of this finding, we conclude that investors seemingly have a pronounced preference for early resolution of uncertainty that causes a sizable early resolution premium as we see it in the data.

5.3 Implied factor structure

The parsimonious version of our model described above, gives rise to a two-factor model. According to Equation (3), the conditional expected excess return on an arbitrary asset j is given by a linear combination of $v_{tran,t}$ and $v_{pers,t}$. The coefficients in this linear combination depend on asset j's exposure to innovations in the two different cycles. One way to estimate these exposures (i.e., betas) in the data is to run regressions of asset j's return on the cycles, which is possible as long as all state variables are observable. In the case of latent state variables, one can alternatively use factor mimicking portfolio returns as independent variables. Natural candidates of such portfolios are claims l and e, because both have exposure to exactly one of the two cycles in our model economy. Denote the coefficients from a regression of asset j's excess return on the excess returns on the late and the early claim by $\beta_{j,l}$ and $\beta_{j,e}$. Then

$$\begin{aligned} \mathbb{E}_t\left[r^j_{t+1} - r^f_{t+1}\right] &\approx \beta_{j,l}\,\mathbb{E}_t\left[r^l_{t+1} - r^f_{t+1}\right] + \beta_{j,e}\,\mathbb{E}_t\left[r^e_{t+1} - r^f_{t+1}\right] \\ &= (\beta_{j,l} + \beta_{j,e})\mathbb{E}_t\left[\frac{1}{2}(r^l_{t+1} + r^e_{t+1}) - r^f_{t+1}\right] + \frac{1}{2}(\beta_{j,l} - \beta_{j,e})\mathbb{E}_t\left[r^l_{t+1} - r^e_{t+1}\right] \end{aligned} \tag{5}$$

The average return $\frac{1}{2}(r^l + r^e)$ can be replaced by the return on the market portfolio, since the two portfolios, the market and the portfolio consisting of claims e and l, have the same exposures to the two cycles. Equation (5) thus shows that we can express the model in terms of a market factor plus a second factor which is the return on a late-minus-early portfolio.

Our model is in line with the augmented CAPM that we use to price IV_{365}/IVD-sorted portfolios in Section 4.5. It should be noted, however, that the rationale of the parsimonious model cannot be applied one-to-one to reality. The LME factor constructed above is first and foremost a factor that quantifies the difference in risk premia paid for exposures to the two cycles. In the data, we consider the difference between late and early resolution stock returns as a factor. In the model, claim e is an early resolution claim at time t only because the cycle it is exposed to is *currently* highly uncertain. In the long-run, its uncertainty is on average not resolved earlier or later than that of the l claim. This is in line with our observation in Section 4.3, that being an early or late resolution stock is a rather transitory characteristic. Once (a part of) the uncertainty is resolved, a stock migrates to a different portfolio.

In a model with $n \gg 2$ cycles, there will always be relatively uncertain and calm cycles, some of which are persistent, while others are rather transitory. Such a model is of course equivalent to an N-factor model and a representation as in Equation (5) can only be an approximation. Constructing LME the way we do it in Section 4.5 can be thought of as follows in the context of our model: The major part of the risk premia paid in the economy at time t is due to the cycles that are currently highly uncertain. By looking at the highest IV quintile only, we reduce the set of factors to those which are the most relevant regarding the early resolution premium. We then split the set of cycles into more persistent and more transitory ones. Stocks in the short leg of the LME portfolio have a strong exposure to one (or a small number of) rather transitory cycles that are currently in a high-risk state. Stocks in the long leg have exposure to other cycles that are currently very uncertain as well, but more persistent. Thus, the LME factor captures variations in those cycles that are currently the most relevant regarding the early resolution premium. Assuming that a single stock's exposure to certain cycles is constant over time, it will only have an exposure to LME in periods in which the respective cycles are particularly uncertain.

As a consequence, a stock's beta with respect to the LME factor must be as time-varying as its IVD. Thus, in an unconditional factor model, LME cannot contribute much to the pricing performance if we use single stocks or the usual sorted portfolios as test assets. The only sensible test assets are IV/IVD sorted portfolios which we use in Section 4.5. The goal of our paper is not to add another factor to the long list of factors that are aimed at pricing standard test assets (such as the 25 Fama-French portfolios). Rather, we show that a particular characteristic of investor preferences leads to a premium in the cross-section of stock returns.

6 Conclusion

We provide empirical evidence for a premium for early resolution of uncertainty. Depending on the approach, this premium is between 5.2 and 7 percent per year and indicates that investors have a preference for early resolution of uncertainty in the sense of Epstein and Zin (1989). As opposed to earlier work, we draw conclusions based on prices of financial assets rather than the behavior of individuals in lab experiments or parameter estimates based on macro or survey data. Because PERU on part of the marginal investor is of great importance in asset pricing and price data is inevitably linked to the preferences of the marginal investor, we believe that our evidence is particularly valuable.

We introduce the duration of implied volatility (IVD) as a novel measure for the timing of uncertainty resolution. Portfolio double sorts with respect to the 365-day implied volatility and IVD result in an average return of the long-short position of more than seven percent for a holding period of one year in the highest implied volatility quintile. We interpret this differential in average returns as a premium for early resolution of uncertainty, since stocks with a short IVD can be interpreted as exhibiting early resolution of uncertainty, while the opposite is true for stocks with a longer IVD. Economically, this means that investors are willing to pay a premium of around seven percent a year to know about the return on their investments earlier.

The return on the above long-short portfolio, which we call the late-minus-early (LME) portfolio, is larger in times of market downturns. In other words, it is particularly in bad times, when investors require compensation for bearing uncertainty for longer. Motivated by the fact that the cross-sectional variation in alphas relative to popular asset pricing models is strongly related to the the interaction between IVD and implied volatility, we augment the standard factor models by the LME factor. It turns out that the augmented factor model prices the double sorted portfolios quite well. Thus, our analysis suggests a risk-based explanation of the early resolution premium.

We propose a general equilibrium model to rationalize these findings. We show that in order to generate a pronounced spread between expected returns on the late and early resolution claim the investor must have a strong preference for early resolution of uncertainty, i.e., the risk-aversion coefficient must exceed the inverse of the elasticity of intertemporal substitution by a sizable amount.

Our findings impose boundaries for the parameters in models of dynamic choice and applications in macro finance. For example, assuming a coefficient of relative risk aversion below 5, implies under a preference for early resolution of uncertainty that the elasticity of intertemporal substitution must be greater than 0.2. This value, however, is at odds with the findings of Hall (1988). On the other hand, Drechsler and Yaron (2011) show that in asset pricing models with long-run risks, market prices of risks have the right sign, if the investor exhibits a preference for early resolution of uncertainty. Such market prices of risk lead to a strongly countercyclical equity risk premium, which is in line with the data (see Martin (2016)). Our results thus support the long-run risk explanation of the large and countercyclical equity risk premium by corroborating one of the key assumptions in these models.

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Table 1: **Returns on investment strategy**

Low IV_{30}	High IV_{30}	Investment strategy
10.86	5.70	5.17
(2.06)	(0.97)	(3.10)

The table shows the average returns on the trading strategy based on pairs. Pairs are formed such that the values for IV_{365} of the two stocks in a pair do not differ by more than one percentage point, while IV_{30} must differ by at least 25 percentage points. The positions are held over the subsequent 12 months. Numbers in parentheses are Newey-West t-statistics with 12 lags. The strategy depends on the order of stocks in our sample (see Appendix A for details). We perform the strategy with 50,000 candidate permutations and report the median return in this table. For all 50,000 permutations, the investment strategy yields significantly positive returns. For more information about the distribution of returns across permutations, see Table C.1 in the appendix.

Table 2: **Investment strategy: factor loadings and alphas**

α	MKT	SMB	HML	RMW	CMA
6.42^{***}	-0.15^{**}				
(3.38)	(-2.38)				
6.54^{***}	-0.15^{***}	-0.11	0.07		
(3.59)	(-3.07)	(-0.82)	(0.64)		
7.71^{***}	-0.22^{***}	-0.15	0.15	-0.15	-0.00
(3.30)	(-2.67)	(-1.12)	(1.40)	(-0.91)	(-0.02)

The table shows the coefficients of a regression of 12-month returns on the investment strategy based on pairs described in Section 3 on the 12-month returns of the following factors: market excess return (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA) (all taken from Kenneth French's website). α denotes the regression intercept and is expressed in percentage points. Numbers in parentheses are Newey-West t-statistics with 20 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 3: **IVD and IV_{365} for double-sorted portfolios**

Panel A: *IVD (in days)*

	Low IVD (early)	2	3	4	High IVD (late)
low IV_{365}	160.05	208.77	211.71	213.73	221.94
2	192.83	208.79	211.70	213.71	220.15
3	194.56	208.78	211.69	213.68	219.57
4	194.85	208.80	211.68	213.66	219.80
high IV_{365}	192.95	208.80	211.67	213.69	218.99

Panel B: IV_{365}

	Low IVD (early)	2	3	4	High IVD (late)
low IV_{365}	0.2202	0.2442	0.2466	0.2461	0.2423
2	0.3345	0.3343	0.3339	0.3330	0.3310
3	0.4212	0.4209	0.4205	0.4197	0.4187
4	0.5336	0.5340	0.5342	0.5336	0.5334
high IV_{365}	0.7809	0.7530	0.7705	0.7868	0.7905

The tables show implied volatility duration (IVD) (computed according to Equation (1)) and 365-day implied volatility (IV_{365}) for 25 portfolios sorted on IV_{365} and IVD. The values shown are the time-series means of the equally weighted means computed at each portfolio formation date. Data are taken from OptionMetrics for the period from January 1996 to December 2015.

Table 4: **Returns on IV_{365}-IVD sorted portfolios**

Panel A: *Value-weighted returns, holding period 12 months*

	low IVD (early)	2	3	4	high IVD (late)	LME
low IV_{365}	9.17***	9.72***	10.25***	10.28***	9.18***	0.00
	(3.13)	(3.27)	(3.59)	(3.93)	(3.27)	(0.00)
2	11.01**	10.86***	12.34***	11.32***	10.95***	−0.06
	(2.4)	(2.80)	(3.49)	(3.20)	(3.01)	(-0.04)
3	11.16*	12.78***	11.78***	12.95***	11.62***	0.46
	(1.87)	(2.65)	(2.69)	(2.96)	(2.77)	(0.17)
4	12.24*	10.92*	11.39*	11.48*	11.23**	−1.01
	(1.69)	(1.72)	(1.86)	(1.93)	(2.25)	(-0.37)
high IV_{365}	4.53	7.56	6.62	11.86	11.70	7.17**
	(0.55)	(0.89)	(0.92)	(1.42)	(1.43)	(1.97)
HML IV	−4.64	−2.16	−3.63	1.59	2.53	
	(-0.68)	(-0.28)	(-0.57)	(0.21)	(0.33)	

Panel B: *Equally-weighted returns, holding period 12 months*

	low IVD (early)	2	3	4	high IVD (late)	LME
low IV_{365}	10.47***	11.47***	11.99***	11.90***	11.47***	1.00*
	(4.32)	(4.12)	(4.35)	(4.40)	(4.39)	(1.65)
2	12.69***	12.63***	12.58***	13.24***	12.40***	−0.29
	(3.78)	(3.78)	(3.85)	(4.22)	(3.94)	(-0.39)
3	12.42***	12.64***	12.77***	13.44***	13.39***	0.97
	(2.93)	(3.29)	(3.42)	(3.72)	(3.72)	(0.59)
4	10.89*	11.02**	11.93**	11.61**	11.40**	0.52
	(1.93)	(2.05)	(2.26)	(2.28)	(2.52)	(0.28)
high IV_{365}	5.29	7.28	6.41	9.19	11.80	6.51***
	(0.67)	(0.95)	(0.91)	(1.24)	(1.59)	(2.97)
HML IV	−5.18	−4.19	−5.58	−2.71	0.33	
	(-0.73)	(-0.59)	(-0.84)	(-0.39)	(0.05)	

Table continues on next page

Panel C: *Value-weighted, holding period 1 month*

	low IVD (early)	2	3	4	high IVD (late)	LME
low IV_{365}	0.76***	0.90***	0.61**	0.72**	0.62**	−0.14
	(2.77)	(3.09)	(2.46)	(2.52)	(2.15)	(-0.71)
2	0.95**	0.81**	1.10***	0.76**	0.79**	−0.16
	(2.33)	(2.08)	(3.12)	(2.07)	(2.00)	(-0.78)
3	0.77	0.94**	1.19***	0.75	0.53	−0.24
	(1.20)	(2.04)	(2.66)	(1.57)	(1.03)	(-0.73)
4	0.99	0.97	0.73	0.52	0.80	−0.19
	(1.47)	(1.48)	(1.07)	(0.75)	(1.06)	(-0.58)
high IV_{365}	−0.22	0.34	0.48	0.66	0.80	1.01**
	(-0.22)	(0.44)	(0.57)	(0.74)	(0.99)	(2.16)
HML IV	−0.98	−0.55	−0.13	−0.06	0.17	
	(-1.19)	(-0.81)	(-0.17)	(-0.07)	(0.24)	

Panel D: *Equally-weighted, holding period 1 month*

	low IVD (early)	2	3	4	high IVD (late)	LME
low IV_{365}	0.93***	0.92***	0.86***	0.87***	0.73***	−0.2**
	(3.77)	(3.55)	(3.27)	(3.36)	(2.83)	(-2.04)
2	1.10***	0.99***	1.06***	0.97***	0.84***	−0.26*
	(3.09)	(3.15)	(3.34)	(3.33)	(2.63)	(-1.67)
3	1.00***	1.05***	0.94***	0.96***	0.74***	−0.27
	(2.27)	(2.68)	(2.66)	(2.59)	(1.88)	(-1.46)
4	0.81	1.03**	0.82	0.80	0.66	−0.15
	(1.48)	(1.96)	(1.53)	(1.54)	(1.16)	(-0.77)
high IV_{365}	0.13	0.31	0.43	0.38	0.83	0.70**
	(0.16)	(0.42)	(0.59)	(0.49)	(1.27)	(2.16)
HML IV	−0.80	−0.61	−0.43	−0.50	0.10	
	(-1.14)	(-0.89)	(-0.64)	(-0.69)	(0.17)	

Twelve month and one month average returns on value-weighted and equally weighted portfolios sorted on IV_{365} and IVD. t-statistics are Newey-West adjusted with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 5: **Realized variance of IV_{365}/IVD sorted portfolios**

Value-weighted returns	12 month holding period					1 month holding period				
	low IVD (early)	2	3	4	high IVD (late)	low IVD (early)	2	3	4	high IVD (late)
low IV_{365}	0.0246	0.0251	0.0244	0.0218	0.0207	0.0015	0.0015	0.0014	0.0015	0.0013
2	0.0588	0.0487	0.0423	0.0441	0.0405	0.0035	0.0030	0.0027	0.0026	0.0027
3	0.1046	0.0801	0.0698	0.0685	0.0618	0.0067	0.0050	0.0047	0.0048	0.0050
4	0.1544	0.1324	0.1258	0.1235	0.0940	0.0109	0.0099	0.0090	0.0085	0.0090
high IV_{365}	0.2077	0.2283	0.1652	0.2451	0.2225	0.0187	0.0170	0.0149	0.0141	0.0144

Equally weighted returns	12 month holding period					1 month holding period				
	low IVD (early)	2	3	4	high IVD (late)	low IVD (early)	2	3	4	high IVD (late)
low IV_{365}	0.0179	0.0228	0.0224	0.0218	0.0195	0.0013	0.0014	0.0014	0.0014	0.0012
2	0.0361	0.0342	0.0336	0.0308	0.0307	0.0027	0.0024	0.0026	0.0022	0.0022
3	0.0629	0.0497	0.0490	0.0447	0.0445	0.0045	0.0040	0.0038	0.0036	0.0034
4	0.1054	0.0954	0.0951	0.0890	0.0745	0.0086	0.0073	0.0076	0.0066	0.0065
high IV_{365}	0.2062	0.1927	0.1637	0.1834	0.1858	0.0159	0.0139	0.0132	0.0120	0.0121

The table shows realized variance of the IV/IVD-sorted portfolios held over one and twelve months.

Table 6: **LME portfolio: alphas and factor loadings**

α	MKT	SMB	HML	RMW	CMA
1.19^{***}	-0.33^{***}				
(2.80)	(-3.09)				
1.06^{**}	-0.29^{***}	0.10	0.43^{**}		
(2.57)	(-2.59)	(0.60)	(2.32)		
0.90^{**}	-0.20	0.14	0.24	0.19	0.29
(2.13)	(-1.46)	(0.81)	(0.79)	(0.61)	(0.84)

The table shows the coefficients of a regression of 1-month returns on the LME portfolio on the following factors: market excess return (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA) (all taken from Kenneth French's website). α denotes the regression intercept and is expressed in percentage points. Numbers in parentheses are Newey-West t-statistics with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 7: **Stocks in the high IV_{365} quintile**

Panel A: *Characteristics*

	low IVD (early)	2	3	4	high IVD (late)	full sample
IVD	192.95	208.8	211.67	213.69	218.98	211.72
IV_{365}	0.7809	0.7530	0.7705	0.7868	0.7905	0.4191
ME (in US-$ mill)	924	657	610	560	662	1234
BM	0.6829	0.5873	0.5769	0.6297	0.6273	0.4376
OP	-0.047	-0.1594	-0.0278	0.0807	-0.0063	0.2238
INV	0.5104	0.4478	0.4335	0.3856	0.3512	0.0908
ILLIQ$\times 10^5$	0.2955	0.3144	0.3335	0.3675	0.3350	0.0816
CFD	23.22	22.98	22.40	23.45	21.60	21.45
IVol	0.0408	0.0385	0.0372	0.0373	0.0342	0.0189
VRP_{30} (ex-ante)	-0.0109	0.0016	-0.0001	0.0022	0.0028	-0.0011
VRP_{30} (realized)	-0.0138	-0.0022	0.0002	0.0007	0.0030	-0.0010
SIR_{IO}	0.5626	0.5806	0.6110	0.5908	0.5951	0.0543

Panel B: *Portfolio betas*

	low IVD (early)	2	3	4	high IVD (late)
MKT	1.6937	1.6848	1.4929	1.3768	1.4809
SMB	0.5548	0.7479	0.7497	0.8359	0.6881
HML	-0.2066	-0.1208	-0.218	-0.3456	0.0469
RMW	-1.4876	-1.0487	-1.3070	-1.2417	-1.3154
CMA	-0.5665	-0.8176	-0.4999	-0.3720	-0.2744
LIQ	-0.1787	-0.2052	0.0722	-0.0626	-0.1170

The table shows characteristics of the stocks in the high IV_{365} quintile. All numbers in the columns early, 2, 3, 4 and late are equally weighted averages across stocks and time. ME is market equity, BM is the ratio of book to market equity, OP is operating profitability as defined in Davis et al. (2000), INV is investment as defined in Fama and French (2015). ILLIQ is illiquidity in the sense of Amihud and Brennan et al. (2013) applied to monthly data, in particular we have $ILLIQ_t = \frac{|r_t|}{Vol_t}$ where Vol_t is the turnover in month t. CFD is Dechow et al.'s (2004) estimate of stocks' cash-flow duration using the parameter estimates from Weber (2016). IVol is idiosyncratic return volatility relative to the Fama and French (1992) three factor model, computed as the daily standard deviation of the residuals from the model. VRP is the equally weighted average of our measure of the monthly variance risk premium, computed either ex ante as the difference $\mathbb{V}\text{ar}(r_{t,30}) - \text{IV}^2_{t,30}$ or realized as $\mathbb{V}\text{ar}(r_{t+1,30}) - \text{IV}^2_{t,30}$. SIR_{IO} serves as a proxy for shorting fees and is the ratio of short interest over institutional ownership as computed in Drechsler and Drechsler (2016). With the exception of LIQ, following the procedure in An et al. (2014), the factors MKT, SMB, HML, RMW CMA were constructed using stock returns from our sample. Liquidity (LIQ) is taken from Robert Stambaugh's website. The column labeled 'full sample' shows the time series mean over the monthly cross-sectional medians of the full sample.

Table 8: **Portfolio migration**

Panel A: *All* IV_{365} *quintiles*

to / **from**	low IVD (early)	2	3	4	high IVD (late)
low IVD	0.4591	0.2085	0.1254	0.0983	0.1087
2	0.1892	0.2638	0.2374	0.1842	0.1253
3	0.1335	0.2250	0.2622	0.2394	0.1400
4	0.1071	0.1792	0.2386	0.2920	0.1831
high IVD	0.1115	0.1217	0.1325	0.1841	0.4502

Panel B: *Top* IV_{365} *quintile*

to / **from**	low IVD (early)	2	3	4	high IVD (late)
low IVD	0.4428	0.2015	0.1452	0.1066	0.1040
2	0.1938	0.2626	0.2490	0.1791	0.1155
3	0.1620	0.2231	0.2691	0.2151	0.1308
4	0.1306	0.1748	0.2354	0.2883	0.1709
high IVD	0.1558	0.1370	0.1501	0.1997	0.3575

The table shows the relative frequency of migrating from the IVD quintile portfolio i to IVD portfolio j in line i and column j. Panel A shows this information unconditional on being in a particular IV_{365} quintile portfolio before switching. Panel B shows this information conditional on being in the top IV_{365} quintile portfolio before switching.

Table 9: **Fama-MacBeth regressions**

	MKT	SMB	HML	RMW	CMA	$IV^2 \times IVD$
CAPM	0.47					
	(1.32)					
	0.47					0.05^{***}
	(1.32)					(2.67)
FF3	0.65^{*}	-0.09	-0.32			
	(1.86)	(-0.39)	(-0.97)			
	0.65^{*}	-0.09	-0.32			0.04^{***}
	(1.86)	(-0.38)	(-0.97)			(2.63)
FF5	0.63^{*}	0.09	-0.25	0.71	-0.23	
	(1.80)	(0.44)	(-0.75)	(1.65)	(-0.50)	
	0.63^{*}	0.09	-0.24	0.71	-0.23	0.05^{***}
	(1.79)	(0.44)	(-0.74)	(1.66)	(-0.49)	(2.69)

The table shows the coefficients from a second stage Fama-MacBeth-regression of single stock returns on the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) (all computed from our sample using the Compustat-CRSP merged database) and the stock characteristic $IVD \times IV^2_{365}$. Numbers in parentheses are Newey-West t-statistics with four lags. Characteristics are demeaned. For the first stage regressions, the betas assigned to each stock are the average value-weighted betas for the respective IV-and-IVD portfolio. FF3 and FF5 denote the model specification from Fama and French (1996) and Fama and French (2015), respectively. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 10: **Market prices of risk**

	MKT	SMB	HML	RMW	CMA	LME	$R^2_{adj.}$
CAPM	0.31						-0.86
	(0.87)						
	0.35					0.95***	-0.28
	(0.97)					(3.14	
FF3	0.57*	−0.29	−0.38				-0.13
	(1.65)	(−0.72)	(−0.63)				
	0.60*	−0.32	−0.06			0.71**	0.42
	(1.74)	(−0.79)	(−0.09)			(2.36)	
FF5	0.56*	0.14	0.24	0.43	0.17		0.01
	(1.59)	(0.30)	(0.35)	(0.99)	(0.51)		
	0.52	0.41	−0.48	0.59	−0.55	0.78**	0.57
	(1.48)	(0.88)	(−0.71)	(1.33)	(−1.37)	(2.55)	

The table shows the coefficients from a second stage Fama-MacBeth-regression of portfolio returns on the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) and our LME factor. All factors are computed from our sample using the Compustat-CRSP merged database. For the first-stage regressions, the betas assigned to each stock are the average value-weighted betas for the respective 365 day IV-and-IVD portfolio. FF3 and FF5 denote the model specification from Fama and French (1992) and Fama and French (2015), respectively. The numbers in parentheses are Newey-West-t-statistics with four lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 11: **Characteristic versus LME**

	MKT	SMB	HML	RMW	CMA	$IV^2 \times IVD$	LME
CAPM	0.34					0.05^{**}	
	(1.06)					(2.32)	
	0.39					0.01	0.91^{***}
	(1.23)					(0.60)	(2.81)
FF3	0.69^{**}	-0.45	-0.41			0.05^{**}	
	(2.15)	(-1.25)	(-1.35)			(2.45)	
	0.69^{**}	-0.34	-0.32			0.02	0.47^{*}
	(2.17)	(-0.98)	(-0.98)			(1.30)	(1.95)
FF5	0.65^{**}	0.17	0.11	0.66^{**}	-0.02	0.04^{**}	
	(2.02)	(0.58)	(0.29)	(2.06)	(-0.08)	(2.26)	
	0.62^{**}	0.38	-0.59	0.71^{**}	-0.44^{**}	0.02	0.51^{**}
	(1.94)	(1.38)	(-1.43)	(2.20)	(-2.17)	(1.34)	(1.9783)

The table shows coefficients from a second stage Fama-MacBeth-regression of single stocks on various factors and $IVD \times IV_{365}^2$ as a stock characteristic. The characteristic is demeaned. All factors are computed from the sample using the Compustat-CRSP merged database. For the first stage regressions, the betas assigned to each stock are the average value-weighted betas for the respective portfolio resulting from a 5×5 double sort on IV_{365} and IVD. FF3 and FF5 denote the model specification from Fama and French (1996) and Fama and French (2015), respectively. The numbers in parentheses are Newey-West t-statistics with four lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 12: **Model parameters**

Preferences	δ	ψ	γ	
	$-\log(.998)$	1.5	1-10	
Cycles		ρ_{tran}	ρ_{pers}	
		.98	.99	
Volatility	$\bar{v}$	ρ_v		σ_v
	$(.044 \cdot .0078)^2$	.9		$.044^2 \cdot .23 \cdot 10^{-5}$
Consumption	μ_c	$\phi_{c,tran}$	$\phi_{c,pers}$	σ_c
	.0015	$1/\sqrt{2}$	$1/\sqrt{2}$	.0078
Market claim	μ_m	$\phi_{m,tran}$	$\phi_{m,pers}$	σ_m
	.0015	$3/\sqrt{2}$	$3/\sqrt{2}$	$4.5 \cdot .0078$
Early claim	μ_e	$\phi_{e,tran}$	$\phi_{e,pers}$	σ_e
	.0015	$6/\sqrt{2} - \phi_{c,tran}/\psi$	$\phi_{c,tran}/\psi$	$4.5 \cdot .0078$
Late claim	μ_l	$\phi_{l,tran}$	$\phi_{l,pers}$	σ_l
	.0015	$\phi_{c,pers}/\psi$	$6/\sqrt{2} - \phi_{c,pers}/\psi$	$4.5 \cdot .0078$

The tables shows the model parameters that we use to calibrate the parsimonious model described in Sections 5.1 and 5.2.

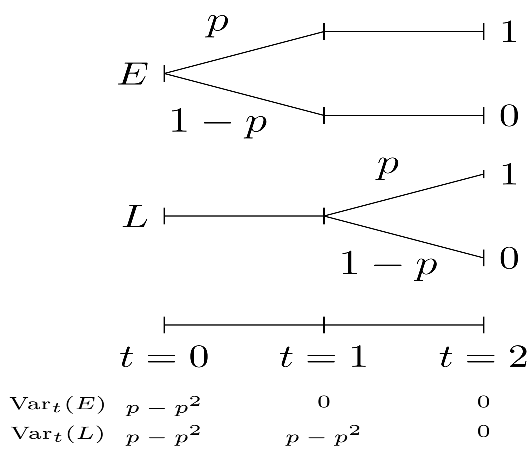


Figure 1: Stylized depiction of a late and early resolution claim

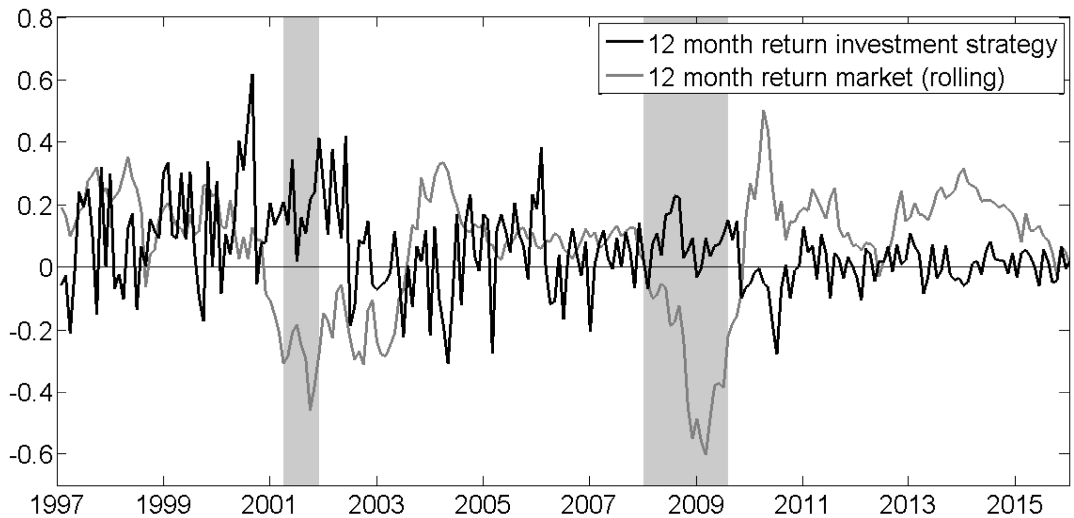
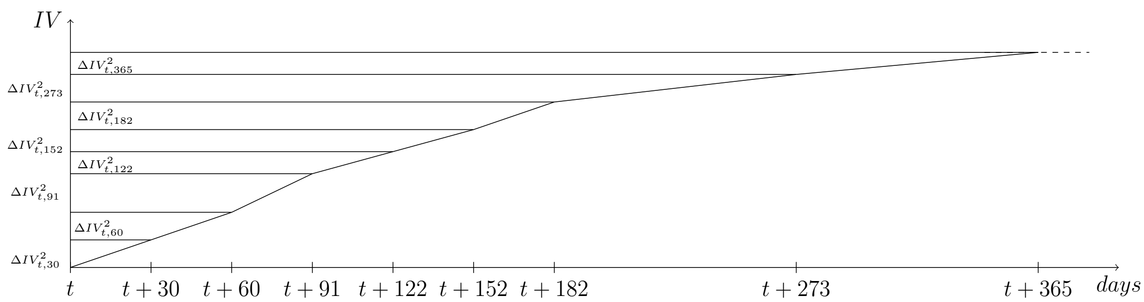
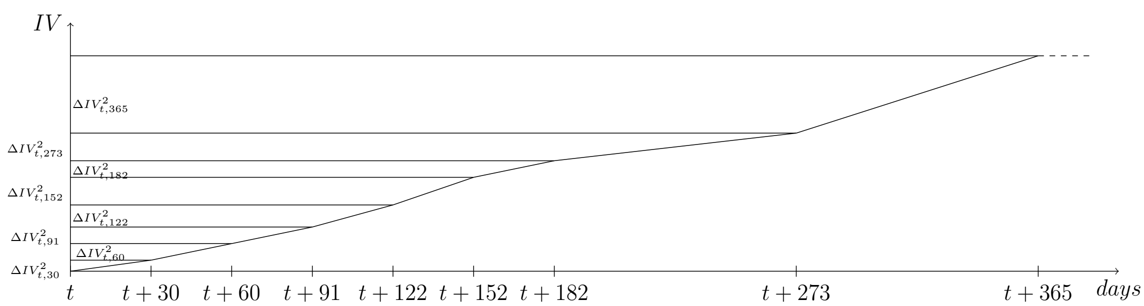


Figure 2: Returns on the market and on the investment strategy based on pairs. The areas shaded in gray denote NBER recessions.



Panel A: Low IVD, early resolution of uncertainty



Panel B: High IVD, late resolution of uncertainty

Figure 3: Graphical representation of IVD

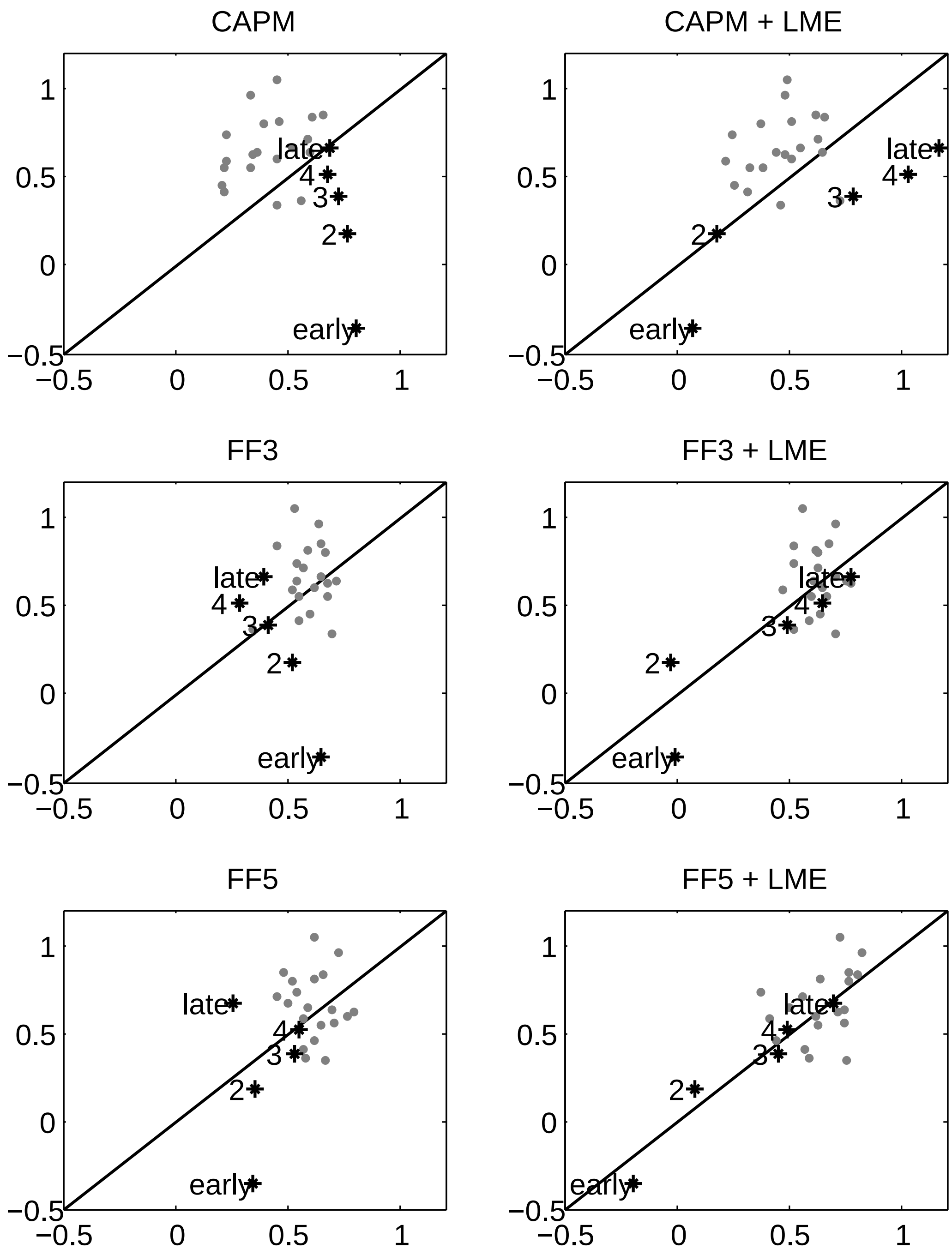


Figure 4: This figure plots model-implied expected returns (on the horizontal axis) against average realized returns (on the vertical axis) on 25 portfolios sorted independently based on IV_{365} and IVD. The left column of graphs shows the CAPM, the Fama and French (1993) three factor model, and the Fama and French (2015) five factor model. The right column shows the respective models augmented by LME. The black stars indicate the five IVD portfolios in the top IV_{365} quintile.

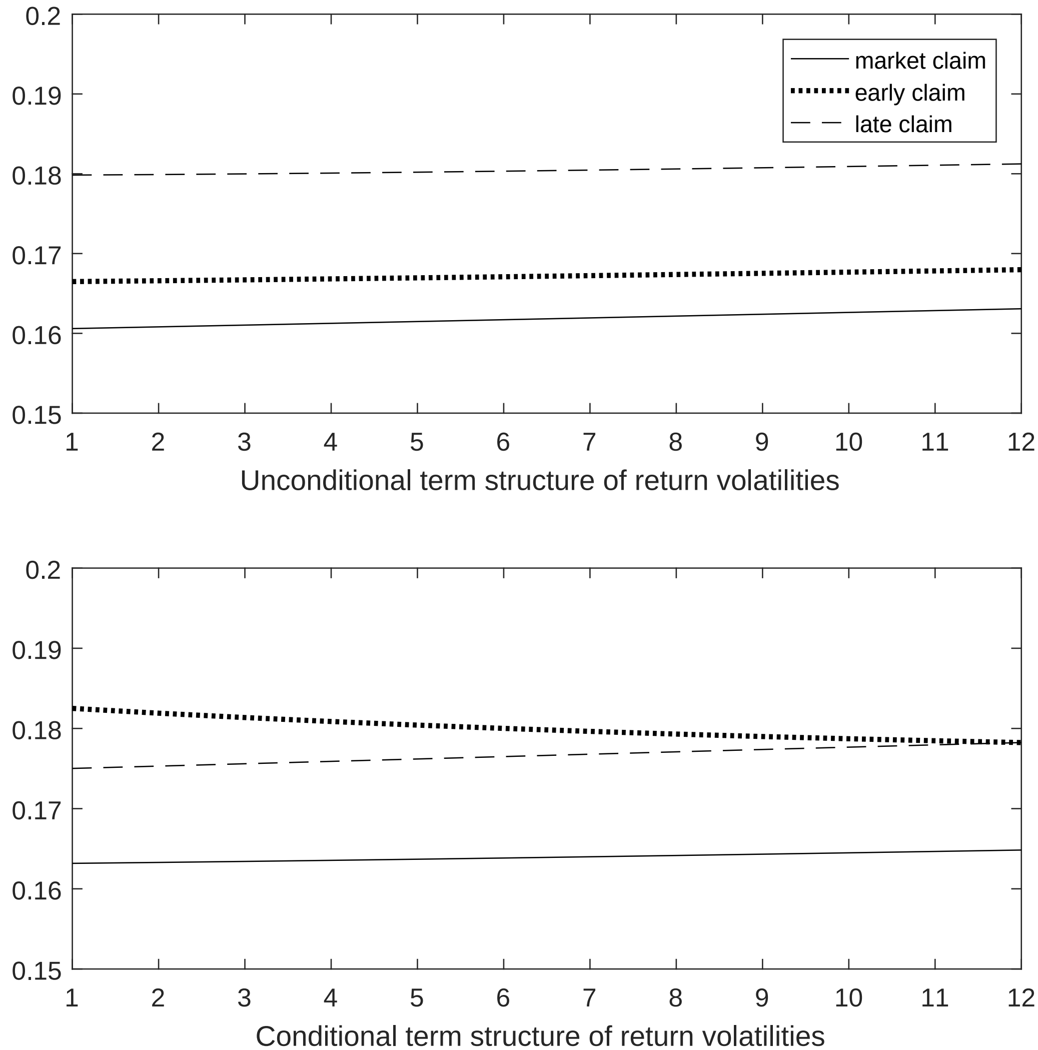


Figure 5: This figure shows model-implied term structures of return volatilities. The return horizon is expressed in months. Return volatilities are expressed in annual terms. The upper figure shows unconditional term structures, i.e. all variance processes are at their steady state values at time 0. The lower figure shows conditional term structures, given that the time 0 values of the state variables are chosen as explained in Section 5.

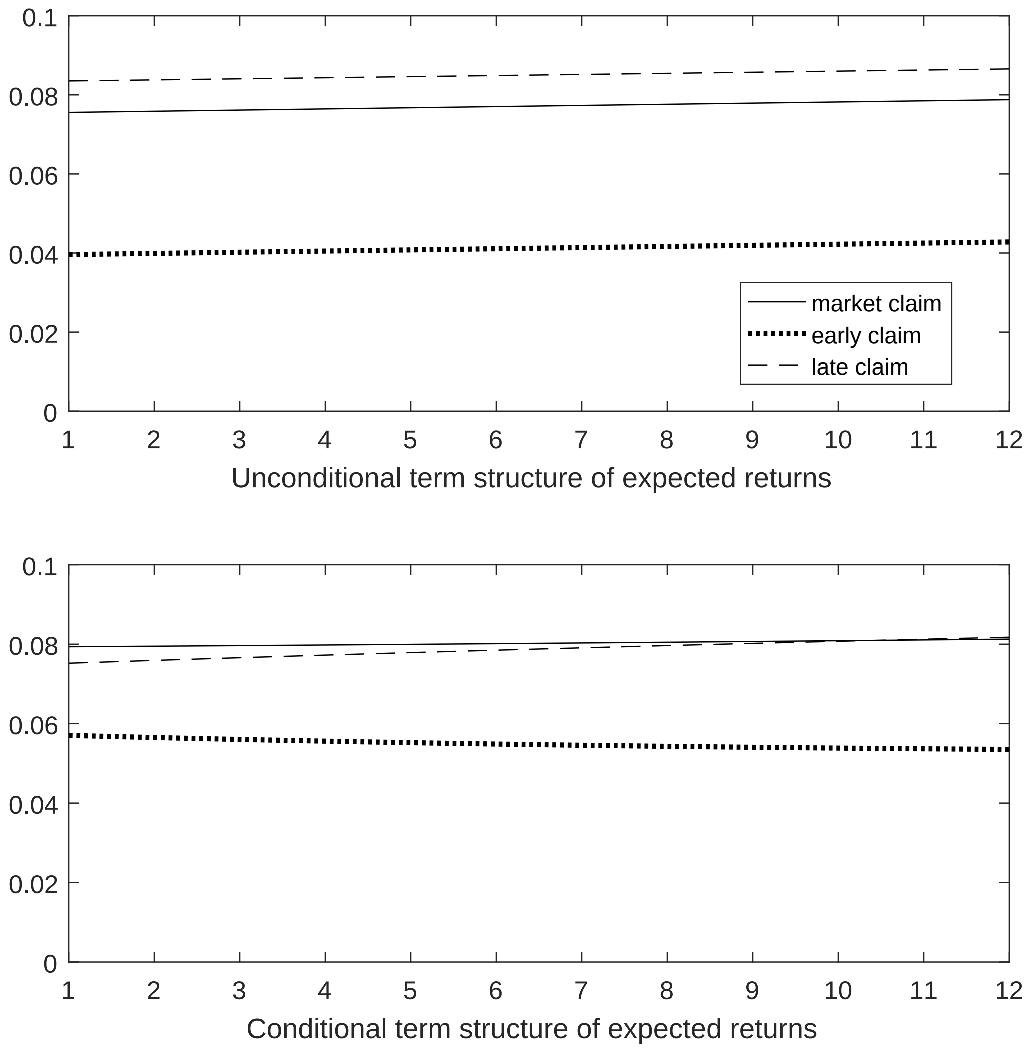


Figure 6: This figure shows model-implied term structures of expected returns. The return horizon is expressed in months. Expected returns are expressed in annual terms. The upper figure shows unconditional term structures, i.e. all variance processes are at their steady state values at time 0. The lower figure shows conditional term structures, given that the time 0 values of the state variables are chosen as explained in Section 5.

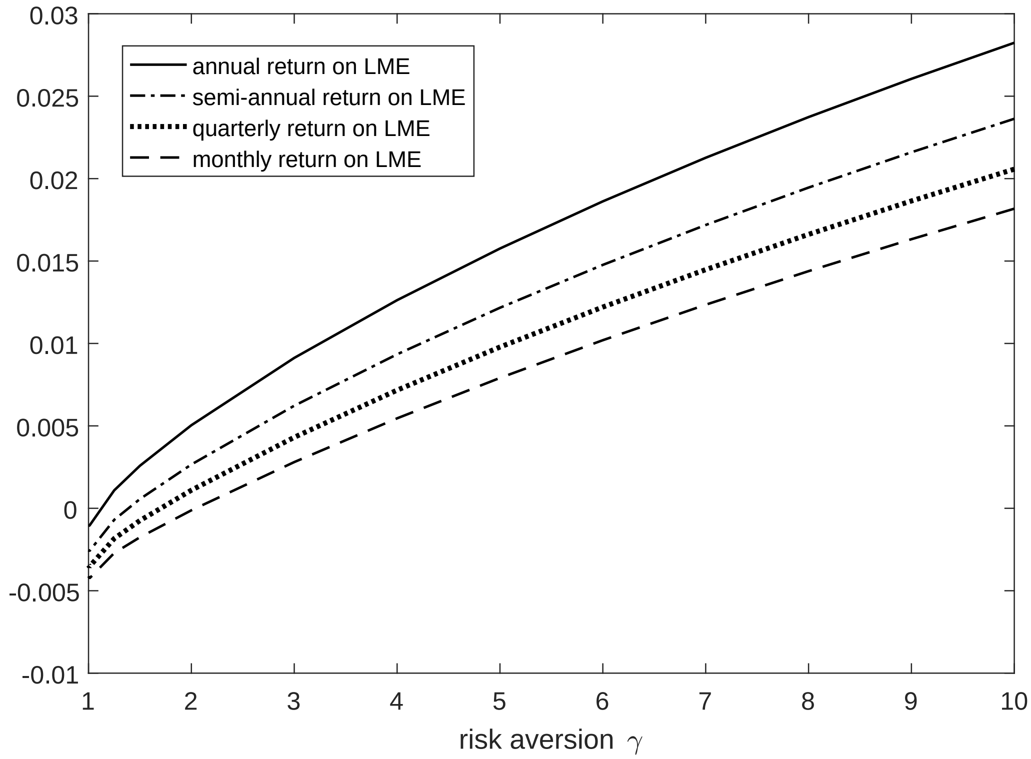


Figure 7: This figure shows the model-implied expected spread between the return on the late and the early claim. Expected returns are expressed in annual terms. The elasticity of intertemporal substitution is set to 1.5 and risk aversion γ varies from 1 to 10. All other parameters are shown in Table 12.

A Details on the investment strategy

This appendix provides further details on the trading strategy described in Section 3. To find pairs of early and late resolution stocks, we proceed as follows:

1. We put stocks in our sample in a random order.
2. Starting with the first stock, we identify all stocks with an IV_{365} differing from the original stock's IV_{365} by no more than 0.01 in absolute value.
3. From this set of stocks, we select the one whose IV_{30} differs most in absolute value from the original stock's IV_{30}. If this difference is larger than 0.25, we add this pair to the sample of pairs for the given month. We exclude the two stocks from the list of candidates.
4. We repeat step 2 with the second stock on the list of candidates and continue until all stocks have been considered.

Obviously, putting stocks in a different order may result in a different set of pairs, since a stock that is excluded from the list of candidate matches is no longer available for other stocks considered later. Still, we have to exclude the matched stock, because we do not want to allow a stock to appear more than once in the sample for a given month, since otherwise a small number of stocks with special characteristics might drive the results.

To test if the success of the strategy depends on the order in which we consider the stocks in the base sample, we rerun the strategy 50,000 times with the order of the stocks being chosen randomly. Tables 1 and 2 report the strategy with the median average return. In all of the 50,000 cases the average return on the investment strategy is significantly positive. Table C.1 contains means, medians and 95% confidence bounds from these 50,000 strategies.

[TABLE C.1 HERE]

We also vary the critical values for the IV differences in the process of identifying pairs described above. Table C.2 shows the results of this robustness check.

We show portfolio return for minimum IV_{30} spreads of 5%, 10%, . . . , 35% and for maximum IV_{365} spreads of 1% (Panel A) and 0.1% (Panel B). In general, the strategy is very robust and becomes more profitable when more extreme spreads are chosen. For example, choosing a maximum IV_{365} difference of 1% and a minimum IV_{30} difference of 35% results in average returns of 7.65% with a *t*-statistic of 3.46. For some calibrations there can be months in which not a single pair meets the requirements. In particular this happens for the calibrations where the difference in IV_{365} has to be below 1% (and 0.1%) and the difference in IV_{30} has to be above 35% in December 2003. In this month, we assume that there is simply no investment at all and the return is zero.

[TABLE C.2 HERE]

We also perform a placebo test and check if the result holds if there is no restriction on the maximum spread in IV_{365}, i.e. whether the whole result is driven by the differences in IV_{30} (Panel C). This is not the case. The returns on the investment strategy without matched IV_{365} are all insignificant.

Table C.3 shows that the strategy is robust to variation in the time to maturity in the long end. Using 270 day or 180 days options yields results similar to the original strategy. Using 60 day options on the short end even amplifies the effect. With 90 days options on the short end, returns are still large but insignificant.

[TABLE C.3 HERE]

B General Equilibrium Model

B.1 The pricing kernel

The general Epstein and Zin (1989) utility log pricing kernel that discounts cash flows at time $t+1$ is given by

$$m_{t\to t+1} = -\delta\theta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta-1)r^w_{t+1} \tag{B.1}$$

where r^w_{t+1} denotes the return on the claim on total wealth (the claim that pays aggregate consumption as dividend) and $\theta = (1-\gamma)/(1-\psi^{-1})$. We will use the convention that whenever there is only one time index attached to the pricing kernel or a return, it denotes the one-period random variable that realizes at the indexed point in time, i.e. $m_{t+\tau} = m_{t+\tau-1\to t+\tau}$ and $r_{t+\tau} = r_{t+\tau-1\to t+\tau}$. The return on total wealth can be approximated in terms of the yet unknown log wealth-consumption ratio wc which we conjecture to be affine in the $2n$ state variables, i.e.,

$$wc_t = A_0 + \sum_{i=1}^{n} A_{x_i} x_{i,t} + \sum_{i=1}^{n} A_{v_i} v_{i,t}. \tag{B.2}$$

The Campbell-Shiller approximation for r^w_t yields

$$r^w_{t+1} \approx \kappa_{wc,0} + \kappa_{wc,1} wc_{t+1} - wc_t + \Delta c_{t,t+1} \tag{B.3}$$

with coefficients

$$\begin{aligned}\kappa_{wc,1} &= \frac{\exp(\bar{wc})}{1+\exp(\bar{wc})}\\ \kappa_{wc,0} &= \ln\left(1+\exp(\bar{wc})\right) - \frac{\exp(\bar{wc})}{1+\exp(\bar{wc})}\bar{wc},\end{aligned}$$

where $\bar{wc}$ denotes the steady state log wealth-consumption ratio.

In order to determine wc, plug (B.1) and (B.3) into the Euler equation to get

$$1 = \mathbb{E}_t\left[e^{m_{t+1}+r^w_{t+1}}\right] = E_t\left[e^{-\delta\theta - \frac{\theta}{\psi}\Delta c_{t,t+1} + \theta(\kappa_{wc,0}+\kappa_{wc,1}wc_{t+1}-wc_t+\Delta c_{t,t+1})}\right] \tag{B.4}$$

Plugging conjecture (B.2) for the wealth consumption ratio into Equation (B.4) yields a system of linear equations with solution

$$\begin{aligned}A_0 &= \frac{1}{1-\kappa_{wc,1}}\Bigg[-\delta + \kappa_{wc,0} + (1-\rho_v)\kappa_{wc,1}\,\bar{v}\sum_{i=1}^{n} A_{v_i} + (1-\psi^{-1})\mu_c\\ &\qquad + \frac{1}{2}\theta\left(\kappa^2_{wc,1}\sigma^2_v\sum_{i=1}^{n} A^2_{v_i} + (1-\psi^{-1})^2\sigma^2_c\right)\Bigg],\\ A_{x_i} &= \frac{(1-\psi^{-1})\phi_{ci}}{1-\kappa_{wc,1}\rho_i},\\ A_{v_i} &= \frac{1}{2}\theta\,\frac{(A_{x_i}\kappa_{wc,1})^2}{1-\kappa_{wc,1}\rho_{vi}}.\end{aligned}$$

Using these coefficients yields the pricing kernel representation

$$-m_{t+1} = m_0 + \sum_{i=1}^{n}(m_{x_i}x_{i,t} + m_{v_i}v_{i,t}) + \lambda_c\sigma_c\varepsilon_c + \sum_{i=1}^{n}(\lambda_{x_i}\sqrt{v_{i,t}}\varepsilon^i_{t+1} + \lambda_{v_i}\sigma_v\varepsilon^{vi}_{t+1})$$

with coefficients

$$
\begin{aligned}
m_0 &= \delta\theta + \gamma\mu_c + (1-\theta)\left(\kappa_{wc,0} + (\kappa_{wc,1}-1)A_0 + (1-\rho_v)\,\kappa_{wc,1}\bar{v}\sum_{i=1}^{n} A_{v_i}\right), \\
m_{x_i} &= (1-\theta)A_{x_i}(\kappa_{wc,1}\rho_i - 1) + \gamma\phi_{ci} = \phi_{ci}/\psi, \\
m_{v_i} &= (1-\theta)A_{v_i}(\kappa_{wc,1}\rho_{vi} - 1)
\end{aligned}
$$

that determine the conditional expected log pricing kernel and market prices of risk that are given by

$$
\begin{aligned}
\lambda_c &= \gamma, \\
\lambda_{x_i} &= (1-\theta)\,\kappa_{wc,1}\,A_{x_i}, \\
\lambda_{v_i} &= (1-\theta)\,\kappa_{wc,1}\,A_{v_i}.
\end{aligned}
$$

B.2 Price-dividend ratios

As before with the return on wealth, we linearize the return r^j on dividend claim d^j using the Campbell Shiller approximation which yields

$$
r^j_{t+1} \approx \kappa_{pd,j,0} + \kappa_{pd,j,1} pd_{j,t+1} - pd_{j,t} + \Delta d^j_{t+1}. \tag{B.5}
$$

where $pd_{j,t}$ denotes the time t price-dividend ratio of asset j. The coefficients are given by

$$
\begin{aligned}
\kappa_{pd,j,1} &= \frac{\exp(\bar{pd}_j)}{1+\exp(\bar{pd}_j)} \\
\kappa_{pd,j,0} &= \ln\left(1+\exp(\bar{pd}_j)\right) - \frac{\exp(\bar{pd}_j)}{1+\exp(\bar{pd}_j)}\bar{pd}_j,
\end{aligned}
$$

where $\bar{pd}_j$ is the steady state of pd_j. We conjecture that the price dividend ratio is affine in the state variables:

$$
pd_{i,t} = B_{j,0} + \sum_{i=1}^{n} B_{j,x_i} x_{i,t} + \sum_{i=1}^{n} B_{j,v_i} v_{i,t} \tag{B.6}
$$

Proceeding in the same fashion as before with the wealth-consumption ratio yields a system of linear equations with solution

$$
\begin{aligned}
B_{j,0} &= \frac{1}{1-\kappa_{pd,j,1}}\Bigg[-\delta\theta - (1-\theta)\left(\kappa_{wc,0} + (\kappa_{wc,1}-1)A_0 + (1-\rho_v)\kappa_{wc,1}\bar{v}\sum_{i=1}^{n} A_{v_i}\right) - \gamma\mu_c + \kappa_{pd,j,0} + \mu_j \\
&\qquad + \frac{1}{2}(\gamma^2\sigma_c^2 + \sigma_j^2) + \sum_{i=1}^{n}\left((1-\rho_v)\kappa_{pd,j,1}\bar{v}B_{j,v_i} + \frac{1}{2}\Big(\kappa_{pd,j,1}B_{j,v_i} - (1-\theta)\kappa_{wc,1}A_{v_i}\Big)^2\sigma_v^2\right)\Bigg], \\
B_{j,x_i} &= \frac{\phi_{ji} - \psi^{-1}\phi_{ci}}{1-\kappa_{pd,j,1}\rho_i}, \\
B_{j,v_i} &= \frac{1}{2}\,\theta\,\frac{(B_{j,x_i}\kappa_{pd,j,1})^2}{1-\kappa_{pd,j,1}\rho_{vi}} + \frac{1}{2}(1-\theta)\frac{(A_{x_i}\kappa_{wc,1} - B_{j,x_i}\kappa_{pd,j,1})^2}{1-\kappa_{pd,j,1}\rho_{vi}}.
\end{aligned}
$$

Note that $B_{j,x_i} = 0$ whenever $\phi_{ji} = \psi^{-1}\phi_{ci}$, as argued in Section 5.2.

B.3 Term structure of expected excess returns

Using Equation (B.5), we write the log return on asset j as

$$r^j_{t+1} = r^j_0 + \sum_{i=1}^{n} r^j_{x_i}\, x_{i,t} + \sum_{i=1}^{n} r^j_{v_i}\, v_{i,t} + \sigma_j \varepsilon^j_{t+1} + \sum_{i=1}^{n} \beta_{j,x_i} \sqrt{v_{i,t}} \varepsilon^i_{t+1} + \sum_{i=1}^{n} \beta_{j,v_i} \sigma_v \varepsilon^{vi}_{t+1}$$

where

$$\begin{aligned} r^j_0 &= \kappa_{pd,j,0} + \mu_j + (\kappa_{pd,j,1} - 1) B_{j,0} + (1-\rho_v)\kappa_{pd,j,1} \bar{v} \sum_{i=1}^{n} B_{j,v_i} \\ r^j_{x_i} &= (\kappa_{pd,j,1}\rho_i - 1) B_{j,x_i} + \phi_{ji} = \phi_{ci}/\psi = m_{x_i} \\ r^j_{v_i} &= (\kappa_{pd,j,1}\rho_v - 1) B_{j,v_i} \\ \beta^j_{x_i} &= \kappa_{pd,j,1} B_{j,x_i} \\ \beta^j_{v_i} &= \kappa_{pd,j,1} B_{j,v_i} \end{aligned}$$

We inductively calculate the coefficients $\pi^j_{0,\tau}$ and $\pi^j_{i,\tau}$ of the term structure of expected returns on asset j according to Equation 3. We start with

$$E_t[r^j_{t+1} - r^f_{t+1}] + \frac{1}{2} Var_t(r^j_{t+1})] = Cov_t(-m_{t+1}, r^j_{t+1}) = \sum_{i=1}^{n} \beta^j_{x_i} \lambda_{x_i} v_{i,t} + \sum_{i=1}^{n} \beta^j_{v_i} \lambda_{v_i} \sigma^2_v, \tag{B.7}$$

such that $\pi^j_{0,1} = \sum_{i=1}^{n} \beta^j_{v_i} \lambda_{v_i} \sigma^2_v$ and $\pi^j_{i,1} = \beta^j_{x_i} \lambda_{x_i}$. For the induction step, note that

$$E_t[r^j_{t\to t+\tau} - r^f_{t\to t+\tau}] + \frac{1}{2} Var_t(r^j_{t\to t+\tau}) = Cov_t(-m_{t\to t+\tau}, r^j_{t\to t+\tau}) \tag{B.8}$$

where $m_{t,t+\tau} = m_{t+1} + \cdots + m_{t+\tau}$ and $r^j_{t\to t+\tau} = r^j_{t+1} + \cdots + r^j_{t+\tau}$. Assume we already know

$$Cov_t(-m_{t\to t+\tau-1}, r^j_{t\to t+\tau-1}) = \pi^j_{0,\tau-1} + \sum_{i=1}^{n} \pi^j_{i,\tau-1} v_{i,t}.$$

We can decompose the expected excess return over τ periods into

$$\begin{aligned} Cov_t(-m_{t\to t+\tau}, r^j_{t\to t+\tau}) = &\sum_{h_1,h_2=2}^{\tau} Cov_t(-m_{t+h_1}, r^j_{t+h_2}) + \sum_{h=2}^{\tau} Cov_t(-m_{t+h}, r^j_{t+1}) \\ &+ \sum_{h=2}^{\tau} Cov_t(-m_{t+1}, r^j_{t+h}) + Cov_t(-m_{t+1}, r^j_{t+1}). \end{aligned} \tag{B.9}$$

The first term on the right-hand side of Equation (B.9) can be written as

$$\begin{aligned} &\sum_{h_1,h_2=2}^{\tau} Cov_t(-m_{t+h_1}, r^j_{t+h_2}) \\ &= \sum_{h_1,h_2=2}^{\tau} \left(E_t\left[Cov_{t+1}(-m_{t+h_1}, r^j_{t+h_2}) \right] + Cov_t\left(E_{t+1}[-m_{t+h_1}], E_{t+1}[r^j_{t+h_2}] \right) \right) \end{aligned} \tag{B.10}$$

where

$$\sum_{h_1,h_2=2}^{\tau} E_t\left[Cov_{t+1}(-m_{t+h_1}, r^j_{t+h_2})\right] = \pi^j_{0,\tau-1} + (1-\rho_v)\bar{v}\sum_{i=1}^{n}\pi^j_{i,\tau-1} + \rho_v\sum_{i=1}^{n}\pi^j_{i,\tau-1}v_{i,t}.$$

For the second term on the right-hand side of Equation (B.10), assume that we already know

$$\sum_{h_1,h_2=2}^{\tau-1} Cov_t\left(E_{t+1}[-m_{t+h_1}], E_{t+1}[r^j_{t+h_2}]\right) = \xi^j_{0,\tau-1} + \sum_{i=1}^{n}\xi^j_{i,\tau-1}v_{i,t},$$

where we start at $\tau = 1$ with $\xi^j_{0,1} = 0$ and $\xi^j_{i,1} = 0$ for all $i = 1, \ldots, n$. Then, we can calculate

$$\begin{aligned}
&\sum_{h_1,h_2=2}^{\tau} Cov_t\left(E_{t+1}[-m_{t+h_1}], E_{t+1}[r^j_{t+h_2}]\right) \\
&\quad = \sum_{h_1,h_2=3}^{\tau} Cov_t\left(E_{t+1}[-m_{t+h_1}], E_{t+1}[r^j_{t+h_2}]\right) + \sum_{h=2}^{\tau} Cov_t\left(E_{t+1}[-m_{t+h}], E_{t+1}[r^j_{t+2}]\right) \\
&\qquad + \sum_{h=2}^{\tau} Cov_t\left(E_{t+1}[-m_{t+2}], E_{t+1}[r^j_{t+h}]\right) - Cov_t\left(E_{t+1}[-m_{t+2}], E_{t+1}[r^j_{t+2}]\right) \\
&\quad = \rho_v^2\xi^j_{0,\tau-1} + \sum_{i=1}^{n}\left(\rho_i^2\xi^j_{i,\tau-1}v_{i,t} + 2\frac{1-\rho_v^{\tau-1}}{1-\rho_v}\sigma_v^2 m_{v_i} r^j_{v_i} + 2\frac{1-\rho_i^{\tau-1}}{1-\rho_i}m_{x_i}r^j_{x_i}v_{i,t} - m_{v_i}r^j_{v_i}\sigma_v^2 - m_{x_i}r^j_{x_i}v_{i,t}\right)
\end{aligned}$$

The remaining three terms in Equation (B.9) are

$$\begin{aligned}
\sum_{h=2}^{\tau} Cov_t(-m_{t+h}, r^j_{t+1}) &= \sum_{i=1}^{n}\left(\lambda_{v_i}r^j_{v_i}\frac{1-\rho_v^{\tau-1}}{1-\rho_v}\sigma_v^2 + \lambda_{x_i}r^j_{x_i}\frac{1-\rho_i^{\tau-1}}{1-\rho_i}v_{i,t}\right) \\
\sum_{h=2}^{\tau} Cov_t(-m_{t+1}, r^j_{t+h}) &= \sum_{i=1}^{n}\left(m_{v_i}\beta^j_{v_i}\frac{1-\rho_v^{\tau-1}}{1-\rho_v}\sigma_v^2 + m_{x_i}\beta^j_{x_i}\frac{1-\rho_i^{\tau-1}}{1-\rho_i}v_{i,t}\right)
\end{aligned}$$

and the latter term is given in Equation (B.7). Putting the pieces together gives

$$\begin{aligned}
\xi^j_{0,\tau} &= \rho_v^2\xi^j_{0,\tau-1} + \left(2\frac{1-\rho_v^{\tau-1}}{1-\rho_v} - 1\right)\sum_{i=1}^{n} m_{v_i}r^j_{v_i}\sigma_v^2 \\
\xi^j_{i,\tau} &= \rho_i^2\xi^j_{i,\tau-1} + \left(2\frac{1-\rho_i^{\tau-1}}{1-\rho_i} - 1\right)m_{x_i}r^j_{x_i} \\
\pi^j_{0,\tau} &= \pi^j_{0,\tau-1} + (1-\rho_v)\bar{v}\sum_{i=1}^{n}\pi^j_{i,\tau-1} + \xi^j_{0,\tau} + \frac{1-\rho_v^{\tau-1}}{1-\rho_v}\sigma_v^2\sum_{i=1}^{n}(\lambda_{v_i}r^j_{v_i} + m_{v_i}\beta^j_{v_i}) + \sum_{i=1}^{n}\beta^j_{v_i}\lambda_{v_i}\sigma_v^2 \\
\pi^j_{i,\tau} &= \rho_v\pi^j_{i,\tau-1} + \xi^j_{i,\tau} + \frac{1-\rho_i^{\tau-1}}{1-\rho_i}(\lambda_{x_i}r^j_{x_i} + m_{x_i}\beta^j_{x_i}) + \beta^j_{x_i}\lambda_{x_i}
\end{aligned}$$

with initial values $\xi^j_{0,1} = 0$, $\xi^j_{i,1} = 0$ for all $i = 1, \ldots, n$, $\pi^j_{0,1} = \sum_{i=1}^{n}\beta^j_{v_i}\lambda_{v_i}\sigma_v^2$, and $\pi^j_{i,1} = \beta^j_{x_i}\lambda_{x_i}$ for all $i = 1, \ldots, n$.

B.4 Term structure of return variances

To calculate the term structure of return variances, we can proceed similarly to Appendix B.3. We can decompose the variance of the return between time t and time $t+\tau$ as follows:

$$Var_t(r^j_{t\to t+\tau}) = \sum_{h_1,h_2=2}^{\tau} Cov_t(r^j_{t+h_1}, r^j_{t+h_2}) + 2\sum_{h=2}^{\tau} Cov_t(r^j_{t+h}, r^j_{t+1}) + Var_t(r^j_{t+1}). \tag{B.11}$$

which is analogous to Equation (B.9). As above, we can inductively calculate the first term on the right-hand side, while the other two are straight-forward. The coefficients $\chi^j_{0,\tau}$ and $\chi^j_{i,\tau}$, for $i = 1,\dots,n$ referred to in Section 5.1 are given by

$$\begin{aligned}
\zeta^j_{0,\tau} &= \rho_v^2 \zeta^j_{0,\tau-1} + \left(2\frac{1-\rho_v^{\tau-1}}{1-\rho_v} - 1\right)\sum_{i=1}^{n}(r^j_{v_i}\sigma_v)^2 \\
\zeta^j_{i,\tau} &= \rho_i^2 \zeta^j_{i,\tau-1} + \left(2\frac{1-\rho_i^{\tau-1}}{1-\rho_i} - 1\right)(r^j_{x_i})^2 \\
\chi^j_{0,\tau} &= \chi^j_{0,\tau-1} + (1-\rho_v)\bar{v}\sum_{i=1}^{n}\chi^j_{i,\tau-1} + \zeta^j_{0,\tau} + 2\frac{1-\rho_v^{\tau-1}}{1-\rho_v}\sigma_v^2\sum_{i=1}^{n}\beta^j_{v_i}r^j_{v_i} + \sum_{i=1}^{n}(\beta^j_{v_i}\sigma_v)^2 + \sigma_j^2 \\
\chi^j_{i,\tau} &= \rho_v\chi^j_{i,\tau-1} + \zeta^j_{i,\tau} + 2\frac{1-\rho_i^{\tau-1}}{1-\rho_i}\beta^j_{x_i}r^j_{x_i} + (\beta^j_{x_i})^2
\end{aligned}$$

with initial values $\zeta^j_{0,1} = 0$, $\zeta^j_{i,1} = 0$ for all $i = 1,\dots,n$, $\chi^j_{0,1} = \sum_{i=1}^{n}(\beta^j_{v_i}\sigma_v)^2 + \sigma_j^2$ and $\chi^j_{i,1} = (\beta^j_{x_i})^2$ for all $i = 1,\dots,n$.

C Additional tables

Table C.1: **Alternative investment strategies (1)**

Panel A: *Return on low IV_{30} portfolio*

	mean	2.5%	median	97.5%
mean	0.1091	0.0994	0.1091	0.1190
t-stat	2.0427	1.8823	2.0422	2.2072
std	0.3172	0.3048	0.3170	0.3306
max	1.2600	1.0752	1.2295	1.6145
min	-0.5216	-0.5737	-0.5183	-0.4849

Panel B: *Return on high IV_{30} portfolio*

	mean	2.5%	median	97.5%
mean	0.0574	0.0550	0.0574	0.0598
t-stat	0.9781	0.9409	0.9783	1.0152
std	0.3432	0.3402	0.3432	0.3462
max	1.2095	1.1672	1.2084	1.2594
min	-0.5638	-0.5779	-0.5631	-0.5505

Panel C: *Return on investment strategy*

	mean	2.5%	median	97.5%
mean	0.0517	0.0416	0.0517	0.0621
t-stat	3.0018	2.3746	2.9875	3.7089
std	0.1436	0.1342	0.1434	0.1535
max	0.6293	0.4814	0.6179	0.8378
min	-0.3577	-0.4528	-0.3554	-0.2767

Summary statistics on the 50,000 alternative investment strategies. For each strategy, we randomly select a permutation and find pairs according to the mechanism explained in Appendix A. The columns show the statistics of the selected investment strategy (see Section 3), the cross-sectional mean, 2.5% quantile, median, and 97.5% quantile of the 50,000 alternative strategies. t-statistics are Newey-West with 12 lags.

Table C.2: **Alternative investment strategies (2)**

Panel A: *Maximum diff. IV_{365}: 0.01*

Min. diff. IV_{30}	low IV_{30}	high IV_{30}	difference	avg. number of stocks
0.05	11.66***	10.34**	1.33**	1645
	(2.86)	(2.35)	(2.24)	
0.10	11.60**	9.32*	2.28**	901
	(2.57)	(1.86)	(2.50)	
0.15	11.53**	7.85	3.68***	525
	(2.35)	(1.44)	(2.98)	
0.20	11.07**	6.83	4.24***	329
	(2.16)	(1.19)	(2.83)	
0.25	10.86**	5.70	5.17***	220
	(2.06)	(0.97)	(3.10)	
0.30	11.10**	4.96	6.15***	154
	(1.99)	(0.83)	(3.30)	
0.35	11.67**	4.03	7.65***	113
	(2.06)	(0.67)	(3.46)	

Panel B: *Maximum diff. IV_{365}: 0.001*

Min. diff. IV_{30}	low IV_{30}	high IV_{30}	difference	avg. number of stocks
0.05	11.84***	10.71**	1.13*	1281
	(2.94)	(2.48)	(1.95)	
0.10	11.41***	9.50**	1.91**	651
	(2.58)	(1.97)	(2.48)	
0.15	11.41**	8.44	2.97***	355
	(2.36)	(1.59)	(2.37)	
0.20	11.39**	7.74	3.65***	210
	(2.24)	(1.40)	(2.60)	
0.25	11.99**	6.44	5.55***	134
	(2.20)	(1.14)	(3.07)	
0.30	13.45**	6.46	6.99***	91
	(2.33)	(1.08)	(3.87)	
0.35	12.48**	6.90	5.58**	65
	(2.14)	(1.11)	(2.50)	

Table continues on next page

Continued: **Alternative investment strategies (2)**

Panel C: *Maximum diff.* IV_{365}*: no restriction*

Min. diff. IV_{30}	low IV_{30}	high IV_{30}	difference	avg. number of stocks
0.05	12.47***	10.11*	2.36	2299
	(3.97)	(1.95)	(0.79)	
0.10	12.44***	9.93*	2.52	2164
	(4.02)	(1.84)	(0.75)	
0.15	12.44***	9.68*	2.75	1977
	(4.10)	(1.72)	(0.73)	
0.20	12.46***	9.35	3.10	1770
	(4.17)	(1.59)	(0.74)	
0.25	12.42***	9.07	3.34	1557
	(4.24)	(1.47)	(0.72)	
0.30	12.25***	8.70	3.55	1351
	(4.28)	(1.35)	(0.70)	
0.35	12.22***	8.25	3.97	1160
	(4.35)	(1.23)	(0.73)	

Summary return statistics for different precisions and minimum spreads at the short end. Numbers in brackets are Newey-West t-statistics with 12 lags. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.3: **Alternative investment strategies (3)**

Panel A: *Maturity long end: 365 days*

Maturity short end	returns low IV	returns high IV	investment strategy	AVG number of stocks
30 days	10.86**	5.70	5.17***	220
	(2.06)	(0.97)	(3.10)	
60 days	11.91**	4.93	6.98***	144
	(2.17)	(0.79)	(3.68)	
90 days	12.42*	6.95	5.47	70
	(2.03)	(1.03)	(1.63)	

Panel B: *Maturity long end: 270 days*

Maturity short end	returns low IV	returns high IV	investment strategy	AVG number of stocks
30 days	11.32**	5.34	5.98***	206
	(2.13)	(0.93)	(3.31)	
60 days	12.69**	4.60	8.09***	129
	(2.28)	(0.77)	(4.28)	
90 days	13.52**	6.60	6.92*	58
	(2.08)	(1.02)	(1.82)	

Panel C: *Maturity long end: 180 days*

Maturity short end	returns low IV	returns high IV	investment strategy	AVG number of stocks
30 days	11.75**	5.69	6.06***	185
	(2.09)	(1.01)	(3.25)	
60 days	12.34**	4.84	7.51***	109
	(1.96)	(0.85)	(2.95)	
90 days	17.76**	10.45	7.31	40
	(2.21)	(1.58)	(1.51)	

Summary return statistics for different maturities of options at the long and short end. Numbers in brackets are Newey-West t-statistics with 12 lags. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.4: **Size/IVD sorted portfolio returns**

	low IVD (early)	2	3	4	high IVD (late)	LME
Small	0.58	0.61	0.86	0.70	0.76	0.18
	(0.99)	(1.23)	(1.59)	(1.16)	(1.50)	(0.75)
2	0.90*	0.95**	1.00**	0.96**	0.95**	0.05
	(1.84)	(2.01)	(2.05)	(2.07)	(2.33)	(0.23)
3	0.95**	0.82**	0.91**	0.66*	0.73*	−0.23
	(2.11)	(2.02)	(2.36)	(1.68)	(1.95)	(-1.17)
4	0.99**	1.04***	0.94***	0.97***	0.81**	−0.18
	(2.42)	(2.83)	(2.72)	(2.71)	(2.17)	(-1.14)
Big	0.73*	0.88**	0.78**	0.73**	0.63*	−0.10
	(1.67)	(2.24)	(2.27)	(2.26)	(1.80)	(-0.49)
SMB	0.15	0.27	−0.08	0.03	−0.13	
	(0.39)	(0.71)	(-0.23)	(0.07)	(-0.33)	

One month average returns on value-weighted portfolios sorted on size and Implied Volatility Duration (IVD). t-statistics are Newey-West with 12 lags. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.5: **Book-to-Market/IVD sorted portfolio returns**

	low IVD (early)	2	3	4	high IVD (late)	LME
value	0.79^{*}	0.83^{*}	0.96^{**}	0.52	0.75^{*}	-0.04
	(1.67)	(1.85)	(1.96)	(1.20)	(1.90)	(-0.16)
2	0.79^{**}	0.79^{**}	0.81^{**}	0.67^{*}	0.59^{*}	-0.21
	(2.10)	(2.06)	(2.36)	(1.89)	(1.81)	(-0.98)
3	0.95^{**}	0.64^{*}	0.73^{**}	0.90^{***}	0.80^{**}	-0.15
	(2.53)	(1.65)	(2.51)	(2.71)	(2.44)	(-0.56)
4	0.76	0.94^{**}	1.02^{***}	0.92^{***}	0.74^{*}	-0.02
	(1.61)	(2.32)	(2.60)	(2.58)	(1.92)	(-0.11)
growth	0.68	0.94^{**}	0.95^{***}	0.97^{**}	0.98^{**}	0.30
	(1.13)	(2.07)	(2.64)	(2.49)	(2.30)	(0.99)
HML	-0.11	0.11	-0.01	0.45	0.23	
	(-0.23)	(0.28)	(-0.02)	(1.17)	(0.51)	

One month average returns on value-weighted portfolios sorted on book-to-market ratio and Implied Volatility Duration (IVD). t-statistics are Newey-West with 12 lags. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.6: **Profitability/IVD sorted portfolio returns**

	low IVD (early)	2	3	4	high IVD (late)	LME
weak	0.42	0.52	0.15	-0.24	0.58	0.17
	(0.53)	(0.70)	(0.21)	(-0.30)	(0.88)	(0.56)
2	0.67	0.66	0.81*	0.42	0.56	-0.11
	(1.23)	(1.36)	(1.92)	(1.02)	(1.20)	(-0.43)
3	0.66	0.79**	0.84*	0.69	0.54	-0.12
	(1.47)	(2.02)	(1.90)	(1.55)	(1.34)	(-0.50)
4	1.05**	1.01***	0.93***	0.78**	0.85**	-0.2
	(2.41)	(2.70)	(2.88)	(2.54)	(2.30)	(-0.77)
robust	1.10***	1.11***	0.99***	0.93***	0.81**	-0.29
	(3.47)	(2.90)	(2.98)	(2.73)	(2.50)	(-1.18)
RMW	0.68	0.60	0.83	1.17*	0.22	
	(1.08)	(0.99)	(1.57)	(1.88)	(0.43)	

One month average returns on value-weighted portfolios sorted on profitability (as defined in Fama and French (2015)) and Implied Volatility Duration (IVD). t-statistics are Newey-West with 12 lags. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.7: **Investment/IVD sorted portfolio returns**

	low IVD (early)	2	3	4	high IVD (late)	LME
conservative	0.81*	0.53	0.89**	0.98**	0.87**	0.05
	(1.74)	(1.18)	(2.22)	(2.56)	(2.44)	(0.23)
2	0.90**	1.33***	1.04***	0.96***	0.72**	−0.18
	(2.39)	(4.18)	(3.63)	(3.24)	(2.11)	(-0.66)
3	1.00**	0.88**	0.90***	0.97***	0.74**	−0.26
	(2.42)	(2.50)	(2.95)	(3.01)	(2.11)	(-0.98)
4	1.18**	1.01***	0.96**	0.54	0.53	−0.65**
	(2.23)	(2.61)	(2.52)	(1.33)	(1.38)	(-2.09)
aggressive	0.08	0.36	0.75	0.38	0.73	0.65***
	(0.14)	(0.74)	(1.55)	(0.79)	(1.58)	(2.73)
CMA	0.74**	0.17	0.14	0.60*	0.14	
	(2.37)	(0.50)	(0.36)	(1.80)	(0.42)	

One month average returns on value-weighted portfolios sorted on investment (as defined in Fama and French (2015)) and Implied Volatility Duration (IVD). t-statistics are Newey-West with 12 lags. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.8: **Illiquidity/IVD sorted portfolio returns**

	low IVD (early)	2	3	4	high IVD (late)	LME
liquid	0.73	0.87^{**}	0.85^{**}	0.58^{*}	0.63^{*}	-0.09
	(1.54)	(2.11)	(2.28)	(1.69)	(1.73)	(-0.36)
2	0.82^{**}	0.85^{**}	0.96^{***}	0.85^{**}	0.78^{**}	-0.04
	(2.02)	(2.42)	(2.93)	(2.26)	(2.31)	(-0.21)
3	0.90^{**}	1.00^{***}	0.94^{***}	0.77^{**}	0.93^{***}	0.03
	(2.45)	(2.72)	(2.68)	(2.23)	(2.84)	(0.25)
4	0.79^{*}	0.75^{*}	0.72^{**}	0.95^{***}	0.63^{*}	-0.16
	(1.95)	(1.92)	(1.98)	(2.95)	(1.69)	(-0.97)
illiquid	0.62	0.71^{*}	0.74^{*}	0.64	0.46	-0.16
	(1.43)	(1.70)	(1.81)	(1.39)	(1.24)	(-0.62)
IML	0.11	0.16	0.11	-0.06	0.18	
	(0.42)	(0.61)	(0.40)	(-0.22)	(0.65)	

One month average returns on value-weighted portfolios sorted on Amihud's (2002) liquidity measure applied to monthly data as in An et al. (2014) and Implied Volatility Duration (IVD). t-statistics are Newey-West with 12 lags. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.9: **Idiosyncratic volatility**

	low IVD (early)	2	3	4	high IVD (late)
low IV	0.0138	0.0118	0.0115	0.0114	0.0108
2	0.0171	0.0159	0.0156	0.0152	0.0148
3	0.0219	0.0207	0.0202	0.0198	0.0192
4	0.0285	0.0269	0.0264	0.0258	0.0248
high IV	0.0408	0.0385	0.0372	0.0373	0.0342

Idiosyncratic volatility relative to the Fama and French (1992) three factor model, computed as the daily standard deviation of the residuals from the model.

Table C.10: **Fama-MacBeth regressions with the variance risk premium**

	MKT	SMB	HML	RMW	CMA	VRP_{30}	VRP_{365}	$IV^2 \times IVD$
CAPM	0.48					-1.32	-0.82^{**}	0.04^{**}
	(1.36)					(-0.95)	(-2.54)	(2.36)
FF3	0.65^{*}	-0.08	-0.23			-1.15	-0.77^{***}	0.04^{**}
	(1.83)	(-0.33)	(-0.76)			(-1.32)	(-2.80)	(2.39)
FF5	0.63^{*}	0.13	-0.15	0.73^{*}	-0.24	-1.98	-0.77^{***}	0.04^{**}
	(1.76)	(0.60)	(0.49)	(1.75)	(-0.55)	(-1.51)	(-2.84)	(2.48)

The table shows the coefficients from a second stage Fama-MacBeth-regression of single stock returns on the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) (all computed from our sample using the Compustat-CRSP merged database), the variance risk premia over 30 and 365 days, VRP_{30} and VRP_{365}, (measured as the difference between realized and implied variance), and $IVD \times IV^2_{365}$. Numbers in parentheses are Newey-West t-statistics with four lags. Characteristics are demeaned. All factors are computed from the sample using the Compustat-CRSP merged database. For the first stage regressions, the betas assigned to each stock are the average value-weighted betas for the respective IV-and-IVD portfolio. FF3 and FF5 denote the model specification from Fama and French (1992) and Fama and French (2015), respectively. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.11: **Fama-MacBeth regressions with idiosyncratic volatility**

	MKT	SMB	HML	RMW	CMA	f(MISP)×IVol	IV^2×IVD
CAPM	0.59					-1.14^{***}	0.08^{**}
	(1.80)					(-6.07)	(2.32)
FF3	0.72^{**}	0.03	-0.27			-1.12^{***}	0.08^{**}
	(2.11)	(0.12)	(-0.80)			(-5.60)	(2.35)
FF5	0.71^{**}	0.14	-0.22	0.45	-0.38	-1.11^{***}	0.08^{**}
	(2.09)	(0.64)	(-0.69)	(1.20)	(-1.06)	(-5.58)	(2.39)

The table shows the coefficients from a second stage Fama-MacBeth-regression of single stock returns on the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) (all taken from Kenneth French's website), IVD×IV^2_{365} and Stambaugh et al.'s (demeaned) mispricing characteristic interacted with idiosyncratic volatility as stock characteristics. The MISP data are taken from Yu Yuan's website. Other specifcations of the function f such as a piece-wise linear function calibrated to the results in the original Stambaugh et al. (2015) paper yield similar results w.r.t. IVD×IV^2_{365}. Numbers in parentheses are Newey-West t-statistics with four lags. Characteristics are demeaned. All factors are computed from the sample using the Compustat-CRSP merged database. For the first stage regressions, the betas assigned to each stock are the average value-weighted betas for the respective size-and-value portfolio. FF3 and FF5 denote the model specifications from Fama and French (1996) and Fama and French (2015), respectively. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.12: **IV/IVD sorted portfolio returns, undervalued stocks**

	early	2	3	4	late	LME
low IV_{365}	0.75***	0.82***	0.61**	0.79***	0.66***	−0.09
	(3.48)	(2.87)	(2.51)	(2.60)	(2.78)	(-0.39)
2	1.09***	1.20***	0.92***	0.68**	0.92***	−0.18
	(3.32)	(2.78)	(2.76)	(2.16)	(2.73)	(-0.67)
3	1.29***	1.63***	1.34***	1.11***	1.17***	−0.12
	(2.76)	(3.53)	(3.12)	(2.71)	(2.83)	(-0.26)
4	2.00***	1.25**	1.15**	0.95**	0.66	−1.34
	(3.00)	(2.38)	(2.43)	(2.18)	(1.18)	(-2.88)
high IV_{365}	0.91	1.29**	1.12	1.24*	2.25***	1.34**
	(1.37)	(2.41)	(1.61)	(1.95)	(2.96)	(1.97)
HML IV	0.16	0.48	0.51	0.46	1.59**	
	(0.25)	(0.83)	(0.71)	(0.69)	(2.31)	

One month average returns on value-weighted portfolios sorted on IV and Implied Volatility Duration (IVD) that are undervalued according to Stambaugh et al.'s mispricing characteristic (values below 20%). Stambaugh et al. (2015) show that (roughly) for the 20 % of stocks that are most undervalued, the sign of the effect of idiosyncratic volatility is positive. *t*-statistics are Newey-West with one lag. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.13: **Fama-MacBeth regressions with E**

	MKT	SMB	HML	RMW	CMA	E	$\text{IV}^2\times\text{IVD}$
CAPM	0.48					-0.57	0.05^{***}
	(-1.15)					(-0.76)	(2.73)
FF3	0.66^{*}	-0.11	-0.33			-0.39	0.04^{***}
	(1.90)	(-0.47)	(-0.98)			(-0.69)	(2.64)
FF5	0.65^{*}	0.08	-0.24	0.66	-0.12	-0.57	0.05^{***}
	(1.84)	(0.40)	(-0.73)	(1.60)	(-0.26)	(-1.00)	(2.70)

The table shows the coefficients from a second stage Fama-MacBeth-regression of single stock returns on the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) (all computed from our sample using the Compustat-CRSP merged database), Drechsler and Drechsler's Rf-expensive (E) factor and the variance risk premia over 30 and 365 days, VRP_{30} and VRP_{365}, (measured as the difference between realized and implied variance), and $\text{IVD}\times\text{IV}^2_{365}$ as stock characteristics. Numbers in parentheses are Newey-West t-statistics with four lags. Characteristics are demeaned. E is computed as in Drechsler and Drechsler (2016) from the stocks in our sample as the portfolio return of the portfolio that is long the risk-free rate and short the highest decile Short interest over institutional ownership ratio (SIR_{IO}) portfolio. For the first stage regressions, the betas assigned to each stock are the average value-weighted betas for the respective IV-and-IVD portfolio. FF3 and FF5 denote the model specification from Fama and French (1992) and Fama and French (2015), respectively. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.14: **Fama-MacBeth regressions with CME**

	MKT	SMB	HML	RMW	CMA	CME	$IV^2 \times$IVD
CAPM	0.71^{**}					0.49	0.05^{***}
	(2.03)					(1.33)	(2.69)
FF3	0.63^{*}	-0.07	-0.32			0.55	0.04^{***}
	(1.78)	(-0.32)	(-0.96)			(0.71)	(2.63)
FF5	0.64^{*}	0.11	-0.23	0.81^{**}	-0.22	-0.54	0.05^{**}
	(1.80)	(0.50)	(-0.69)	(2.16)	(-0.48)	(-0.98)	(2.69)

The table shows the coefficients from a second stage Fama-MacBeth-regression of single stock returns on the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) (all computed from our sample using the Compustat-CRSP merged database), a version of Drechsler and Drechsler's cheap-minus-expensive (CME) factor and the variance risk premia over 30 and 365 days, VRP_{30} and VRP_{365}, (measured as the difference between realized and implied variance), and IVD$\times \text{IV}_{365}^2$ as stock characteristics. Numbers in parentheses are Newey-West t-statistics with four lags. Characteristics are demeaned. CME is computed analogous to the factor CME in Drechsler and Drechsler (2016) from the stocks in our sample as the equally-weighted portfolio return of the portfolio that is long the lowest decile portfolio of stocks sorted by the ratio of short interest over institutional ownership (SIR_{IO}) and short the highest decile portfolio. For the first stage regressions, the betas assigned to each stock are the average value-weighted betas for the respective IV-and-IVD portfolio. FF3 and FF5 denote the model specification from Fama and French (1992) and Fama and French (2015), respectively. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.15: **LME betas for portfolios generated by different sorts**

Panel A: *IV and IVD sorted*

	early	2	3	4	late
low IV	-0.0439	-0.0067	0.0813	0.0784	0.0602
2	-0.0364	0.0396	0.0876	0.0240	0.0915
3	-0.0548	-0.0600	-0.0442	-0.0425	-0.0323
4	-0.1206	-0.1012	-0.1206	-0.0059	-0.0753
high IV	-0.8529	-0.7600	-0.1711	0.1017	0.2820

$Std(\hat{\beta}) = 0.2420$

Panel B: *Size and Value sorted*

	growth	2	3	5	value
small	0.0400	0.0374	0.0126	-0.0403	-0.0753
2	0.0021	0.0673	-0.0135	-0.0329	0.0108
3	-0.0219	0.0074	-0.0295	0.0250	-0.0146
4	-0.1160	-0.0185	-0.0002	0.0202	0.0156
big	0.0086	-0.0093	-0.0445	0.0356	0.0511

$Std(\hat{\beta}) = 0.0402$

Panel C: *Size and Profitability sorted*

	weak	2	3	4	robust
small	0.0176	-0.0423	-0.0227	-0.1468	0.0183
2	-0.0137	0.0352	-0.0094	0.0099	-0.0459
3	-0.0506	-0.0586	-0.0351	0.0601	0.0512
4	-0.1284	-0.0702	-0.0462	0.0164	0.0110
big	0.0253	0.0315	-0.0475	0.0020	-0.0116

$Std(\hat{\beta}) = 0.0506$

Panel D: *Size and Investment sorted*

	conservative	2	3	4	aggressive
small	-0.0164	-0.0518	-0.0147	-0.0099	-0.0188
2	-0.0243	0.0096	0.0184	0.0124	0.0012
3	-0.0596	0.0434	-0.0171	-0.0031	0.0187
4	0.0154	0.0276	0.0292	-0.0226	-0.1532
big	0.0076	-0.0100	-0.0085	-0.0596	0.0284

$Std(\hat{\beta}) = 0.0401$

Betas of portfolios sorted on various characteristics on the LME factor. Betas on the LME factor are estimated controlling for the SMB, HML, RMW, CMA and LIQ factors. The LIQ factor is taken from Robert Stambaugh's website. All other factors are computed from stock returns in our sample following the procedure in Fama and French (1992) and Davis et al. (2000). $Std(\hat{\beta})$ is the standard deviation of the betas across portfolios.

Table C.16: **Fama-MacBeth regressions**

	MKT	SMB	HML	X	$IV^2 \times IVD$
X = PS-LIQ	0.63^{*}	-0.06	-0.34	1.07	0.04^{***}
	(1.77)	(-0.28)	(-1.00)	(1.22)	(2.62)
X = Sadka-LIQ	0.50	0.04	-0.47	0.23	0.05^{***}
	(1.26)	(0.14)	(-1.23)	(1.44)	(2.69)
X = MOM	0.62^{*}	-0.01	-0.33	0.11	0.05^{***}
	(1.75)	(-0.04)	(-0.99)	(0.18)	(2.67)
X = STR	0.62^{*}	-0.02	-0.31	-1.14	0.05^{***}
	(1.77)	(-0.08)	(-0.91)	(-1.47)	(2.69)
X = LTR	0.63^{*}	-0.09	-0.30	-0.77^{*}	0.04^{***}
	(1.79)	(-0.39)	(-0.89)	(-1.69)	(2.64)
X = UMO	0.62^{*}	0.09	-0.33	1.01^{*}	0.05^{***}
	(1.76)	(0.47)	(-0.96)	(1.66)	(2.72)
X = BAB	0.54	0.04	-0.45	0.39	0.05^{***}
	(1.28)	(0.16)	(-1.12)	(0.43)	(2.70)
X = PMU	0.58	-0.01	-0.34	0.53^{**}	0.05^{***}
	(1.46)	(-0.02)	(-0.86)	(2.25)	(2.63)
X = QMJ	0.64^{*}	0.02	-0.24	0.20	0.05^{***}
	(1.81)	(0.10)	(-0.71)	(0.65)	(2.68)
X = CME	0.63^{*}	-0.07	-0.32	0.55	0.04^{***}
	(1.78)	(-0.32)	(-0.96)	(0.71)	(2.63)
X = E	0.66^{*}	-0.11	-0.33	-0.39	0.04^{***}
	(1.90)	(-0.47)	(-0.98)	(-0.69)	(2.64)
X = MGMT	0.65^{*}	-0.03	-0.31	0.46	0.04^{***}
	(1.84)	(-0.13)	(-0.93)	(0.72)	(2.61)
X = PERF	0.63^{*}	0.03	-0.27	0.31	0.05^{***}
	(1.76)	(0.14)	(-0.82)	(0.55)	(2.68)

The table shows the coefficients from a second stage Fama-MacBeth-regression of single stock returns on the market excess return (MKT), size factor (SMB), value factor (HML) (all computed from our sample using the Compustat-CRSP merged database), one further factor and $IVD \times IV^2_{365}$. The factors X are explained in Table C.18. Numbers in parentheses are Newey-West t-statistics with four lags. $IVD \times IV^2_{365}$ is demeaned as described in Section 4.4. For the first stage regressions, the betas assigned to each stock are the average value-weighted betas for the respective IV-and-IVD portfolio. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.17: **Fama-MacBeth regressions**

	MKT	SMB	HML	X	LME	$R^2_{adj.}$
X = PS-LIQ	0.57	−0.11	−0.26	1.32*	0.71**	0.48
	(1.63)	(-0.30)	(-0.44)	(1.75)	(2.35)	
X = Sadka-LIQ	0.54	−0.19	−0.14	−0.04	0.90***	0.37
	(1.38)	(-0.41)	(-0.20)	(-0.35)	(2.80)	
X = MOM	0.56	−0.06	0.02	0.64	0.59**	0.49
	(1.62)	(-0.15)	(0.03)	(0.79)	(2.02)	
X = STR	0.62*	−0.36	0.02	0.17	0.71**	0.39
	(1.80)	(-0.88)	(0.03)	(0.31)	(2.37)	
X = LTR	0.61*	−0.31	−0.05	0.32	0.66**	0.40
	(1.75)	(-0.78)	(-0.08)	(0.44)	(2.26)	
X = UMO	0.59*	−0.13	−0.01	0.38	0.66**	0.44
	(1.72)	(-0.34)	(-0.02)	(0.83)	(2.26)	
X = BAB	0.54	−0.14	−0.06	0.09	0.87**	0.32
	(1.33)	(-0.29)	(-0.09)	(0.19)	(2.55)	
X = PMU	0.54	−0.01	−0.08	0.28	0.92***	0.38
	(1.38)	(-0.01)	(-0.12)	(0.58)	(2.83)	
X = QMJ	0.59*	0.11	0.16	0.29	0.71**	0.46
	(1.69)	(0.24)	(0.25)	(0.83)	(2.37)	
X = CME	0.61*	−0.34	−0.08	−0.11	0.73**	0.40
	(1.75)	(-0.84)	(-0.13)	(-0.26)	(2.42)	
X = E	0.59*	−0.32	−0.03	−0.53	0.71**	0.39
	(1.74)	(-0.78)	(-0.05)	(-0.73)	(2.36)	
X = MGMT	0.58*	−0.31	−0.22	−0.13	0.73**	0.40
	(1.68)	(-0.77)	(-0.35)	(-0.37)	(2.40)	
X = PERF	0.56	−0.00	−0.01	0.58	0.61**	0.47
	(1.61)	(-0.00)	(-0.01)	(0.86)	(2.10)	

The table shows the coefficients from a second stage Fama-MacBeth-regression of single stock returns on the market excess return (MKT), size factor (SMB), value factor (HML) (all computed from our sample using the Compustat-CRSP merged database), one further factor and $\text{IVD}\times\text{IV}^2_{365}$. The factors X are explained in Table C.18. Numbers in parentheses are Newey-West t-statistics with four lags. $\text{IVD}\times\text{IV}^2_{365}$ is demeaned as described in Section 4.4. For the first stage regressions, the betas assigned to each stock are the average value-weighted betas for the respective IV-and-IVD portfolio. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table C.18: **Explanation of additional factors**

PS-LIQ	Liquidity factor as in Pastor and Stambaugh (2003) taken from Robert Stambaugh's website.
Sadka-LIQ	Liquidity factor as in Sadka (2006) taken from Ronnie Sadka's website. Time series ends in December 2012.
MOM	Momentum factor taken from Kenneth French's website.
STR	Short term reversal factor taken from Kenneth French's website.
LTR	Long term reversal factor taken from Kenneth French's website.
UMO	Undervalued minus overvalued factor as in Hirshleifer and Jiang (2010) taken from David Hirshleifer's website.
BAB	Betting against beta factor as in Frazzini and Pedersen (2014) taken from the AQR data library. Time series ends in March 2012.
PMU	Profitable minus unprofitable factor as in Novy-Marx (2013) taken from Robert Novy-Marx's website. Time series ends in December 2012.
QMJ	Quality minus junk factor as in Asness et al. (2014) taken from the AQR data library.
CME	Cheap minus expensive factor as in Drechsler and Drechsler (2016) constructed from own sample. Equally-weighted returns on the portfolio that is long he lowest decile portfolio of stocks sorted by the ratio of short interest over institutional ownership (SIR_{IO}) and short the highest decile portfolio.
E	Expensive factor as in Drechsler and Drechsler (2016) constructed from own sample. Return on portfolio that is long the risk-free rate (one-month T-bill rate from Kenneth French's website) and short the highest decile short interest over institutional ownership (SIR_{IO}) portfolio.
MGMT	First mispricing factor as in Stambaugh and Yuan (2016) taken from Yu Yuan's website.
PERF	Second mispricing factor as in Stambaugh and Yuan (2016) taken from Yu Yuan's website.

The table gives detailed information about the factors used for the robustness checks in Tables C.16 and C.17.