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 the resolution of uncertainty about a stock's cash flows. The shorter the IVD, the earlier the resolution of uncertainty. Portfolio sorts indicate that investors demand on average about seven percent return per year in exchange for a late resolution of uncertainty, and this premium cannot be explained by standard factor models. We find that the premium is higher in times of increased economic uncertainty and low market returns. We show in a general equilibrium model that the expected excess returns on high IVD stocks exceed those of low IVD stocks if and only 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 usually hard to estimate.

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

JEL: G12, E44, D81

1 Introduction

The supreme challenge in asset pricing research is to explain the trade-off between risk and return. Why do stocks have such high returns overall, and why do some stocks persistently have higher returns than others? For what kind of uncertainty[1] do investors demand a compensation? In this paper we ask a different question, namely *when* the risk occurs, instead of *what* type of risk the investor is facing. When agents dynamically optimize their consumption and portfolio choices then, given that risk is time-varying, not only the *amount* of risk but also the *timing* of its resolution should matter for 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 factors.

Whether the marginal investor indeed has PERU is of major importance in many asset pricing models. For example, in the long-run risk model by Bansal and Yaron (2004) and its subsequent extensions, this type of preferences is necessary to generate countercyclical risk premia, low and smooth interest rates, and a sizable equity premium, i.e., to reproduce key stylized facts from the data. In these models, the representative agent exhibits PERU when the coefficient of relative risk aversion is greater than the inverse of the elasticity of intertemporal substitution. However, it is notoriously difficult to obtain reliable empirical estimates for these two preference parameters (see 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., the time-additive constant relative risk aversion (CRRA) model) 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

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

between stocks featuring late and early resolution of cash-flow uncertainty. We interpret this difference as the premium investors require to be compensated for a later instead of 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 both pay off one dollar with probability p at time $t = 4$. The difference between the claims is that, for claim E, all uncertainty about the outcome is resolved at $t = 2$, whereas uncertainty about the payoff of claim L is resolved only at $t = 4$. 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 $t = 2$, whereas the variance of claim L stays at $p(1 - p)$ until $t = 4$. 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 in the cross-section of stocks. We argue that the investor exhibits PERU if the return on type E stocks is lower than the return on type L stocks. To identify pairs of stocks with the above properties we suggest to make use of option-implied volatilities (IVs). More precisely, we consider two stocks as similar when their IVs over a long horizon from t to T are close to each other, while the IVs over a shorter horizon from t to $T_0 < T$ are markedly different. Since the variance over the long horizon is almost the same, the two stocks exhibit the same amount of long-term uncertainty. On the other hand, the remaining variance from T_0 to T must be smaller for the stock with the higher short-term IV, so that uncertainty is resolved earlier. In accordance with our motivating example in Figure 1 we label the stock with the higher short-term IV a type E claim, while the other one would be of type L. The return difference between L and E stocks in the respective pairs is on average 2.8 percent per year with a t-statistic of 2.5. This return difference cannot be explained by exposures return to the usual set of factors proposed by Fama and French (2015) and Pastor and Stambaugh (2003).

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 an independent double sort of the stocks in our sample into quintiles for IV (for a maturity of 365 days) and IVD. We call the extreme portfolios with the highest and the lowest-IVD stocks 'late' and 'early', respectively. We find a significantly positive average return on the 'late-minus-early' (LME) portfolio which is evidence in favor of the representative investor exhibiting PERU. This return differential is most pronounced within the group of stocks with high IV, where the return on the LME-portfolio is positive at around seven percent per year and significant at conventional levels. The fact that we find a significant LME return only for stocks with high IV is not surprising: When the overall level of uncertainty is low, its resolution naturally is less relevant to the investor.

The excess return of this LME-portfolio varies over time and is higher in times of high economic uncertainty and negative returns on the aggregate stock market. Similar to the investment strategy based on pairs, 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 the usual second-stage Fama-MacBeth regressions. Cross-sectional dispersion in this variable explains 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 investors' (time-varying) need to have uncertainty resolved early. Once we add this factor to the Fama-MacBeth regressions, the significance of the characteristic vanishes, such that a risk-based explanation of the early resolution premium seems likely.

We rationalize our empirical findings in the context of a general equilibrium model in the spirit of Bansal and Yaron (2004). We extend their model by generalizing the volatility structure via the introduction of short-lived and persistent volatility components. In this model we then price type E and L dividend claims. The key result of our theoretical analysis is that the expected return on the L stock is higher than on the E stock, if and only if the investor's degree of relative risk aversion exceeds the inverse of her elasticity of intertemporal substitution, i.e., if the investor exhibits PERU.

The rest of the paper is structured as follows. In Section 2, we review the related literature. The data are discussed in Section 3. In Section 4, we present and discuss the investment strategy based on pairs. Motivated by the results from this exercise, we introduce the concept of IVD in Section 5 and perform a variety of tests to assess its explanatory power in the cross-section. Our general equilibrium model is presented in Section 6. Section 7 concludes. The appendix contains additional information about the investment strategy and details about the solution of the model.

2 Related literature

Our paper is related to several strands of the literature. Most importantly, by providing empirical evidence in favor of an early resolution premium using only easily observable financial market data and by showing theoretically that the existence of such a premium is actually equivalent to a certain preference structure, we provide robust and in a sense non-parametric support for the common assumption of a PERU in the sense of Epstein and Zin (1989).

The issue of whether the representative agent exhibits PERU is particularly important in asset pricing models with recursive preferences, such as Bansal and Yaron (2004), Drechsler and Yaron (2011) to name just two, 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.

The timing of uncertainty resolution is also relevant in the context of utility losses due to the very fact that uncertainty is not resolved right away. For example, Epstein et al. (2014) compute the fraction of lifetime utility which an agent is willing to forgo in exchange for complete knowledge about a given future uncertain consumption stream.

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. With the original Epstein and Zin (1989) Euler equation as moment condition and using the stock market as measure of aggregate wealth, they find estimates of γ around 1 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. Under the assumption of jointly lognormal and homoscedastic consumption growth and returns, the problem of having to specify a proxy for aggregate wealth can be circumvented, as shown by Campbell (1993). Based on this, Attanasio and Weber (1989) find a γ of about five and an EIS around 2, which is in favor of a preference for early resolution of uncertainty.

An inherently different approach to estimating preference parameters is from survey data where the socio-economic background of survey respondents is a crucial piece of information. In an asset pricing context, this means that it stands to reason whether the survey respondents could be marginal investors. Vissing-Jørgensen and Attanasio (2003) provide evidence that among stockholders, the EIS is well above 1. There is also some experimental evidence in favor of a preference for early resolution, see, e.g., the papers by Brown and Kim (2014) or Meissner and Pfeiffer (2015). Overall, however, no clear picture emerges from the existing empirical and experimental literature. We provide additional non-parametric empirical evidence which supports the notion of PERU.

Our paper also relates to the literature on option-implied information about the cross-section of stock returns, such as An et al. (2014) and many of the papers quoted there. The work by Johnson (2016) and Xie (2014) is in a certain sense similar to ours, because they also relate the cross-sectional pricing of stocks to properties of implied volatilities across maturities, but they are interested in the sensitivity of stocks to changes in the slope of the VIX term structure, i.e., market-wide implied volatility, whereas we focus on the timing pattern of uncertainty resolution in individual stocks and its implication for expected returns.

3 Data

We use end of month data on the implied volatility surface provided by OptionMetrics IvyDB for the period from January 1996 to August 2015 for maturities of 91, 60, 122, 152, 182, 273 and 365 days. For liquidity reasons, we only use at-the-money (ATM) data implied by call prices.

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 one dollar or less are excluded. Delisting returns are included wherever available. Over the entire sample period we consider 7148 stocks and their respective volatility surfaces.

Data on the monthly risk-free rate are from Kenneth French's website. Accounting data are from the CRSP-Compustat merged database. We perform a series of analyses using portfolio returns computed as in Fama and French (2015) based on the stocks in our sample. Their constituent quantities are computed as in Davis et al. (2000) and Fama and French (2015). Amihud's (2002) illiquidity measure is computed on a monthly level as in An et al. (2014). Our estimation of the expected cash-flow duration follows the procedure in Dechow et al. (2004) with parameters from Weber (2016) but using Dechow et al.'s parameters instead does not alter the results qualitatively.

4 An investment strategy

4.1 Pairs of stocks

Our main argument in this paper is that option-implied volatilities provide information about the profile of uncertainty resolution. At the end of each month, we look for pairs of stocks with similar 365-day implied volatility (IV_{365}) but rather different 30 day IV (IV_{30}). In particular, we look for pairs of stocks for which the 365-day IVs differ by at most 1 percentage point (e.g. 20% vs. 21%), while the difference between annualized 30-day IVs is at least 15 percentage points. In the spirit of the motivating example in Figure 1, we go the stock with lower IV_{30} long and the other one short. We then exclude both stocks from the sample and continue until no further pair is left which meets the above criteria.[2] 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. We hold all long-short positions for twelve months, which in our sample yields a statistically significant average return of 2.79 percent per year, as shown in Table 1.

[TABLE 1 HERE]

The returns on the strategy cannot be explained by standard risk factors. In fact, as shown in Table 2, the strategy has considerable excess returns relative to the respective factor models.

[TABLE 2 HERE]

4.2 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

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

of uncertainty: Consider two stocks with the same return variance over a long horizon T. If one of the stocks has a higher variance over a short horizon T_0, it must have lower variance over the period from T_0 to T to make up for the higher short term variance. In terms of the timing of uncertainty resolution, this means that the one with the higher short term variance exhibits early resolution of uncertainty relative to the stock with the lower variance from t to T_0.Because the long horizon variance is equal for both stocks, overall uncertainty is the same. All else equal, if the marginal investor has a preference for early resolution of uncertainty, the expected return on the stock with the later resolution should be higher to compensate the investor for having to wait longer until uncertainty is resolved.

The positive return on the investment strategy described above is in line with a negative premium for early resolution of uncertainty. Moreover, the negative estimates of market beta from table 2 point to another interesting aspect. In times of market downturns (and increased macroeconomic uncertainty), returns on our strategy are particularly high. It thus seems that it is especially in these periods, when investors are rewarded with a pronounced premium for bearing uncertainty for longer. This feature can also be observed in the time series plotted in Figure 2.

[FIGURE 2 HERE]

We use IVs, i.e., risk-neutral ($\mathbb{Q}$-)volatilities, as a (somewhat noisy) forward-looking measure of physical ($\mathbb{P}-$) volatilities. The problem that this measure is potentially imprecise is mitigated by the fact that we only consider *differences* in IVs both across maturities for a given stock as well as across stocks. Moreover, in line with Busch et al. (2011), we find that there is a close relationship between IV and realized volatility in our sample (see Section 5.2).

5 Implied Volatility Duration

5.1 Definition

The trading strategy from the previous section depends upon finding pairs of stocks satisfying the criteria described above with respect to their one-month and twelve-month IVs. For many stocks we do not find a counterpart that meets the conditions. The average number of pairs in a month is 271, covering about 23 percent of the stocks in the sample at that time. It would be favorable to consider a broader set of stocks at each point in time. Moreover, it would be interesting to have a characteristic that indicates how late uncertainty is resolved and that can be assigned to every single stock. Such a criterion is introduced in the following.

We define the Implied Volatility Duration (IVD) of stock i at time t as

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

where $\Delta IV_{t,i,j}^2 = IV_{i,t,t+\tau_j}^2 - IV_{i,t,t+\tau_{j-1}}^2$ denotes the increment in the squared implied volatility of stock i between day $t+\tau_{j-1}$ and day $t+\tau_j$. In particular, $IV_{i,t,t+\tau_j}^2$ denotes the implied variance at time t of an ATM option on stock i maturing in τ_j days. OptionMetrics reports annualized values, so we scale the implied variances by multiplying by $\tau_j/365$.

We set $\tau_0 = 0$ and, thus, $IV_{i,t,t+\tau_0}^2 = 0$, such that the increment over the first interval is equal to the implied variance over the first interval: $\Delta IV_{t,i,1}^2 = IV_{i,t,t+\tau_1}^2$. For our empirical exercise, we decided to use all maturities available in OptionMetrics up to one year, i.e. $J = 8$ and $\tau_1 = 30$, $\tau_2 = 60$, $\tau_3 = 91$, $\tau_4 = 122$, $\tau_5 = 152$, $\tau_6 = 182$, $\tau_7 = 273$, and $\tau_8 = 365$.

The interpretation of IVD is similar to that of the well-known Macaulay duration of a coupon bond: Note that $\sum_{j=1}^{J} \Delta IV_{i,t,j}^2$ is equal to $IV_{i,t,t+\tau_J}^2$, so the increments over the subperiods are normalized by the overall implied variance over the full year. Multiplying the parts of this sum by the corresponding number of days to maturity and summing up the resulting terms results in an average period length weighted by the variance of the stock return over the respective subperiod. Consequently, our characteristic describes the time span after which most of the variance is expected to have realized. At the same time, comparing the characteristic of two different stocks provides us with a notion of when uncertainty is resolved, in particular, for which stock uncertainty is resolved earlier. Figure 3 gives a stylized depiction of the quantities involved in computing IVD with an early (upper figure) and late (lower figure) resolution claim.

[FIGURE 3 HERE]

Intuitively, IVD is related to the area below the curves in the graph. A larger area indicates that uncertainty is expected to be resolved earlier, which corresponds to a shorter IVD.

5.2 Returns on sorted portfolios

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, we independently double sort all stocks into 25 portfolios based on IVD and the 365 day implied volatility ($\mathrm{IV}_{t,t+365}$, for short IV_{365}). Table 3 provides information about the average IVD (in panel 1) and IV_{365} (in panel 2) of these portfolios.

[TABLE 3 HERE]

IVD usually varies between 193 and 222 days, a sizeable spread of close to one month. There is also large variation in IV across stocks with values between 22 and 79 percent. Within each column in Panel A of Table 3, there is very little variation in IVD. Likewise, within each row in Panel B, IV_{365} does not vary in a pronounced fashion. 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, with a time-series average of the cross-sectional correlation coefficients close to zero.

We now study returns on the portfolios formed as described above. In particular, in every IV_{365}-quintile we analyze the returns on portfolios that are long in high IVD stocks and short in low IVD stocks. We call these portfolios late minus early (LME) portfolios.

[TABLE 4 HERE]

Table 4 shows 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 in all tested specifications. As an example, forming a new value weighted LME portfolio from high IV_{365} stocks every month and (similarly to our investment strategy in Section 4) holding this portfolio for 12 months results in an average return of more than 7 percent per year (see Panel A). For lower IV_{365}-quintiles, there is no significant difference between returns on high IVD and low IVD stocks in any of the tested specifications.

We call the positive return on the LME portfolio the *early resolution premium*. The fact that it is only pronounced among the group of high IV_{365} stocks is plausible: When uncertainty about a stock's return is low anyway there is little reason to believe that the timing of the resolution of this uncertainty should matter much. In line with that, there is a strong relation between the return on the strategy based on pairs as described in Section 4 and the one descibed here as can be seen in Figure 4.

[FIGURE 4 HERE]

The LME returns in the highest IV_{365} quintile as reported in Panel B of Table 4 show that the return difference between high IVD and low IVD stocks is significantly positive for a holding period of one month as well. So rolling over the strategy with a one month holding period would result in a return of even more than 12 percent per year.

The positive average return over one month shows that it is not the absolute amount of risk, but the timing of its resolution which matters in this case. The standard risk-based intuition would suggest a negative sign, since the stocks in the long portfolio are those with on average lower short-term risk and should consequently exhibit lower returns. We study the implications of different attitudes towards the timing of uncertainty resolution for one month returns more thoroughly in Section 6.

[TABLE 5 HERE]

In Table 5 we present the realized variances of the IV/IVD-sorted portfolio returns. Most importantly, IV does indeed predict realized variance, i.e., realized variance increases monotonically in IV_{365}. We expect early resolution stocks to have a higher realized variance over the first month. This is indeed the case. 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.

Over 12 months however, realized variances should be roughly the same between the late and early resolution portfolios. Expected return differentials should not be driven by absolute uncertainty levels but by the timing of its resolution. This is also the case. 12 month realized variances are roughly equal and the null hypothesis of equal variances cannot be rejected. We are aware that the 12 month returns most likely violate the assumptions of the F-test so we also perform Levene's test for the 12 month holding period returns. We cannot reject the null of equal variances with p-values of 0.76 (value-weighted) and 0.57 (equally weighted).

Just as in Section 4, we investigate if standard asset pricing models are able to explain the high returns on the LME portfolio. Table 6 shows that this is not the case. All alphas are substantial and statistically significant. Just like the returns from the investment strategy in Section 4, LME returns seem to be negatively related to the return on the aggregate market portfolio.

[TABLE 6 HERE]

5.3 Portfolio characteristics

Table 7 displays a number of statistics characterizing the five IVD-sorted portfolios in the top IV_{365} quintile. We also show the time series average of the cross-sectional median of each characteristic, to find out how representative the top IV_{365} stocks are for the entire sample.

[TABLE 7 HERE]

Our first observation is that stocks in the top IV_{365} quintile tend to have a rather low market capitalization. This raises the question, whether the timing of the resolution of uncertainty may only be important for small stocks rather than stocks with uncertain returns (high IV_{365} stocks). To address this concern, we perform an independent double sort with respect to size (market equity) and IVD. Table 8 shows that this procedure does not yield significantly positive returns for the LME portfolios. We thus conclude that the early resolution premium is indeed a phenomenon that is special to high uncertainty stocks.

[TABLE 8 HERE]

Similarly, we find that high IV_{365} stocks are typically value stocks that have low operating profitability, high investments and are rather illiquid, compared to the median characteristics of the stocks in our sample. Running the corresponding double sorts on IVD and the above criteria does not yield significant returns. The only exception is investment which is highly correlated with IV.

Interestingly and more importantly, Table 7 shows that within the top IV portfolios, there is hardly any variation in any of the characteristics along the IVD dimension. There are no clear patterns when it comes to size, book-to-market-equity-ratio, profitability, and liquidity. Moreover, the timing of the resolution of uncertainty seems to be unrelated to the timing of cash flows. The term structure of equity and the duration of stocks' cashflows have received great attention recently in papers such as Weber (2016). From the empirical side, it should first be noted that our option-implied measure focuses on the horizon of up to one year whereas estimates in the spirit of Dechow et al. (2004) are aimed at the entirety of future cashflows with a focus on forecasting cashflows over a horizon of between ten and fifteen years. From the empirical evidence on the value premium and in particular from research on the cash flow duration of equity in the aforementioned papers, claims to high duration cash flows have lower returns. This is different from our finding with respect to volatility duration of stocks with late resolution of uncertainty (i.e. high volatility duration) having higher returns. In our sample, the cash flow duration of the portfolios in our sort on IV_{365} and IVD is unrelated to IVD. Estimates of cashflow duration as in Dechow et al. (2004) compute the average time of cash payments weighted by the expected value of these cashflows. IVD as a measure of the timing of uncertainty resolution provides something related but also very different. In the context of a discounted cash flow model, IVD incorporates not only information about the expected timing of cashflows but also about the degree of certainty with which market participants expect these cash flows.

We also estimate betas for the five IVD quintile portfolios by running multivariate regressions on the six factors listed in Panel B of Table 7. As described earlier, there is again a negative relation between IVD and CAPM beta. Again, however, this relation could only explain a negative expected return on the LME portfolio, which makes the high positive returns on the LME portfolio even more striking. Apart from the CAPM betas, all other betas do not show a monotonic relation across IVD sorted portfolios.

5.4 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 Fama-MacBeth regressions of single stock excess returns on common factors as well as on IVD as a stock characteristic. To avoid econometric issues with overlapping returns, we use monthly returns. To make sure that the estimation of the factor betas is not hampered by idiosyncratic noise on the individual stock level, we estimate all betas on 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. We also estimate betas on alternative portfolios (different number of portfolios and different sorting criteria) and find that our results are very robust to this variation.

In Section 5.2, we found that the return differential between late and early resolution stocks is substantial only in the top IV_{365} quintile. In other words, the timing of uncertainty resolution matters only when uncertainty is high. A way to capture this would be to incorporate an interaction term between IVD and a dummy equal to one for stocks that are in the top IV_{365} quintile. It is, however, not likely that the relevance of uncertainty resolution kicks in at a certain threshold and remains stable with respect to the level of IV_{365} for values of IV_{365} greater than that threshold. We rather observe that the effect becomes more pronounced if we consider subsets of stocks with even higher IV_{365}: The average return to the LME portfolio held for 12 months is about seven percent in the top IV_{365}-quintile, ten percent in the top IV_{365}-decile and thirteen percent in the top IV_{365}-ventile. As a consequence, we construct the interaction term $\mathrm{IVD}\times\mathrm{IV}_{365}^2$.

The interaction term is by construction positive for all stocks at each point in time. It could happen that it picks up a possibly positive alpha from the asset pricing model, even if the variation in pricing errors is not related to the characteristic. To avoid such spurious inference, we demean IVD before calculating the interaction terms. As IVD and IV_{365}^2 are virtually independent, the interaction term itself is also on average zero and large for stocks with high IV_{365}^2.

[TABLE 9 HERE]

Results are presented in Table 9. The interaction term is highly significant and explains pricing errors relative to all three standard factor models. The coefficient is very stable across model specifications, the estimated value is plausible. Multiplying the estimated coefficient of

0.05 percent by the average implied variance in the top IV_{365} quintile of around 0.6, yields a value of 0.03, such that increasing the implied volatility duration by one day ceteris paribus leads to a higher abnormal return of three bp per month. The average IVD-spread between the high and low IVD quintile in our sorts is around 30 days, implying a return difference of around one percent per month between the quintile portfolios. This value is in line with our findings in Section 5.2.

The coefficients of the factor betas, i.e. the risk premia associated with the respective factor, are barely significant and vary considerably across model specifications. The only exception is the market factor for which the risk premium is positive and quite stable. Moreover, the estimates is quite close to the average excess return on the market portfolio of about 0.7 percent, just as predicted by theory.

5.5 Factor structure in high IV stocks

So far, we have documented a positive relation between IVD and expected returns within the group of stocks with high IV_{365}. This phenomenon could be called an anomaly. Whether the returns are really anomalous of course depends on the considered asset pricing model. We now investigate if there is a risk-based explanation of the early resolution premium, i.e., if the pricing model can be augmented to account for the effect described above. In particular, a stock's high IVD may just be a signal for a strong exposure of that stock's return to a latent factor priced by investors.

The return time series as well as the economic motivation for the sorting strategy suggest the use of a *late-minus-early* portfolio, LME, as a proxy of the new latent factor in the augmented pricing model. To construct the proxy, we perform an independent double sort on IV_{365} and IVD into 5x2 portfolios. LME is the difference between value weighted returns on the two top IV_{365} portfolios with the high IVD portfolio on the long side. The procedure is similar to the one described in Section 5.2 with the difference that we do not form 5x5 portfolios. In particular, we do not consider the difference between quintiles portfolios to avoid mechanical relations between portfolio returns and the factor which would then be the difference of returns on two of the test assets.

To test whether LME is priced, we perform a cross-sectional regression with GMM, i.e. we jointly estimate the betas and market prices of risks as well as their standard errors. As test assets we use the 25 portfolios sorted independently with respect to IV_{365} and IVD, described in Section 5.2. The advantage of this sort is that it generates sufficient variation across LME betas in order to identify the market price of risk.

[TABLE 10 HERE]

Estimates of the market prices of risks are presented in Table 10. We find that the LME premium is positive and large in all tested specifications. In line with theory, the market price of risk is consistently estimated around 0.8 percent in all specifications, which is close to the return difference between IVD quintile portfolios (see Table 4). The estimates of the LME coefficient are all highly significant, while we barely find significant estimates for any of the other factors.

We also find that the pricing performance on the 25 test portfolios, measured by the cross-sectional R^2, increases considerably when including LME into the asset pricing model. For example, adding LME to the market factor in a simple two factor model increases the cross-sectional R^2 from 6% to 52%. Adding LME to the best model tested, the Pastor and Stambaugh (2003) model, more than doubles the R^2 from 28% to 61%. In Figure 5, we plot the model-implied vs. the average realized returns on the 25 test assets for different models.

[FIGURE 5 HERE]

As can also be seen from the figure, the pricing performance of the four standard models without LME (the figures on the lefthand side) is consistently disappointing for the five top IV_{365} quintile portfolios. Adding LME largely reduces the mispricing on this subset of portfolios. This effect is driving the large increases in R^2 that we see in Table 10. The augmented models perform only slightly better compared to the respective benchmark when it comes to pricing the 20 portfolio returns in the lower IV_{365} quintiles (marked grey). This again documents that those models are not able to explain the early resolution premium.

The fact that the increase in pricing performance is limited to the five top IV_{365} quintile portfolios again points to the scope of our analysis. LME is supposed to explain variation in a specific group of stocks for which we observe that the timing of the resolution of uncertainty is relevant. The fact that a factor explains the early resolution premium indicates that there is a common component in the returns on late resolution stocks (and early resolution stocks) and that investors claim a compensation for holding stocks with a high exposure to this common source of variation. Stocks outside of this group (i.e. stocks with low IV_{365}) are not exposed to the common component and, consequently, their model-implied returns are not affected by adding LME to the factor model.

As a litmus test of LME, we run Fama MacBeth regressions with single stocks, just as in Section 5.4, but include LME betas in the cross-sectional regression. Ultimately, if the model augmented by LME is supposed to explain the early resolution premium well, the factor should mitigate the explanatory power of the characteristic IVD. We estimate betas on the 25 IV_{365}/IVD sorted portfolios to ensure sufficient variation in LME betas. The results are shown in Table 11.

[TABLE 11 HERE]

We observe that the interaction term becomes insignificant as soon as we include LME into the asset pricing model for almost all tested specifications. Only in the augmented Pastor and Stambaugh (2003) model, the characteristic retains some explanatory power in excess of the LME factor. All in all, we consider our findings as strong evidence in favor of a risk-based explanation for the early resolution premium.

6 A general equilibrium model

In the following we present a simple long-run risk model in the spirit of Bansal and Yaron (2004). We show that a preference for early resolution of uncertainty and volatility processes that allow for type E and type L uncertainty resolution profiles can generate the empirically observed features regarding the return differential between late and early resolution stocks. We show further that this return differential is solely driven by the investor's preferences.

Consider an agent with preferences described by an Epstein-Zin utility function:

$$U_t(C_t, U_{t+1}) = \left[(1 - e^{-\delta})C_t^{1-\frac{1}{\psi}} + e^{-\delta}\left(E_t\left[U_{t+1}^{1-\gamma}\right]\right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right]^{\frac{1}{1-\frac{1}{\psi}}}, \tag{2}$$

where time t utility U_t is defined over current consumption C_t and the continuation utility U_{t+1}. γ denotes the relative risk aversion, ψ is the elasticity of intertemporal substitution, and δ denotes the time preference parameter. Note that if $\gamma = \frac{1}{\psi}$, the agent has time-additive CRRA preferences. Log consumption growth exhibits the following dynamics:

$$\Delta c_{t+1} = \mu_c + x_t + \sigma_c\sqrt{v_t + w_t}\epsilon_{t+1}^c, \tag{3}$$

where x is the long-run consumption growth process with

$$x_{t+1} = \rho_x x_t + \sigma_x\sqrt{v_t + w_t}\epsilon_{t+1}^x. \tag{4}$$

Moreover, there are two dividend processes with log growth

$$\Delta e_{t+1} = \mu_e + \phi_e x_t + \sigma_e\sqrt{v_t}\epsilon_{t+1}^e \tag{5}$$

$$\Delta l_{t+1} = \mu_l + \phi_l x_t + \sigma_l\sqrt{w_t}\epsilon_{t+1}^l. \tag{6}$$

Each of the two volatility processes v and w is the sum of a persistent component $v_p(w_p)$ and a short-lived component $v_s(w_s)$ with dynamics

$$v_{p,t+1} = \bar{v}_p + \rho_{vp}\left(v_{p,t} - \bar{v}_p\right) + \sigma_{vp}\sqrt{v_{pt}}\epsilon^{vp}_{p,t+1} \tag{7}$$

$$v_{s,t+1} = \bar{v}_s + \rho_{vs}\left(v_{s,t} - \bar{v}_s\right) + \sigma_{vs}\sqrt{v_{st}}\epsilon^{vs}_{s,t+1} \tag{8}$$

$$w_{p,t+1} = \bar{w}_p + \rho_{wp}\left(w_{p,t} - \bar{w}_p\right) + \sigma_{wp}\sqrt{w_{pt}}\epsilon^{wp}_{p,t+1} \tag{9}$$

$$w_{s,t+1} = \bar{w}_s + \rho_{ws}\left(w_{s,t} - \bar{w}_s\right) + \sigma_{ws}\sqrt{w_{st}}\epsilon^{ws}_{s,t+1} \tag{10}$$

To model the different speeds of mean reversion, we assume that the coefficients ρ are larger for the persistent than for the short-lived components, i.e. $\rho_{vp} > \rho_{vs}$ and $\rho_{wp} > \rho_{ws}$. The difference in the persistence provides enough flexibility to model the expectations about the volatility of each claim such that we can differentiate between long-run and short-run volatility and thereby set up claims with late and early resolution of uncertainty. For illustrative purposes, we adopt a symmetric parameterization where $\rho_{vp} = \rho_{wp} > \rho_{vs} = \rho_{ws}$, $\bar{v}_s = \bar{v}_p = \bar{w}_s = \bar{w}_p$, $\sigma_{vs} = \sigma_{vp} = \sigma_{ws} = \sigma_{wp}$, $\mu_e = \mu_l$. The only difference between the volatility processes is in the persistence parameters and the initial values $v_{p,0}, v_{s,0}, w_{p,0}$ and $w_{s,0}$. A stylized depiction of the volatility processes that add up to a late and early resolution volatility process is depicted in Figure 6: A large but short-lived (small but persistent) and a small but persistent component (large but short-lived) aggregate to an early (late) uncertainty resolution profile.

[FIGURE 6 HERE]

The model can be solved in a standard fashion, for details, we refer the reader to appendix B.1. We then compute the expected returns for what is similar to our empirical LME strategy: The difference in expected returns between claim e with volatility process v and claim l with volatility process w. Claim e (l) is the early (late) resolution claim, meaning that it is volatile (stable) at first but then rather stable (volatile). This is modeled by a large (small) but short-lived (persistent) process v_s (w_p) and a small (large) but persistent (short-lived) process v_p (w_s).

Figure 7 shows the results for different preference parameter specifications but with all other parameters fixed. Our calibration follows Bansal and Yaron (2004) with the persistence parameter of the more persistent volatility processes as in Bansal et al. (2011).

[FIGURE 7 HERE]

We find that for all parameter values where $\gamma = \frac{1}{\psi}$, the expected returns of both claims are exactly equal. In figure 7 this is the intersection of the return difference surface and the grey γ-ψ-plane through the origin. If $\gamma < \frac{1}{\psi}$, i.e. with a preference for late resolution of uncertainty, the expected return of the late resolution claim is less than that of the early resolution claim: the return difference surface lies below the plane through the origin. Finally, when the marginal investor has a preference for early resolution of uncertainty ($\gamma > \frac{1}{\psi}$), the expected return on the late resolution claim exceeds that on the early resolution claim.

In Figure 7, we fixed a certain level of the exogenously given dividend volatility for illustrative purposes. In order to exactly transfer our empirical approach to the model, we need to match implied volatilities of both dividend claims for the long maturity: Keeping the entire parameterization fixed except for the initial values of $v_{p0}, v_{s0}, w_{p0}, w_{s0}$ we derive conditions on the initial values such that implied variances are matched. Plugging these initial values that ensure a matched implied variance into the expressions for the expected returns, one can see that it is the preference specification commonly dubbed 'preference for early resolution of uncertainty' that drives the difference in expected return between claim with a difference in short horizon implied volatility but similar long horizon volatility, thereby confirming the results from Figure 7. For details, we refer the reader to Appendix B.3.

7 Conclusion

We provide the first empirical evidence for a premium for early resolution of uncertainty. This premium amounts to 7 percent per year and is paid to investors who are willing to bear uncertainty about the return for longer. Our findings indicate 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 behaviors of individuals in lab experiments.

To uncover the early resolution premium in stock return data, we introduce *Implied Volatility Duration* (IVD), a novel measure for the timing of uncertainty resolution. Portfolio sorts w.r.t. implied volatility and its duration result in average returns of the long-short position of 1 percent if the holding period is one month and 7 percent if the holding period is one year. To assess the economic magnitude of this finding, imagine an investor who can choose between the portfolio of low IVD stocks, which exhibit an early resolution of uncertainty, and high IVD-stocks, which exhibit a late resolution of uncertainty. The spread in IVD between these two ends amounts to one month. Thus, investors are willing to give up a compensation of 7 percent per year in exchange of knowing one month earlier about the return on their investments.

We find that the return on the "late-minus-early" portfolio (that is the long-short position described above) yields a larger return in times of increased uncertainty and market downturns. In other words, it is particularly in bad times when investors are rewarded for bearing uncertainty for longer. In line with that, the portfolio return has a negative market beta. We find that cross-sectional variation in "alphas" relative to the common asset pricing models are strongly related to the characteristic IVD interacted with implied volatility. Motivated by that, we augment standard factor models by a new factor which is the return on a "late-minus-early" portfolio. This factor is supposed to proxy variation in the investors' need to have uncertainty resolved early. 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 rather than a behavioral one.

To build the bridge between these empirical findings and decision theory, we consider a consumption-based general equilibrium model in which a rational agent with recursive preferences prices claims to uncertain future payoffs. In particular, we introduce a sophisticated volatility structure in the long-run risk model of Bansal and Yaron (2004) and let the investor price two different claims that only differ with respect to the expected evolution of dividend (and thus return) volatility. We show that the difference between expected returns on the late and early resolution claim is positive if and only if the investor's coefficient of relative risk aversion is greater than the inverse of her elasticity of intertemporal substitution.

Our findings impose boundaries for the parameters in models of dynamic choice and applications in macro finance, in particular asset pricing and asset allocation. Once we assume that the coefficient of relative risk aversion should be below 5, our results imply that the elasticity of intertemporal substitution must be above 0.2, a value that is at odds with the findings of Hall (1988). Drechsler and Yaron (2011) show that in asset pricing models with long-run risks, the market price of trend consumption growth risk is positive if the investor's risk aversion coefficient exceeds the inverse of her elasticity of intertemporal substitution. Moreover, the market price of variance risk is then negative. These channels lead to a strongly countercyclical risk premium which is in line with the data (see Martin (2016)). Our results lend support to the long-run risk explanation of the large and countercyclical risk premium by corroborating one of the main assumptions made by its advocates, namely that investors prefer early resolution of uncertainty.

A Details on the investment strategy

This appendix provides more details on the trading strategy introduced in Section 4. To find pairs of early and late resolution stocks, we proceed as follows:

1. In each month, we sort stocks with respect to their IV_{365}. This constitutes our list of candidate matches.
2. Beginning with the stock with the lowest IV_{365}, we identify all stocks that have an IV_{365} that is no more than 0.01 away from the original stock's IV_{365}.
3. From those stocks, we select the one whose IV_{30} is farthest away from the original stock's IV_{30}.
4. If the difference is larger than 0.15, we add this pair to the list of pairs for the given month. We exclude the two stocks from the list of candidates.
5. We repeat step 2 with the second stock on the list of candidates and continue until all stocks have been considered.

The sorting step 1 of the above procedure is somewhat arbitrary but ensures that our results are replicable. Obviously, putting stocks in a different order may result in other pairs, because a match of the stock we consider first is no longer available as possible match for other stocks we consider later. We, however, do not want to allow that certain stocks appear several times in the list of pairs, because it may lead to the case where a small number of stocks (that are matches for many other stocks) drive the results.

To test if the success of the strategy depends on how we put stocks into order, we rerun the strategy 10000 times and choose another random permutation of the list of candidates in every month before starting the search for pairs. The return on all 10000 instances of the investment strategy are positive. In particular, it turns out that the investment strategy discussed above is a very conservative one. The average return difference between low IV_{30} and high IV_{30} stocks is 5.17 percent. In particular, while the average return on low IV_{30} stocks is 10.91 percent, similar to the number reported in Table 1, the average return on the high IV_{30} stocks is only 5.74 percent per year. Details are provided in Table 12.

[TABLE 12 HERE]

We also change the cutoff values from 1% for the short end and 15% for the long end. Table 13 shows returns on strategies based on various choices of these cutoffs. 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 8.5% with a t-statistic of 3.73. For some calibrations there is not a single pair that 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 13 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 are all insignificant.

B General Equilibrium Model

B.1 Pricing kernel

The general Epstein and Zin (1989) utility log pricing kernel is given by:

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

with r^w_{t+1} denoting the return on total wealth (the consumption claim in equilibrium). 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 five state variables:

$$wc_t = A_{wc,0} + A_{wc,x} x_t + A_{wc,vp} v_{pt} + A_{wc,vs} v_{st} + A_{wc,wp} w_{pt} + A_{wc,ws} w_{st}. \tag{B.2}$$

Using the Campbell-Shiller approximation, r^w_t can be approximated as follows:

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

with coefficients:

$$\kappa_{wc,1} = \frac{\exp(\bar{wc})}{1 + \exp(\bar{wc})}, \quad \kappa_{wc,0} = \ln\left(1 + \exp(\bar{wc})\right) - \tfrac{\exp(\bar{wc})}{1+\exp(\bar{wc})} \bar{wc} \tag{B.4}$$

In order to determine wc, plug B.3 into the Euler equation to get:

$$\begin{aligned} E_t\left[e^{m_{t,t+1} + r^w_{t+1}}\right] &= 1 \\ \Leftrightarrow E_t\left[e^{-\delta\theta - \frac{\theta}{\psi}\Delta c_{t+1} + \theta r^w_{t+1}}\right] &= 1 \\ \Leftrightarrow E_t\left[e^{-\delta\theta - \frac{\theta}{\psi}\Delta c_{t,t+1} + \theta(\kappa_{wc,0} + \kappa_{wc,1} wc_{t+1} - wc_t + \Delta c_{t,t+1})}\right] &= 1 \end{aligned} \tag{B.5}$$

Plugging the conjecture for the wealth consumption ratio into (B.5) yields a systems of equations with solution

$$\begin{aligned} A_{wc,0} &= \frac{\delta - (1 - \frac{1}{\psi})\mu_c - \kappa_{wc,0}}{\kappa_{wc,1} - 1} \\ &\quad - \kappa_{wc,1} \frac{A_{wc,vp}(1-\rho_{vp})\bar{v}_p + A_{wc,vs}(1-\rho_{vs})\bar{v}_s + A_{wc,wp}(1-\rho_{wp})\bar{w}_p + A_{wc,ws}(1-\rho_{ws})\bar{w}_s}{\kappa_{wc,1} - 1} \end{aligned} \tag{B.6}$$

$$A_{wc,x} = \frac{1 - \frac{1}{\psi}}{1 - \kappa_{wc,1}\rho} \tag{B.7}$$

$$A_{wc,ki} = -\frac{\kappa_{wc,1}\rho_{ki} - 1}{\kappa^2_{wc,1}\theta\sigma^2_{ki}} \pm \sqrt{\left(\frac{\kappa_{wc,1}\rho_{ki} - 1}{\kappa^2_{wc,1}\theta\sigma^2_{ki}}\right)^2 - \frac{\sigma^2_c\left(1 - \frac{1}{\psi}\right)^2 + \kappa^2_{wc,1} A^2_{wc,x}\sigma^2_x}{\kappa^2_{wc,1}\sigma^2_{ki}}} \tag{B.8}$$

with $k \in \{v, w\}, i \in \{p, s\}$. To get an economically meaningful result, we choose the root with $\operatorname{sgn}\left(\frac{\kappa_{wc,1}\rho_{ki}-1}{\kappa^2_{wc,1}\theta\sigma^2_{ki}}\right)$ such that $\lim_{\sigma_c \to} \lim_{\sigma_x \to 0} A_{wc,ki} = 0$ (see also Tauchen (2005)).

B.2 Price-dividend ratios

The return r_d on dividend claim d with $d \in \{e, l\}$ and associated volatility processes ki can be approximated linearly in terms of its price-dividend ratio pd_d and dividend growth Δd

$$r_{d,t+1} \approx \kappa_{pd,d,0} + \kappa_{pd,d,1} pd_{d,t+1} - pd_{d,t} + \Delta d_{t+1}. \tag{B.9}$$

with coefficients:

$$\kappa_{pd,d,1} = \frac{\exp(\bar{pd}_d)}{1 + \exp(\bar{pd}_d)}, \quad \kappa_{pd,d,0} = \ln\left(1 + \exp(\bar{pd}_d)\right) - \tfrac{\exp(\bar{pd}_d)}{1+\exp(\bar{pd}_d)} \bar{pd}_d \tag{B.10}$$

where $\bar{pd}_d$ is defined as the long-run mean of pd_d. The price dividend ratio is assumed to be affine in the state variables:

$$pd_{d,t} = A_{pd,d,0} + A_{pd,d,x} x_t + A_{pd,d,vp,t} v_{pt} + A_{pd,d,vs,t} v_{st} + A_{pd,d,wp,t} w_{pt} + A_{pd,d,ws,t} w_{st} \tag{B.11}$$

Plugging the guess into the Euler equation for claim d yields an equation system with solutions

$$\begin{aligned}
A_{pd,0} &= \frac{-\delta - \frac{\mu_c}{\psi} + \mu + \kappa_{pd,0} + \kappa_{pd,1}\left(A_{pd,d,vp}(1-\kappa_{vp})\bar{v}_p + A_{pd,d,vs}(1-\kappa_{vs})\bar{v}_s\right)}{1-\kappa_{pd,1}} \\
&\quad + \frac{\kappa_{pd,1}\left(A_{pd,d,wp}(1-\kappa_{wp})\bar{w}_p + A_{pd,d,ws}(1-\kappa_{ws})\bar{w}_s\right)}{1-\kappa_{pd,1}} && \text{(B.12)} \\
A_{pd,d,x} &= \frac{\phi_d - \frac{1}{\psi}}{1 - \kappa_{pd,1}\rho_x} && \text{(B.13)} \\
A_{pd,d,ki} &= -\frac{\kappa_{pd,1}\kappa_{ki} - 1 + (\theta-1)\kappa_{wc,1}\kappa_{pd,1}A_{wc,ki}\sigma_{ki}^2}{\kappa_{pd,1}^2\sigma_{ki}^2} \\
&\quad \pm \Bigg\{ \left(\frac{\kappa_{pd,1}\kappa_{ki} - 1 + (\theta-1)\kappa_{wc,1}\kappa_{pd,1}A_{wc,ki}\sigma_{ki}^2}{\kappa_{pd,1}^2\sigma_{ki}^2}\right)^2 \\
&\quad - \frac{1}{\kappa_{pd,1}^2\sigma_{ki}^2}\Big(2(\theta-1)(\kappa_{wc,1}\rho_{ki} - 1)A_{wc,ki} + (\theta-1)^2\kappa_{wc,1}^2 A_{wc,ki}^2\sigma_{ki}^2 \\
&\quad + (\theta-1)^2\kappa_{wc,1}^2 A_{wc,x}^2\sigma_x^2 + \sigma_d^2 + \kappa_{pd,1}^2 A_{pd,x}^2\sigma_x^2 + \gamma^2\sigma_c^2 \\
&\quad + 2(\theta-1)\kappa_{wc,1}\kappa_{pd,1}A_{wc,x}A_{pd,x}\sigma_x^2\Big)\Bigg\}^{\frac{1}{2}} && \text{(B.14)}
\end{aligned}$$

where we choose the root such that $\lim_{\sigma_c \to 0} \lim_{\sigma_x \to 0} A_{pd,d,ki} = 0$, again see Tauchen (2005). Note that if k is not the associated volatility process of claim d, the σ_d term in the square root does not show up.

B.3 Implied Variance matching condition

We compute and match the implied variances:

$$E_0^{\mathbb{Q}}\left[E_1\left[e^{2(r^e_{1,2}+r^e_{2,3})}\right] - E_1\left[e^{r^e_{1,2}+r^e d_{2,3}}\right]^2 - E_1\left[e^{2(r^l_{1,2}+r^l_{2,3})}\right] + E_1\left[e^{r^l_{1,2}+r^l_{2,3}}\right]^2\right] = 0 \tag{B.15}$$

Each of the returns in equation B.15 is a function of the four free parameters $v_{p0}, v_{s0}, w_{p0}, w_{s0}$ but we are not able to solve for the parameters in closed form. B.15 is of the form

$$\ln\left(e^{x+y} - e^{x+y'}\right) - \ln\left(e^{x+z} - e^{x+z'}\right) = 0 \tag{B.16}$$

which we therefore approximate with

$$y - y' - z' + z = 0. \tag{B.17}$$

Since we have adopted a symmetric approach with equal long-run means for the four processes, the parameters will be of the form $k_{i0} = \bar{k}_i \pm 0.5g_i$ where $g_i = v_i - w_i$, leaving us with 2 degrees of freedom. If we furthermore exogenously set g_p, i.e. we decide on the size of the difference between the two persistent volatility processes at $t = 0$, equation B.17 is uniquely identified yielding the multiple by which g_p must be larger than g_s in order for the $\mathbb{Q}$-variances of the two claims to be equal.

The results are depicted in figure 8 and confirm the result with fixed exogenous volatility process.

[FIGURE 8 HERE]

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Table 1: **Investment strategy based on pairs: returns**

Low IV_{30}	High IV_{30}	Investment strategy
10.73	7.94	2.79
(2.23)	(1.46)	(2.52)

Average 12 month returns on the investment strategy. Pairs are formed such that the 365 day-IVs of the two stocks in a given pair do not differ by more than one percentage point, while 30 day-IVs must differ by at least 15 percentage points. Numbers in parentheses are Newey-West t-statistics with 12 lags.

Table 2: **Investment strategy based on pairs: alphas**

α	Mkt	SMB	HML	RMW	CMA	LIQ
3.99^{***}	-0.15^{***}					
(3.42)	(-2.94)					
4.18^{***}	-0.15^{***}	-0.15^{**}	0.08^{*}			
(4.72)	(-3.95)	(-2.15)	(1.91)			
3.87^{***}	-0.13^{**}	-0.16^{***}	0.05	0.02	0.06	
(3.56)	(-2.16)	(-2.65)	(0.66)	(0.18)	(0.41)	
3.84^{***}	-0.13^{**}	-0.16^{***}	0.05	0.02	0.06	0.00
(2.91)	(-2.13)	(-2.69)	(0.66)	(0.18)	(0.42)	(0.08)

Regression of 12-month investment strategy returns on 12 month common risk factors: The market return (Mkt), Small-minus-Big (SMB), High-Minus-Low book to market equity ratio (HML), robust-minus-weak profitability (RMW), conservative-minus-aggressive investment (CMA) (all from Kenneth French's website) and the liquidity risk factor LIQ from Robert Stambaugh's website. α denotes the regression constant and is expressed in percent. Numbers in brackets are Newey-West t-statistics with 20 lags. ***, **, and * indicate significance at the one, five and ten percent level, respectively.

Table 3: **Summary statistics: IV and IVD**

Panel A: *Implied Volatility Duration*

	early	2	3	4	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: *Implied Volatility over 365 days*

	early	2	3	4	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 characteristics Implied Volatility Duration (IVD) and IV_{365} for 25 portfolios sorted on IV_{365} and IVD.

Table 4: **IV/IVD sorted portfolio returns**

Panel 1A: *Value-weighted 12 month returns*

	early	2	3	4	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)
HMLIV	−4.64	−2.16	−3.63	1.59	2.53	
	(-0.68)	(-0.28)	(-0.57)	(0.21)	(0.33)	

Panel 1B: *Equally-weighted 12 month returns*

	early	2	3	4	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)
HMLIV	−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 2A: *Value-weighted 1 month returns*

	early	2	3	4	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)
HMLIV	-0.98	-0.55	-0.13	-0.06	0.17	
	(-1.19)	(-0.81)	(-0.17)	(-0.07)	(0.24)	

Panel 2B: *Equally-weighted 1 month returns*

	early	2	3	4	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)
HMLIV	-0.80	-0.61	-0.43	-0.50	0.10	
	(-1.14)	(-0.89)	(-0.64)	(-0.69)	(0.17)	

Twelve and one month average returns on value-weighted and equally weighted portfolios sorted on 365-day-implied volatility (IV_{365}) 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 5: **Realized variance**

equally weighted returns

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

value-weighted returns

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

Realized Variance of the IV/IVD-sorted portfolios' returns held for one- and twelve month periods. F-tests of the null hypothesis of equal variances in the top IV quintile late and early resolution portfolios can be rejected for the 1 month returns and cannot be rejected for the 12 month period. For the 12 month holding period, the assumption of independent return observations is very likely untenable. We therefore also performed Levene's test for the 12 month period. Levene's test could not reject the null of equal variances with p-values of 0.76 (value-weighted) and 0.57 (equally-weighted) for 12 month returns.

Table 6: **Alphas of the Late-minus-Early (LME) portfolio**

α	MKT	SMB	HML	RMW	CMA	LIQ
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)	
0.86^{**}	-0.21	-0.13	0.25	0.17	0.29	0.06
(2.09)	(-1.46)	(0.78)	(0.85)	(0.56)	(0.83)	(0.58)

Regression of 1-month returns on the LME portfolio on common risk factors (from Kenneth French's (Mkt, SMB, HML, RMW and CMA) and Robert Stambaugh's (LIQ) website, respectively). Numbers in brackets are Newey-West t-statistics with 12 lags.

Table 7: **Portfolio characteristics**

	early	2	3	4	late	mean
			Panel A: *Characteristics*			
AVG IVD	192.95	208.8	211.67	213.69	218.98	211.72
AVG 360d IV	0.7809	0.753	0.7705	0.7868	0.7905	0.4191
AVG ME in Mio $	924	657	610	560	662	1234
BM in 0.001	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	24.33	24.33	24.33	24.33	23.95	24.33
			Panel B: *Portfolio betas*			
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	

Portfolio characteristics of the stocks in the highest IV quintile. AVG is average 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 Amihud's illiquidity measure. CFD is Dechow et al.'s estimate of stocks' cash-flow duration using the parameter estimates from Weber (2016). With the exception of LIQ, following the procedure in An et al. (2014), the factors were constructed using stock returns from our sample. The mean is the time series mean over the cross-sectional medians.

Table 8: **Size/IVD sorted portfolio returns**

	early	2	3	4	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 9: **Regression coefficients**

	MKT	SMB	HML	RMW	CMA	LIQ	$IV^2 \times IVD$
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)	(-0.96)				(2.63)
FF5	0.63^{*}	0.09	-0.25	0.71^{*}	-0.23		
	(1.8)	(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)
PS	0.63^{*}	-0.06	-0.34			1.04	
	(1.77)	(-0.28)	(-1.01)			(1.19)	
	0.63^{*}	-0.06	-0.34			1.07	0.04^{***}
	(1.77)	(-0.28)	(-1.00)			(1.22)	(2.62)

Regression coefficients from a second stage Fama-MacBeth-regression of single stock returns on various factors and $IVD \times IV^2_{365}$ as a stock characteristic. Numbers in brackets are Newey-West t-statistics with 4 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, FF5 and PS denote the model specification from Fama and French (1992), Fama and French (2015) and Pastor and Stambaugh (2003) , respectively. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 10: **Lambdas**

	MKT	SMB	HML	RMW	CMA	LIQ	LME	$R^2_{adj.}$
CAPM	0.38							-0.45
	(0.96)							
	0.43						1.03^{***}	0.21
	(1.12)						(2.83)	
FF3	0.57^{*}	−0.15	-0.69^{**}					0.22
	(1.73)	(−0.37)	(−2.05)					
	0.56^{*}	−0.12	−0.51				0.77^{***}	0.51
	(1.72)	(−0.30)	(−1.56)				(2.72)	
FF5	0.60^{*}	0.19	-0.68^{*}	0.28	0.38^{*}			0.23
	(1.85)	(0.57)	(−1.95)	(0.82)	(1.74)			
	0.58^{*}	0.08	−0.47	0.26	0.21		0.76^{***}	0.50
	(1.80)	(0.24)	(−1.40)	(0.79)	(0.99)		(2.69)	
PS	0.57^{*}	−0.16	-0.68^{**}			−0.11		0.18
	(1.74)	(−0.38)	(−2.21)			(0.29)		
	0.56^{*}	−0.15	−0.46			0.07	0.78^{***}	0.49
	(1.73)	(−0.36)	(−1.59)			(0.17)	(2.71)	

Regression coefficients from a second stage Fama-MacBeth-regression of portfolio returns on various factors. Terms in brackets are Newey-West-t-statistics. All factors except for LIQ 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 365 day IV-and-IVD portfolio. This ensures sufficient variation in LME-betas. FF3, FF5 and PS denote the model specification from Fama and French (1992), Fama and French (2015) and Pastor and Stambaugh (2003) ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 11: **Characteristic vs LME**

	MKT	SMB	HML	RMW	CMA	LIQ	$IV^2 \times IVD$	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)	(1.98)
PS	0.65^{**}	-0.15	-0.62^{**}			2.16^{***}	0.04^{**}	
	(2.06)	(-0.52)	(-2.03)			(3.28)	(2.23)	
	0.67^{**}	-0.19	-0.48			1.58^{***}	0.40	0.03^{*}
	(2.10)	(-0.63)	(-1.55)			(2.73)	(1.63)	(1.77)

Regression coefficients from a second stage Fama-MacBeth-regression of single stocks on various factors and $IVD \times IV_{365}^2$ as a stock characteristic. α denotes the regression constant. Numbers in brackets are Newey-West t-statistics with 4 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 5×5 IV_{365}-and-IVD portfolio. FF3, FF5, and PS denote the model specification from Fama and French (1992), Fama and French (2015) and Pastor and Stambaugh (2003), respectively. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 12: **Alternative investment strategies**

	selected	mean	0.025	0.5	0.975
	Panel A: *Return on low IV_{30}^2 portfolio*				
mean	0.10734	0.1091	0.1025	0.1091	0.1158
t-stat	2.23344	2.0462	1.9339	2.0461	2.1580
std	0.27882	0.3171	0.3079	0.3169	0.3276
max	0.99030	1.2626	1.0835	1.2331	1.6172
min	-0.50158	-0.5221	-0.5757	-0.5752	-0.4872
	Panel B: *Return on high IV_{30}^2 portfolio*				
mean	0.07942	0.0574	0.0550	0.0574	0.0598
t-stat	1.46351	0.9779	0.9398	0.9778	1.0154
std	0.31143	0.3432	0.3402	0.3432	0.3463
max	1.16031	1.2094	1.1675	1.2085	1.2575
min	-0.53375	-0.5640	-0.5780	-0.5634	-0.5505
	Panel C: *Return on investment strategy*				
mean	0.02792	0.0517	0.0447	0.0517	0.0588
t-stat	2.51765	3.0418	2.5862	3.0376	3.5169
std	0.08914	0.1436	0.1349	0.1435	0.1526
max	0.40503	0.6316	0.4875	0.6198	0.8420
min	-0.25064	-0.3577	-0.4526	-0.3553	-0.2753

Summary statistics on the 10000 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 4), the cross-sectional mean, 2.5% quantile, median, and 97.5% quantile of the 10000 alternative strategies. t-statistics are Newey-West with 12 lags.

Table 13: **Alternative investment strategies (2)**

Min. spread short end	returns low IV	returns high IV	investment strategy	AVG number of pairs
Panel A: *Precision long end: 0.01*				
5%	11.4***	10.43**	0.97	1759
	(2.82)	(2.33)	(1.49)	
10%	11.09**	9.31*	1.78**	940
	(2.5)	(1.85)	(2.0)	
15%	10.73**	7.94	2.79**	542
	(2.23)	(1.46)	(2.52)	
20%	10.64**	7.09	3.55**	336
	(2.09)	(1.22)	(2.42)	
25%	11.12**	5.69	5.43***	223
	(2.09)	(0.97)	(2.94)	
30%	11.04*	5.07	5.98***	156
	(1.91)	(0.86)	(3.22)	
35%	12.43**	3.93	8.5***	114
	(2.05)	(0.66)	(3.73)	
Panel B: *Precision long end: 0.001*				
5%	11.72***	10.81**	0.91	1314
	(2.91)	(2.48)	(1.59)	
10%	11.22**	9.48**	1.74**	657
	(2.54)	(1.97)	(2.28)	
15%	11.28**	8.43	2.85**	357
	(2.36)	(1.58)	(2.44)	
20%	11.05**	7.75	3.3**	211
	(2.2)	(1.4)	(2.37)	
25%	11.5**	6.44	5.05***	135
	(2.11)	(1.14)	(2.93)	
30%	12.52**	6.54	5.98***	91
	(2.17)	(1.09)	(3.45)	
35%	11.46**	7.16	4.3***	65
	(1.99)	(1.15)	(2.18)	

Table continues on next page

Continued: **Alternative investment strategies (3)**

	Panel C: *Precision long end: no restriction*			
5%	12.24***	10.11*	2.13	2174
	(4.13)	(1.72)	(0.46)	
10%	12.14***	9.79*	2.35	1940
	(4.16)	(1.62)	(0.48)	
15%	12.01***	9.48	2.54	1713
	(4.19)	(1.52)	(0.49)	
20%	11.89***	9.13	2.77	1498
	(4.24)	(1.41)	(0.5)	
25%	11.79***	8.71	3.08	1301
	(4.29)	(1.31)	(0.53)	
30%	11.6***	8.33	3.27	1121
	(4.34)	(1.21)	(0.53)	
35%	11.46***	7.91	3.55	959
	(4.44)	(1.12)	(0.56)	

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.

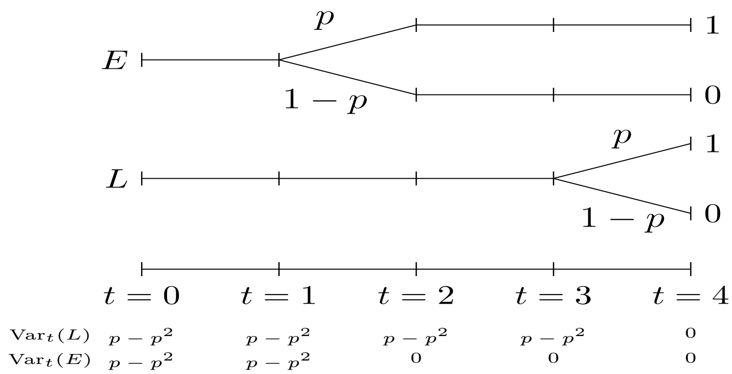


Figure 1: Stylized depiction of a late and early resolution claim

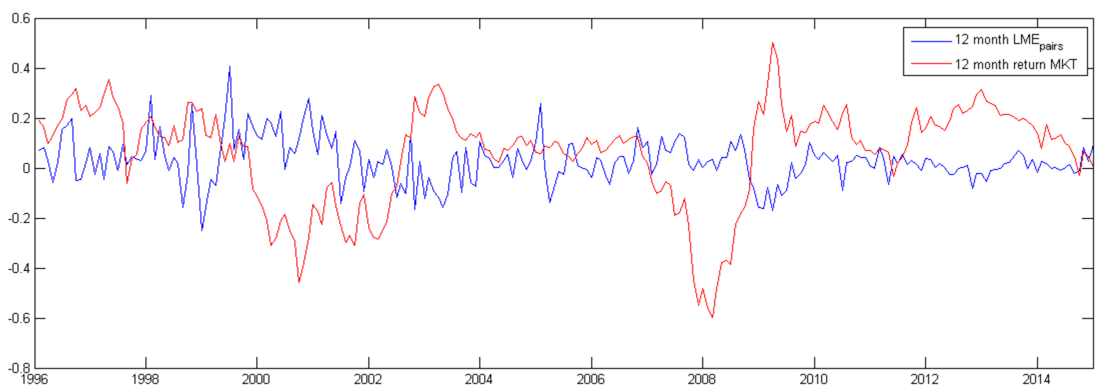


Figure 2: Twelve month returns on the market factor and the investment strategy based on pairs.

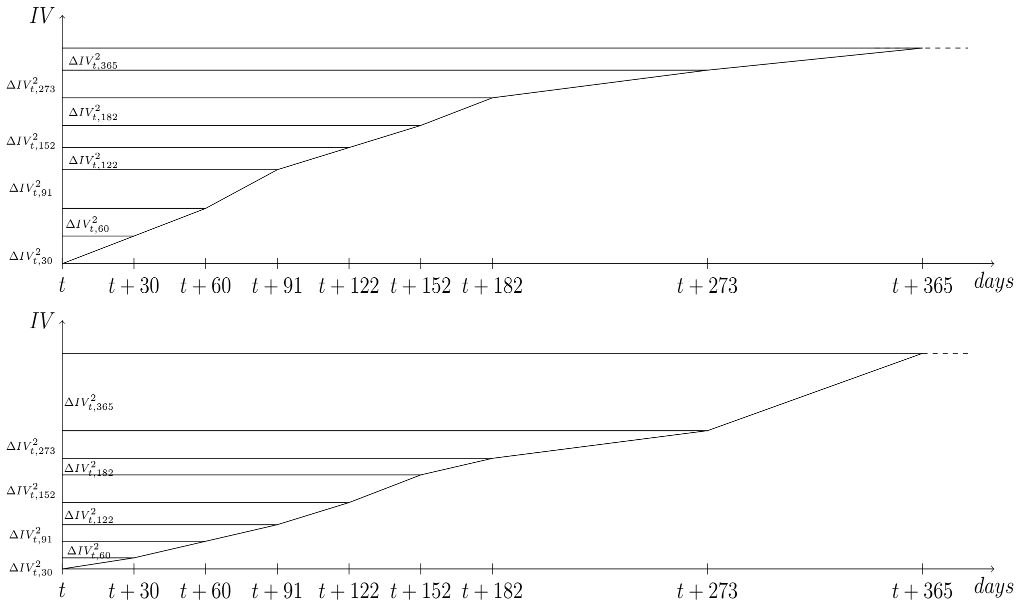


Figure 3: Stylized depiction of the quantities involved in computing IVD with a early (low IVD, in the upper figure) and late (high IVD, in the lower figure) resolution claim.

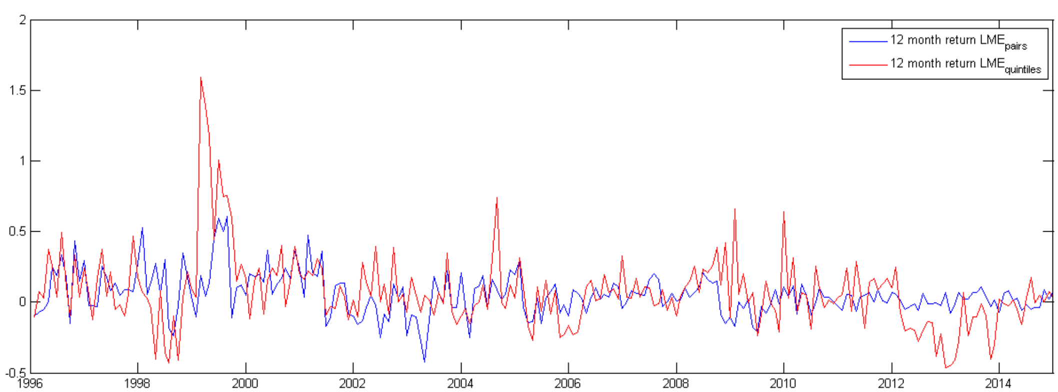


Figure 4: Twelve month returns on the LME portfolios constructed from the investment strategy based on pairs and the quintiles of stocks sorted by IV and IVD.

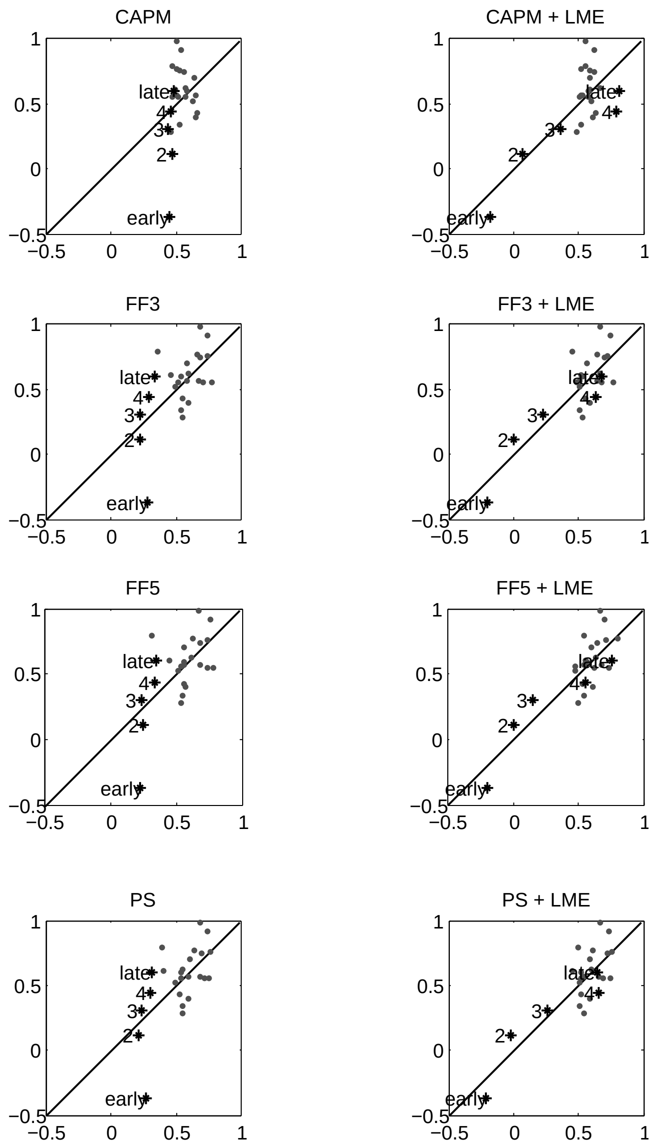


Figure 5: This figure plots model-implied expected returns (on the horizontal axis) against average realized returns (on the vertical axis) on 25 independently double sorted portfolios based on the criteria IV_{365} and IVD. The two plots on top show the CAPM and the CAPM augmented by LME, the two plots below show the Fama and French (1993) three factor model and the same model augmented by LME, the two plots below show the Fama and French (2015) five factor model and the same model augmented by LME, and the lower two plots show the Pastor and Stambaugh (2003) model and the same model augmented by LME. The black stars indicate the five portfolios in the top IV_{365} quintile.

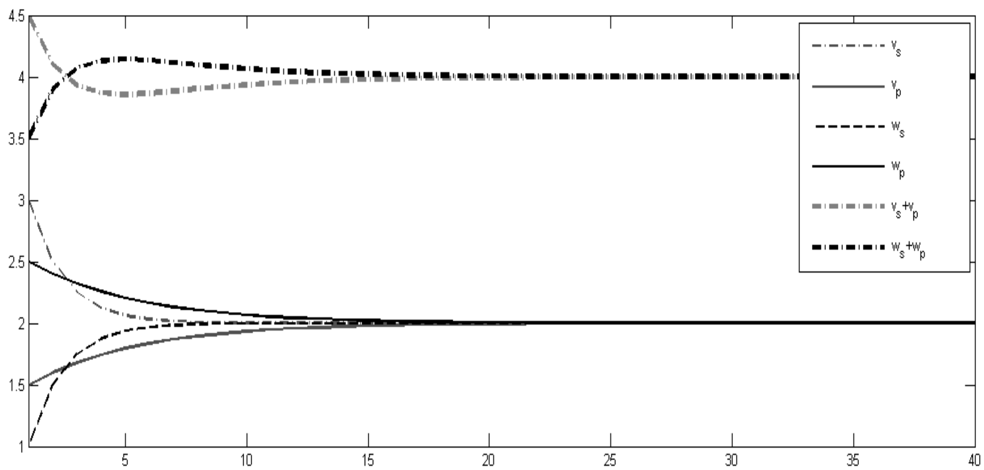
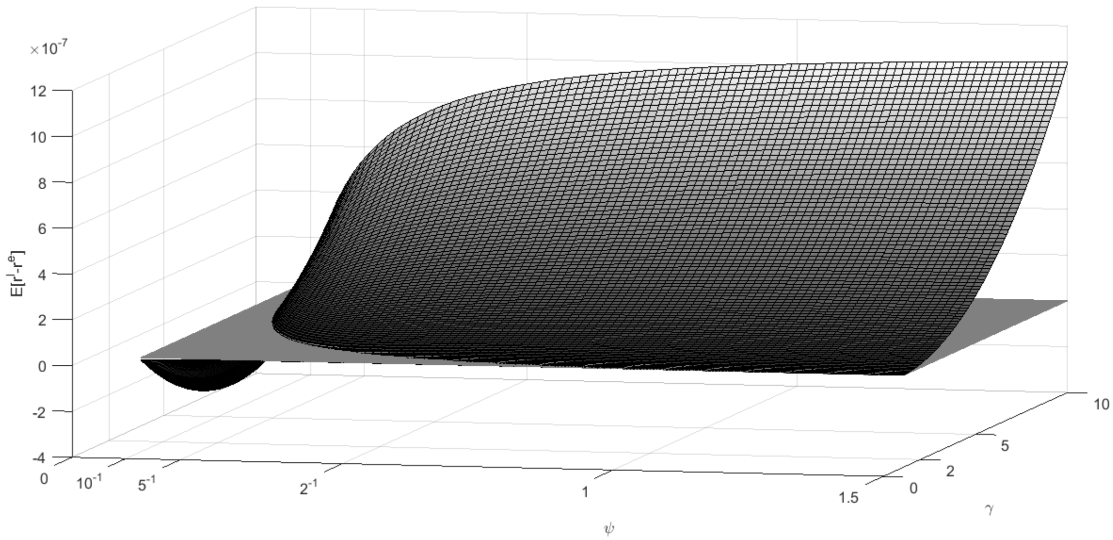


Figure 6: Stylized depiction of volatility processes with different persistence aggregating to an early and late uncertainty resolution profile



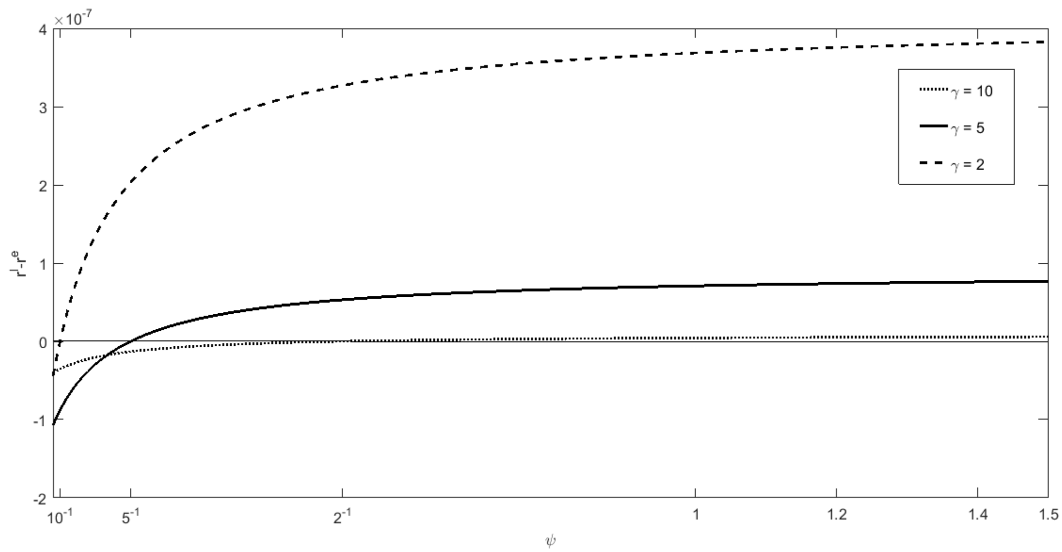


Figure 7: One-period expected return difference between the late and early resolution claim as described in section 6 for different values of relative risk aversion γ and ψ. Parameterization similar to Bansal and Yaron (2004): $\bar{v}_p = \bar{v}_s = \bar{w}_p = \bar{w}_s = 0.25 \cdot 0.0078^2 = \bar{\nu}$, $\kappa_{vs} = \kappa_{ws} = 0.987$, $\kappa_{vp} = \kappa_{wp} = 0.99$, $\sigma_{vs} = \sigma_{ws} = \sigma_{vp} = \sigma_{wp} = 0.23 \cdot 10^{-5} \cdot \bar{\nu}^{-\frac{1}{2}}$, $\rho_x = 0.979$, $\sigma_x = 0.044$, $\phi_e = \phi_l = 3$, $\sigma_e = 4.5 \cdot 10^{-1}$, $\mu_c = \mu_e = \mu_l = 0.0015$, $\delta = -\ln 0.998$. Initial volatility values are set symmetrically around the long-run means.

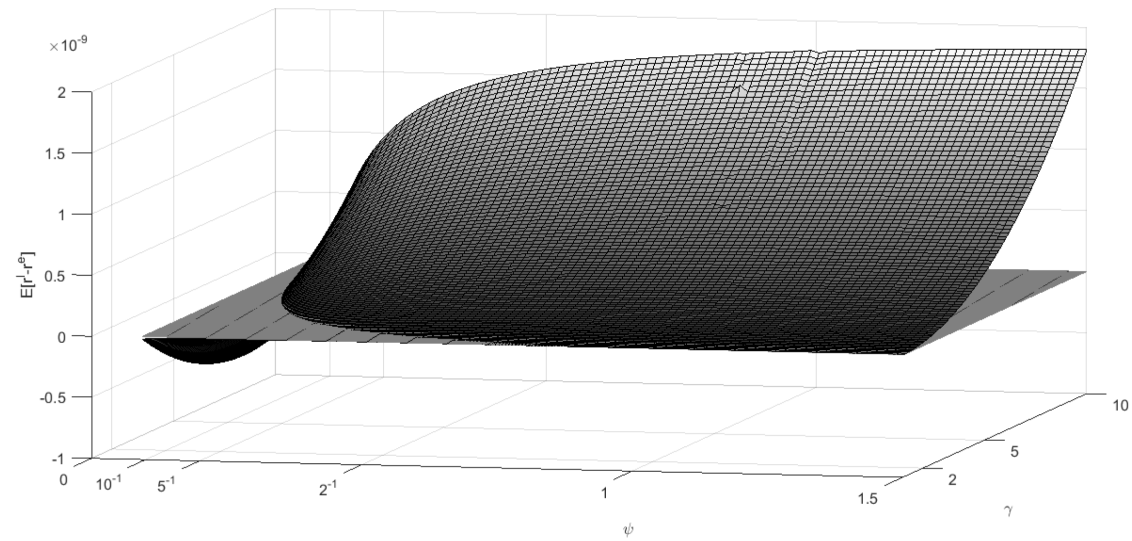


Figure 8: One-period expected return difference between the late and early resolution claim as described in Section 6 for different values of relative risk aversion γ and EIS ψ. Parameterization similar to Bansal and Yaron (2004), however, to ensure that for all parameter values, the solution to the model is well-defined, some parameter values, including the long-run means of the volatility processes around which their initial values are set symmetrically, have to be chosen to be rather large: $\kappa_{vs} = \kappa_{ws} = 0.8$, $\kappa_{vp} = \kappa_{wp} = 0.9$, $\sigma_{vs} = \sigma_{ws} = \sigma_{vp} = \sigma_{wp} = 0.04$, $\rho_x = 0.979$, $\sigma_x = 0.044$, $\phi_e = \phi_l = 3$, $\sigma_e = 4.5 \cdot 10^{-1}$, $\mu_c = \mu_e = \mu_l = 0.0015$, $\delta = -\ln 0.998$. $\bar{v}_p = \bar{v}_s = \bar{w}_p = \bar{w}_s = 0.5 = \bar{\nu}$.