Implied Volatility Duration and the Early Resolution Premium

Christian Schlag* Julian Thimme† Rüdiger Weber‡

This version: February 1, 2017

Abstract

We introduce *Implied Volatility Duration* (IVD) as a new measure for the timing of the resolution of uncertainty about future stock returns. A short IVD implies an early resolution of uncertainty in expectation. 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. In a general equilibrium model, we show that the expected excess returns on long IVD stocks can only exceed those of short IVD stocks 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

JEL: G12, E44, D81

* House of Finance, Research Center SAFE, Goethe-University Frankfurt, Theodor-W.-Adorno-Platz 3, 60323 Frankfurt am Main. E-mail: schlag@finance.uni-frankfurt.de

† House of Finance, Goethe-University Frankfurt, Theodor-W.-Adorno-Platz 3, 60323 Frankfurt am Main. E-mail: julian.thimme@hof.uni-frankfurt.de

‡ House of Finance, Goethe-University Frankfurt, Theodor-W.-Adorno-Platz 3, 60323 Frankfurt am Main. E-mail: ruediger.weber@hof.uni-frankfurt.de

The authors would like to thank Bob Dittmar, Stephan Jank, Holger Kraft, Christoph Meinerding, and seminar participants at Frankfurt (Goethe) for valuable comments and suggestions. Christian Schlag gratefully acknowledges research and financial support from SAFE, funded by the State of Hessen initiative for research LOEWE.

1 Introduction

The supreme challenge in asset pricing research is to explain how risk and attitudes towards risk translate into market prices. In this paper we focus on the timing of uncertainty resolution, that is *when* uncertainty is resolved, rather than *what* type of and *how much* uncertainty the investor faces.[1] Dynamic choice theory implies that if investors have non-neutral preferences about 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 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 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. It is, however, 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., 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 cash-flow uncertainty and interpret this difference as the premium investors require to be compensated 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

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

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 stocks in the cross-section. 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 whose IVs over a long horizon from t to T are close to each other: Since the variances over the long horizon are almost the same, the two stocks exhibit 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 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 claim, while the other one is of type L.

The average return difference between L and E stocks in the respective pairs is 7 percent per year with a t-statistic of 3.2. As we show in regression analyses, this return difference cannot be explained by the exposures of these returns 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 a 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. Within the stocks with high IV, we find a significantly positive average return of around seven percent on the 'late-minus-early' (LME) portfolio which is evidence in favor of the representative investor exhibiting PERU. 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. We find that 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 appears likely.

We rationalize our empirical findings in 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 can only be higher than on the E stock, 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. Our model also gives rise to a linear factor model, which includes the market factor that, just as in the classic CAPM, accounts for the *level* of uncertainty and a *late-minus-early* factor that accounts for the *timing of uncertainty resolution*.

The rest of the paper is structured as follows. In Section 2, we review the related literature. The data are discussed in Section 3.1. In Section 3, 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 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 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 points to a certain preference structure, we provide robust and in a sense non-parametric support for the common assumption of PERU in the sense of Epstein and Zin (1989).

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 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 unrealistically high discount for early resolution of uncertainty. For example, the dynamics of Bansal and Yaron (2004) imply that the investor would 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 to not require the existence of a long-run risk component in consumption growth.

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 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. 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.

Other authors estimate preference parameters using 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 which together with normally assumed values for risk aversion greater than 1 would imply PERU. There is also some experimental evidence in favor of PERU provided by e.g. Brown and Kim (2014) or Meissner and Pfeiffer (2015). In an earlier study, Ahlbrecht and Weber (1996) find disparate evidence.

Somewhat related to this paper, Jagannathan and Liu (2015) gather evidence in favor of a preference for early resolution of uncertainty using a learning model. 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 approach is model-free.

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 An investment strategy

3.1 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 30, 60, 91, 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 taken from Kenneth French's website. Accounting data are taken 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. The quantities used for sorting 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).

3.2 Pairs of stocks

Our main idea in this paper is to compare returns on stocks that provide late and early resolution of uncertainty. In analogy to the introductory example, we look for pairs of stocks where one stock is expected to be volatile in the near future and the other is volatile later. To take this idea to the data, we use option implied volatilities as source of information about investors' volatility expectations. 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. 30% vs. 31%), while the difference between annualized 30-day IVs is at least 25 percentage points. In the spirit of the motivating example in Figure 1, we go the stocks with lower IV_{30} long and the other one short.[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, and in our sample this yields a statistically significant average return of 6.99 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 alpha relative to the respective factor models.

[TABLE 2 HERE]

3.3 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 a long horizon T. If one

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

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. In line with intuition (and as discussed thoroughly in the context of a general equilibrium model in Section 5), only if the marginal investor exhibits PERU, 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 positive premium for holding stocks which provide 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 (and in general increased macroeconomic uncertainty), 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 the time series plotted in Figure 2, which shows the returns on the market and the investment strategy for the subsequent 12 months. For instance, during the recent financial crisis in the years 2007 to 2008, the investment strategy described above earned substantial positive returns.

[FIGURE 2 HERE]

3.4 Risk-neutral and physical volatility

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 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^2s of 18 and 31 percent, respectively. To make sure that our results are not driven by variance risk premia of the single stocks, i.e. the differences between $\mathbb{P}$- and $\mathbb{Q}$-variances, we control for variance risk premia in Fama-MacBeth regressions (see Section 4.4).

4 Implied Volatility Duration

4.1 Definition

The trading strategy from the previous section depends on finding pairs of stocks satisfying the criteria described above with respect to their 30-day and 365-day IVs. The restrictions we impose are rather tight, so it is not really surprising that for many stocks we do not find a counterpart that meets the conditions. The average number of pairs is 220, thereby covering about 19 percent of the stocks in our sample at a given time. It would be preferable to consider a broader set of stocks at each point in time. Moreover, it would be desirable to have a characteristic that indicates how late uncertainty is resolved and which can be assigned to every single stock at every point in time. Such a criterion is introduced in the following.

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

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

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

The interpretation of IVD is similar to that of the well-known Macaulay duration of a coupon bond: Note that $\sum_{j=1}^{J} \Delta IV^2_{i,t,j}$ is equal to $IV^2_{i,t,t+\tau_J}$, so the increments over the subperiods are normalized by the overall implied variance over the full year. Multiplying the terms in this sum by the corresponding number of days to maturity and summing them up results in the average time over which the total variance of the stock return is expected to have realized. Comparing this characteristic across different stocks tells us for which stock uncertainty is resolved earlier. Figure 3 presents a stylized depiction of the quantities involved in computing IVD for an early (upper figure) and late (lower figure) resolution stock. Going from time t to time $t + 365$, the term structure of implied volatility rises to its IV_{365} level. To compute IVD, increases in IV, $\Delta IV_{t,j}$, in the respective time intervals are weighted by the end points of these intervals and summed up. Thus, IVD is roughly equal to the striped area above the curves in the graph. Intuitively, the larger the striped area, the higher IVD, and the later uncertainty is expected to be resolved.

[FIGURE 3 HERE]

4.2 Portfolios sorted on IVD

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 perform an independent double sort of all stocks into 25 portfolios based on IVD and IV_{365}. Table 3 provides information about the average IVD (in panel A) and IV_{365} (in panel B) of the stocks in 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.[3]

We now study portfolio returns. 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 cases. 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 3) holding this portfolio for twelve months results in an average return of about seven 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*. We observe that the premium becomes more pronounced if we consider subsets of stocks with even higher IV_{365}. The average return on 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. The fact that the early resolution premium is more pronounced among the group of high IV_{365} stocks is plausible: When overall uncertainty is high, the timing of its resolution

[3] 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.

matters a lot. In contrast, for stocks with low overall uncertainty the timing of uncertainty resolution is not relevant.

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 risk over the first month and should consequently exhibit lower returns. We study the implications of different attitudes towards the timing of uncertainty resolution for short term returns more thoroughly in our general equilibrium model in Section 5.

[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 for 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 using Levene's test with p-values of 0.76 (value-weighted) and 0.57 (equally weighted).

Just as in Section 3, 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 3, LME returns seem to be negatively related to the return on the aggregate market portfolio.

[TABLE 6 HERE]

4.3 Portfolio characteristics

Table 7 displays a number of statistics characterizing the five IVD-sorted portfolios in the top IV_{365} quintile. In the utmost right column we also show 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 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, 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 for stocks with uncertain returns (high IV_{365} stocks). To address this concern, we perform an independent double sort of the entire sample with respect to market equity and IVD. This procedure does not yield significantly positive returns for the LME portfolios in any of the size quintiles. We thus conclude that the early resolution premium is indeed a phenomenon that is not special to small stocks, only.

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. 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.

It is natural to wonder if there is a relation between implied volatility duration and cash-flow duration. Table 7 shows that this is not the case. There is no pattern in cash-flow duration, computed as in Dechow et al. (2004), along the IVD dimension. This is not surprising given that IVD is based on second moments. Cash-flow duration measures the timing weighted by first moments of cashflows, thereby providing an estimate of the expected average dividend payout date.

High IV stocks also have high idiosyncratic volatility as measured relative to the Fama and French (1992) three factor model. Not surprisingly, idiosyncratic volatility decreases in IVD. While the early resolution premium may contribute to the explanation of the idiosyncratic volatility puzzle, we cannot claim that it fully explains the puzzle. As can be seen from the mean idiosyncratic volatility, the differences in idiosyncratic volatility along the IV dimension are much more pronounced than in the IVD dimension.

We also report expected and realized variance risk premia. These are defined as the difference between (lagged) realized return volatility (estimated from daily returns) and implied volatility. Variance risk premia seem to be decreasing in absolute value as IVD rises. This is not surprising. Within the stocks in the high-IV_{365} quintile, those with a higher IV_{30} are usually sorted into the short IVD portfolio and high IV_{30} is mechanically related to a highly negative variance risk premium. We show in the next section that variance risk premia do not drive our results.

In Panel B of Table 7, we report betas for the five IVD quintile portfolios estimated by running multivariate regressions on the six factors listed. Just as with the investment strategy based on pairs, discussed in Section 3, there is a negative relation between IVD and CAPM betas, which makes the high positive returns on the LME portfolio even more striking. The other betas do not show a monotonic pattern across IVD sorted portfolios.

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 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 4.2, we found that the return differential between late and early resolution stocks is substantial only for high IV_{365} stocks. We observe that 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. We assume a linear relation and consider the interaction term $IVD \times IV_{365}^2$ at the stock level.

The interaction term is by construction positive for all stocks in the cross-section. It could happen that it picks up a possibly positive alpha, even if the variation in pricing errors is not related to the characteristic. To avoid this effect, 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 in absolute terms for stocks with high IV_{365}^2.

[TABLE 8 HERE]

Results are presented in Table 8. The interaction term is highly significant and explains pricing errors relative to all four standard factor models. The coefficient is very stable across model specifications and the estimated value is very 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 basis points 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 4.2.

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 estimate is quite close to the average excess return on the market portfolio of about 0.7 percent, just as predicted by theory.

IVD is based on implied variance, which itself consists of the sum of physical variance expectation and the variance risk premium for a given maturity. As seen in Table 7, low IVD stocks have lower variance risk premia, as measured by the difference between realized and implied variance. We check if the explanatory power of our characteristic is due to its relation to variance risk premia, which may be strongly related to expected returns. Because IVD contains information from the term structure of up to one year, we include the variance risk premia of the individual stocks over 30 and 365 days as controls. As can be seen in Table 8, this does not alter our results.

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 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 sorting procedure as well as the economic motivation for the sorting strategy suggest the use of a *late-minus-early* portfolio return, LME, as a proxy of the new latent factor in the augmented pricing model. 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 4.2. The advantage of this sort is that it generates sufficient variation across LME betas in order to identify the market price of risk. To construct the proxy for the latent factor, 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 4.2 with the difference that we do not form 5x5 portfolios. In particular, we do not consider the difference between quintile 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.

[TABLE 9 HERE]

Estimates of the market prices of risks are presented in Table 9. 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 (or slightly higher for the version with only the market factor). This is close to the average 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 best model tested, the Pastor and Stambaugh (2003) model, more than doubles the R^2 from 18% to 49%. In Figure 4, we plot the model-implied vs. the average realized returns on the 25 test assets for different models.

[FIGURE 4 HERE]

As can also be seen from the figure, the pricing performance of the four standard models without LME (left column of graphs) is consistently poor for the five top IV_{365} quintile portfolios. Adding LME substantially reduces the mispricing on this subset of portfolios. This effect is driving the large increases in R^2 that we see in Table 9. 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).

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, as in Section 4.4, 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 reduce 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 10.

[TABLE 10 HERE]

The interaction term becomes insignificant as soon as we include LME into the asset pricing model for almost all of the 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.

5 A general equilibrium model

5.1 Preferences and endowment

In the following we present a general equilibrium model with long-run risks in the spirit of Bansal and Yaron (2004), that rationalizes the stylized facts established in the previous sections. 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. We also suggest an economic interpretation of the LME factor and its relation to asset returns in the cross-section. The model solution is described thoroughly in Appendix B.1.

Consider an agent with preferences described by a recursive value function

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

i.e., time t utility U_t is a function of current consumption C_t and the continuation utility U_{t+1}. 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:

$$\Delta c_{t+1} = \mu_c + x_t + \sqrt{v_t} \varepsilon_{t+1}^{cv} + \sqrt{w_t} \epsilon_{t+1}^{cw},$$

where x is the long-run expected consumption growth process with

$$x_{t+1} = \rho_x x_t + \sigma_x (\sqrt{v_t} \varepsilon_{t+1}^{xv} + \sqrt{w_t} \varepsilon_{t+1}^{xw}).$$

Besides the state variable x that models the time-varying growth rate of consumption, there are two state variables that model time-variation in uncertainty about consumption growth. As opposed to Bansal and Yaron (2004), we use two instead of one process to allow for different resolution profiles across volatility components. In particular, we assume in the following that the uncertainty quantified by v is resolved early, i.e. v_t is expected to be large for periods t shortly after t_0 and small for periods t in the more distant future. The state variable w has the opposite profile: w is expected to be low in the early periods after t_0 and relatively high later on.[4]

Technically, we assume that each of the two volatility processes are sums of a persistent component $v_p(w_p)$ and a short-lived component $v_s(w_s)$. The dynamics of these components are:

$$
\begin{aligned}
v_{p,t+1} &= \mu_u + \rho_p \left(v_{p,t} - \mu_u\right) + \sigma_u \sqrt{v_{p,t}}\; \varepsilon^{vp}_{p,t+1} \\
v_{s,t+1} &= \mu_u + \rho_s \left(v_{s,t} - \mu_u\right) + \sigma_u \sqrt{v_{s,t}}\; \varepsilon^{vs}_{s,t+1} \\
w_{p,t+1} &= \mu_u + \rho_p \left(w_{p,t} - \mu_u\right) + \sigma_u \sqrt{w_{p,t}}\; \varepsilon^{wp}_{p,t+1} \\
w_{s,t+1} &= \mu_u + \rho_s \left(w_{s,t} - \mu_u\right) + \sigma_u \sqrt{w_{s,t}}\; \varepsilon^{ws}_{s,t+1}
\end{aligned}
$$

The long-run mean and unconditional volatilities of the four state variables are chosen equally. However, we choose $\rho_p > \rho_s$, i.e. v_p and w_p are more persistent than v_s and w_s. By choosing different initial values for the processes in t_0, we can calibrate the processes such that v (w) exhibits early (late) resolution, while the expected average level of the volatility over a long horizon is the same for v and w.

[FIGURE 5 HERE]

The expected evolution of the four volatility components and the aggregates v and w are presented in Figure 5. A large but short-lived component v_s and a small but persistent component v_p aggregate to an early uncertainty resolution profile for v. Similarly, a small but persistent component w_p and a large but short-lived component w_s aggregate to a late uncertainty resolution profile w. In particular, we choose the following symmetric initial values: $v_{p,0} = 0.9\mu_u$, $v_{s,0} = 1.15\mu_u$, $w_{p,0} = 1.1\mu_u$, and $w_{s,0} = 0.85\mu_u$.

[4]We analyze the model's implications for asset returns at time t_0. As time goes by and the state variables evolve stochastically over time, the roles of v and w may change.

Importantly, the aggregates v and w are on average equal in the long-run. Conditional on t_0-information, however, they have different uncertainty resolution profiles. Moreover, adding up both processes yields a measure of *aggregate uncertainty* $v_t + w_t$ which is equal to $4\mu_u$ in t_0 and also equal to $4\mu_u$ in expectation at all future points in time. As a consequence, the volatility of consumption growth, as well as volatility of the trend growth rate of consumption, do not exhibit an early or late resolution profile. The variance of both processes is proportional to $v_t + w_t$ and, thus, stable in expectation.

5.2 A cross-section of stocks

Besides the consumption stream, there are dividends paid by a cross-section of firms whose stocks are traded. We assume that the growth rate of the dividends paid by firm i evolves as

$$\Delta d^i_{t+1} = \mu_i + \phi_i x_t + \sigma_i \left(\sqrt{\zeta_i^2 v_t}\, \varepsilon^{cv}_{t+1} + \sqrt{(1-\zeta_i^2) w_t}\, \varepsilon^{cw}_{t+1} \right)$$

We show in Appendix B.2, that the conditional expected excess return on asset i is

$$\mathbb{E}_t \left[r^i_{t+1} - r^f_t \right] + \frac{1}{2}\sigma_{r,t} = \underbrace{\gamma \sigma_i (\zeta_i v_t + \sqrt{1-\zeta_i^2} w_t)}_{SRR^i_t} + \underbrace{\pi_{i,vp} v_{p,t} + \pi_{i,vs} v_{s,t} + \pi_{i,wp} w_{p,t} + \pi_{i,ws} w_{s,t}}_{LRR^i_t}, \quad (1)$$

where $1/2\, \sigma_{r,t}$ is a Jensen term. As is well-known from the long-run risk literature, we can decompose the expected excess return into a short-run risk premium SRR^i_t and a long-run risk premium LRR^i_t.

To analyze the impact of the short- and long-run risk premium on expected excess returns on stocks that exhibit different timings regarding uncertainty resolution, we introduce two particular dividend claims. We consider a claim on dividends d^e, which is characterized by $\zeta_e = 1$, and a claim on dividends d^l, which is characterized by $\zeta_l = 0$. The volatility of dividend growth Δd^e_{t+1} is proportional to v_t and, thus, expected to be high in the early periods after t_0, but low in later periods. We can thus interpret claim e as an asset that exhibits early resolution of uncertainty. The opposite is true for claim l, which can be interpreted as an asset that exhibits late resolution of uncertainty. In line with our notation in the earlier sections, we call the difference $\mathbb{E}_{t_0}[r^l - r^e]$ between expected returns on the late and the early claim the *early resolution premium.*

The short-run risk premium is the product of the risk aversion coefficient γ and the time t_0 covariance of stock i's dividend growth with consumption growth. As long as the agent is risk-averse ($\gamma > 0$), due to $v_0 > w_0$, the short-run risk premium of claim e is larger than the short-run risk premium of claim l. It is well-known and also applies to our model, that if the agent has time-additive CRRA preferences, i.e. $\gamma = \frac{1}{\psi}$, the long-run risk premium vanishes. Hence, our model implies that an agent who is indifferent about the timing of uncertainty resolution claims a higher return on claim e than on claim l, yielding a *negative* early resolution premium. This is in line with intuition: An agent with time-additive preferences favors the asset that is less risky over the next period, without considering later periods.

[FIGURE 6 HERE]

We now analyze the long-run risk premium. The π's in Equation (1) are equilibrium quantities whose interpretation is more involved than the short-run risk premium. For different values of γ, we plot the difference between the long-run risk premia on stocks l and stock e as a function of the IES in Figure 6. It can be observed that the difference in long-run risk premia is positive whenever $\gamma > \frac{1}{\psi}$ and it is negative whenever $\gamma < \frac{1}{\psi}$. The key ingredient is that $\pi_{e,vp}$ is greater than $\pi_{e,wp}$ (while $\pi_{l,vp}$ is smaller than $\pi_{l,wp}$), as long as $\gamma > \frac{1}{\psi}$. This is in line with economic intuition: The more the agent prefers early resolution of uncertainty, the greater is the impact of the persistent component in the volatility processes.[5] In other words, an agent

[5] The initial values of the volatility processes used to generate Figure 6 are the chosen as described in Section 5.1. 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, we derive conditions on the initial values such that implied variances are matched. By plugging these values into the expressions for the expected returns, we confirm the results from Figure 6. For details, on the implied volatility matching condition, see Appendix B.3.

with a preference for early resolution of uncertainty claims a compensation for holding an asset whose persistent volatility component is high, even though current volatility is low.

As a result, the short-run risk part of expected excess returns always works in the direction of a negative early resolution premium. The long-run risk part amplifies this negative premium if the agent exhibits a preference for late resolution of uncertainty ($\gamma < \frac{1}{\psi}$). However, if the agent prefers early resolution of uncertainty, i.e. $\gamma > \frac{1}{\psi}$, the long-run risk part mitigates and may even offset the negative early resolution premium. An agent with a strong preference for early resolution of uncertainty claims a higher risk premium for holding stock l than for holding stock e. This meets our intuition from earlier sections. If the agent has a strong preference for early resolution of uncertainty, the late-minus-early portfolio has a positive expected return.

5.3 Implied factor structure

For a reasonable range of parameterizations, the coefficients $\pi_{i,vp}$ and $\pi_{i,vs}$ are close together, such that, with the definitions $\pi_{i,v} = \pi_{i,vp} + \pi_{i,vs}$ and $\pi_{i,w} = \pi_{i,wp} + \pi_{i,ws}$, we may write LRR_t^i in Equation (1) in the following form:

$$LRR_t^i \approx \pi_{i,v}v_t + \pi_{i,w}w_t = \pi_{i,u}(v_t + w_t) + \pi_{i,lme}(w_t - v_t)$$

where $\pi_{i,u} = \frac{1}{2}(\pi_{i,v} + \pi_{i,w})$ denotes the loading of the conditional expected excess return on aggregate uncertainty and $\pi_{i,lme} = \frac{1}{2}(\pi_{i,w} - \pi_{i,v})$ denotes the loading on the difference between the processes exhibiting late and early resolution of uncertainty. Out of the four parameters μ_i, ϕ_i, σ_i, and ζ_i which characterize the dividends on asset i only the latter three are relevant for expected returns. In particular, $\pi_{i,u}$ depends on the leverage ϕ_i and the volatility level σ_i, while ζ_i controls the coefficient $\pi_{i,lme}$.

In line with intuition, for the early resolution claim $\pi_{e,v} > \pi_{e,w}$, such that $\pi_{e,lme}$ is negative. In contrast to that, $\pi_{l,lme}$ is positive. Choosing $\phi_e = \phi_l$ and $\sigma_e = \sigma_l$ implies that $\pi_{e,u} = \pi_{l,u}$ such that the long-run risk premium on the difference portfolio is

$$LRR_t^l - LRR_t^e \approx \underbrace{(\pi_{l,u} - \pi_{e,u})(v_t + w_t)}_{=0} + (\pi_{l,lme} - \pi_{e,lme})(w_t - v_t)$$

In most calibrations, the long-run risk premium makes up the major part of the expected excess return, such that the following approximation holds:

$$\mathbb{E}_t[r_{t+1}^l - r_{t+1}^e] \approx (\pi_{l,lme} - \pi_{e,lme})\,(w_t - v_t),$$

We also consider a third asset which is the claim on aggregate dividends d^m (the stock market portfolio), for which we assume $\zeta_m^2 = 0.5$. This claim has the same exposure to both shocks ε^{cv} and ε^{cw}, and, thus, has a flat expected volatility structure. Due to the symmetry of the volatility processes, it is easy to show that $\pi_{m,lme} = 0$. This is an intuitive finding: Just as with consumption growth, uncertainty about aggregate dividend growth is always proportional to aggregate uncertainty $v_t + w_t$. Overall, our model thus implies

$$\begin{aligned}\mathbb{E}_t[r_{t+1}^i - r_t^f] &\approx \pi_{i,u}(v_t + w_t) + \pi_{i,lme}(w_t - v_t)\\ &\approx \beta_{i,u}\,\mathbb{E}_t[r_{t+1}^m - r_t^f] + \beta_{i,lme}\,\mathbb{E}_t[r_{t+1}^l - r_{t+1}^e],\end{aligned}$$

where $\beta_{i,u} := \frac{\pi_{i,u}}{\pi_{m,u}}$ and $\beta_{i,lme} := \frac{\pi_{i,lme}}{\pi_{l,lme} - \pi_{e,lme}}$. The first coefficient $\beta_{i,u}$ can be interpreted as a standard CAPM beta. It is above (below) one, if a stock's exposure to shocks in consumption or the trend growth rate of consumption, i.e. systematic risk, is stronger (weaker) than the exposure of the stock market. We only consider the two processes v and w and, thus, our model implies a two-factor model. The multi-factor structure that is suggested by the empirical literature could for example be modeled by defining a separate volatility process for the trend growth rate or other state variables that cause time-variation in expected returns.

The second factor in our model, besides the market factor, is the difference between expected returns on two claims that exhibit late and early resolution of uncertainty. The exposure

$\beta_{i,lme}$ of a stock i to that factor can be estimated by running time-series regressions on the difference between returns on stocks that exhibit late and early resolution of uncertainty. For the empirical counterpart of the difference portfolio from the model, which we consider in Section 4, we only used stocks in the highest IV_{365}-quintile to make sure that overall uncertainty is approximately equal.

6 Conclusion

We provide empirical evidence for a premium for early resolution of uncertainty. This premium amounts to 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 behaviors of individuals in lab experiments or parameter estimates based on macro- or survey data.

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 7 percent for a holding period of one year. To assess the economic relevance 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 over one year in exchange for knowing 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 popular 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.

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 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 can only be positive 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 in these models, namely that the representative investor exhibits a preference for early resolution of uncertainty.

A Details on the investment strategy

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

1. Beginning with the stock with the lowest SECID, we identify all stocks that have an IV_{365} that is not farther away than 0.01 from the original stock's IV_{365}.
2. From these stocks, we select the one whose IV_{30} is farthest away from the original stock's IV_{30}.
3. If the difference is larger than 0.25, we add this pair to the list 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.

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 before starting the search for pairs. The return on all 10000 instances of the investment strategy are significantly positive. It turns out that the investment strategy discussed above is a particularly profitable one. On average, the return difference between low IV_{30} and high IV_{30} stocks is 5.17 percent. While the average return on high IV_{30} stocks is 5.74 percent, similar to the number reported in Table 1, the average return on the low IV_{30} stocks is only 10.91 percent per year and, thus, lower than the 12.61 percent of the selected strategy. Details are provided in Table 11.

[TABLE 11 HERE]

We also change the cutoff values from 1% for the short end and 25% for the long end. Table 12 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 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 12 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.

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:

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

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

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

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

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

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

B.2 Price-dividend ratios

The return r_i on dividend claim d^i can be approximated linearly in terms of its price-dividend ratio pd_i and dividend growth Δd^i

$$r^i_{t+1} \approx \kappa_{pd,i,0} + \kappa_{pd,i,1} pd_{i,t+1} - pd_{i,t} + \Delta d^i_{t+1}. \tag{B.9}$$

with coefficients:

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

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

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

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

$$\begin{aligned}
A_{pd,i,0} = {} & \frac{-\delta - \frac{\mu_c}{\psi} + \mu_i + \kappa_{pd,i,0} + \kappa_{pd,i,1}\mu_u\left(A_{pd,i,vp}(1-\rho_{vp}) + A_{pd,i,vs}(1-\rho_{vs})\right)}{1-\kappa_{pd,i,1}} \\
& + \frac{\kappa_{pd,1}\mu_u\left(A_{pd,i,wp}(1-\rho_{wp}) + A_{pd,i,ws}(1-\rho_{ws})\right)}{1-\kappa_{pd,i,1}} && \text{(B.12)} \\
A_{pd,i,x} = {} & \frac{\phi_i - \frac{1}{\psi}}{1-\kappa_{pd,i,1}\rho_x} && \text{(B.13)} \\
A_{pd,i,kj} = {} & -\frac{\kappa_{pd,i,1}\rho_j - 1 + (\theta-1)\kappa_{wc,1}\kappa_{pd,i,1}A_{wc,kj}\sigma_u^2}{\kappa_{pd,1}^2\sigma_u^2} \\
& \pm \Bigg\{ \left(\frac{\kappa_{pd,i,1}\rho_j - 1 + (\theta-1)\kappa_{wc,1}\kappa_{pd,i,1}A_{wc,kj}\sigma_u^2}{\kappa_{pd,i,1}^2\sigma_u^2}\right)^2 \\
& \quad - \frac{1}{\kappa_{pd,i,1}^2\sigma_u^2}\Bigg(2(\theta-1)(\kappa_{wc,1}\rho_j - 1)A_{wc,kj} + (\theta-1)^2\kappa_{wc,1}^2 A_{wc,kj}^2\sigma_u^2 \\
& \quad + \left(\kappa_{pd,i,1}A_{pd,i,x} + (\theta-1)\kappa_{wc,1}A_{wc,x}\right)^2\sigma_x^2 \\
& \quad + \left(\gamma - \sigma_i\left(\zeta_i \mathbb{1}_{k=v} + \sqrt{1-\zeta_i^2}\,\mathbb{1}_{k=w}\right)\right)^2 \Bigg)\Bigg\}^{\frac{1}{2}} && \text{(B.14)}
\end{aligned}$$

where we choose the root such that $\lim_{\sigma_c \to 0}\lim_{\sigma_x \to 0} A_{pd,i,kj} = 0$, again see Tauchen (2005).

The conditional expected excess return is

$$\mathbb{E}_t[r^i_{t+1} - r^f_t] + \frac{1}{2}Var(r^i_{t+1}) = -Cov_t(m_{t,t+1}, r^i_{t+1}) = SRR^i_t + LRR^i_t \tag{B.15}$$

where

$$SRR_t^i = \gamma\sigma_u \left(\zeta_i(v_{s,t} + v_{p,t}) + \sqrt{1-\zeta_i^2}(w_{s,t} + w_{p,t})\right)$$

$$LRR_t^i = (1-\theta)\kappa_{wc,1}\kappa_{pd,i,1}\Bigg(A_{wc,x}A_{pd,i,x}\sigma_x(v_{s,t} + v_{p,t} + w_{s,t} + w_{p,t}) \tag{B.16}$$

$$+ \sigma_u^2\left(A_{wc,vs}A_{pd,i,vs}v_{s,t} + A_{wc,vp}A_{pd,i,vp}v_{p,t} + A_{wc,ws}A_{pd,i,ws}w_{s,t} + A_{wc,wp}A_{pd,i,wp}w_{p,t}\right)\Bigg)$$

B.3 Implied Variance matching condition

We compute and match the implied variances:

$$E_0^{\mathbb{Q}}\left[E_1\left[e^{2(r_{1,2}^e + r_{2,3}^e)}\right] - E_1\left[e^{r_{1,2}^e + r^e d_{2,3}}\right]^2 - E_1\left[e^{2(r_{1,2}^l + r_{2,3}^l)}\right] + E_1\left[e^{r_{1,2}^l + r_{2,3}^l}\right]^2\right] = 0 \tag{B.17}$$

Each of the returns in equation B.17 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.17 is of the form

$$\ln\left(e^{x+y} - e^{x+y'}\right) - \ln\left(e^{x+z} - e^{x+z'}\right) = 0 \tag{B.18}$$

which we therefore approximate with

$$y - y' - z' + z = 0. \tag{B.19}$$

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.19 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.

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

Low IV_{30}	High IV_{30}	Investment strategy
12.61	5.63	6.99
(2.36)	(0.96)	(3.20)

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 25 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
8.37^{***}	-0.17^{*}					
(3.23)	(-1.92)					
8.60^{***}	-0.17^{**}	-0.16	0.086			
(3.48)	(-2.46)	(-0.95)	(0.68)			
9.85^{***}	-0.25^{**}	-0.24	0.15	-0.20	0.10	
(3.18)	(-2.19)	(-1.56)	(1.29)	(-0.85)	(0.37)	
9.23^{***}	-0.25^{**}	-0.26^{*}	0.15	-0.22	0.12	0.08
(2.82)	(-2.11)	(-1.88)	(1.23)	(-0.94)	(0.45)	(0.81)

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: IVD and IV_{365}**

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

Implied Volatility Duration (IVD) and 365-day implied volatility (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	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
	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	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

Realized Variance of the IV/IVD-sorted portfolios' returns held for one- and twelve month periods.

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*			
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 m \$	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
			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. ME 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 and CFD is Dechow et al.'s (2004) estimate of stocks' cash-flow duration using the parameter estimates from Weber (2016). iVol is idiosyncratic 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 as the difference $\mathbb{V}\text{ar}(r_{t,30}) - \text{IV}^2_{t,30}$ as the ex-ante, time $t-$measurable estimate and $\mathbb{V}\text{ar}(r_{t+1,30}) - \text{IV}^2_{t,30}$ as realized premium. 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 over the entire sample.

Table 8: **Regression coefficients**

	MKT	SMB	HML	RMW	CMA	LIQ	VRP 30 days	VRP 365 days	$IV^2 \times IVD$
CAPM	0.51								
	(1.41)								
	0.51								0.05^{**}
	(1.41)								(2.56)
	0.52						-1.31	-0.81^{**}	0.04^{**}
	(1.44)						(-0.92)	(-2.45)	(2.28)
FF3	0.68^{*}	-0.07	-0.35						
	(1.91)	(-0.27)	(-1.01)						
	0.68^{*}	-0.07	-0.35						0.04^{**}
	(1.91)	(-0.27)	(-1.01)						(2.52)
	0.68^{*}	-0.05	-0.26				-1.73	-0.76^{***}	0.04^{**}
	(1.87)	(-0.21)	(-0.80)				(-1.27)	(-2.69)	(2.32)
FF5	0.67^{*}	0.11	-0.27	0.69	-0.23				
	(1.85)	(0.52)	(-0.80)	(1.55)	(-0.48)				
	0.67^{*}	0.11	-0.27	0.69	-0.23				0.05^{***}
	(1.85)	(0.52)	(-0.79)	(1.56)	(-0.47)				(2.58)
	0.67^{*}	0.15	-0.17	0.7^{*}	-0.25		-1.97	-0.76^{***}	0.04^{**}
	(1.81)	(0.68)	(-0.54)	(1.65)	(-0.54)		(-1.45)	(-2.73)	(2.40)
PS	0.66^{*}	-0.04	-0.36			0.97			
	(1.83)	(-0.18)	(-1.04)			(1.10)			
	0.66^{*}	-0.04	-0.36			1.00			0.04^{**}
	(1.83)	(-0.18)	(-1.04)			(1.13)			(2.51)
	0.66^{*}	-0.02	-0.27			0.99	-1.75	-0.76^{***}	0.04^{**}
	(1.80)	(-0.10)	(-0.84)			(1.12)	(-1.29)	(-2.69)	(2.30)

Regression coefficients from a second stage Fama-MacBeth-regression of single stock returns on various factors, the variance risk premium (measured as the difference between realized variance and the implied variance) 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 9: **Lambdas**

	MKT	SMB	HML	RMW	CMA	LIQ	LME	$R^2_{adj.}$
CAPM	0.34							-0.88
	(0.94)							
	0.38						0.98***	-0.28
	(1.05)						(3.15)	
FF3	0.60*	−0.33	−0.29					-0.22
	(1.71)	(−0.79)	(−0.47)					
	0.64*	−0.34	0.04				0.75**	0.37
	(1.80)	(−0.83)	(0.06)				(2.42)	
FF5	0.60*	0.12	0.38	0.39	0.15			0.01
	(1.65)	(0.25)	(0.55)	(0.87)	(0.45)			
	0.55	0.43	−0.38	0.57	−0.60		0.83***	0.52
	(1.53)	(0.88)	(−0.56)	(1.23)	(−1.47)		(2.61)	
PS	0.54	0.09	−0.59			2.47***		0.17
	(1.48)	(0.23)	(−1.09)			(2.81)		
	0.60	−0.11	−0.19			1.43*	0.74**	0.44
	(1.68)	(−0.30)	(−0.32)			(1.86)	(2.40)	

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 10: **Characteristic vs LME**

	MKT	SMB	HML	RMW	CMA	LIQ	$IV^2 \times IVD$	LME
CAPM	0.38						0.05^{**}	
	(1.15)						(2.23)	
	0.43						0.01	0.96^{***}
	(1.32)						(0.54)	(2.87)
FF3	0.72^{**}	-0.46	-0.37				0.05^{**}	
	(2.23)	(-1.24)	(-1.21)				(2.36)	
	0.73^{**}	-0.33	-0.28				0.02	0.51^{**}
	(2.23)	(-0.93)	(-0.85)				(1.22)	(2.02)
FF5	0.69^{**}	0.18	0.19	0.65^{*}	-0.01		0.04^{**}	
	(2.10)	(0.61)	(0.49)	(1.92)	(-0.05)		(2.14)	
	0.66^{**}	0.41	-0.54	0.70^{**}	-0.45^{**}		0.02	0.53^{**}
	(2.01)	(1.49)	(-1.28)	(2.18)	(-2.17)		(1.28)	(2.02)
PS	0.69^{**}	-0.14	-0.61^{**}			2.22^{***}	0.04^{**}	
	(2.13)	(-0.47)	(-1.97)			(3.29)	(2.10)	
	0.71^{**}	-0.19	-0.45			1.59^{***}	0.03^{*}	0.42^{*}
	(2.17)	(-0.59)	(-1.45)			(2.66)	(1.67)	(1.67)

Regression coefficients from a second stage Fama-MacBeth-regression of single stocks on various factors and $IVD \times IV^2_{365}$ 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 11: **Alternative investment strategies**

	selected	mean	0.025	0.5	0.975
			Panel A: *Return on low* IV_{30}^2 *portfolio*		
mean	0.1261	0.1091	0.0995	0.1091	0.1190
t-stat	2.3630	2.0422	1.8826	2.0413	2.2066
std	0.3142	0.8069	0.7716	0.8065	0.8448
max	1.1884	1.2601	1.0768	1.2306	1.6198
min	-0.4888	-0.5213	-0.5733	-0.5182	-0.4845
			Panel B: *Return on high* IV_{30}^2 *portfolio*		
mean	0.0563	0.0574	0.0550	0.0574	0.0598
t-stat	0.9629	0.9779	0.9402	0.9779	1.0151
std	0.3423	0.8866	0.8785	0.8866	0.8948
max	1.2093	1.2094	1.1675	1.2083	1.2594
min	-0.5616	-0.5638	-0.5781	-0.5630	-0.5509
			Panel C: *Return on investment strategy*		
mean	0.0699	0.0517	0.0418	0.0516	0.0621
t-stat	3.2046	3.0021	2.3752	2.9862	3.7034
std	0.1584	0.2611	0.2260	0.2605	0.3001
max	0.6851	0.6293	0.4800	0.6175	0.8382
min	-0.4471	-0.3575	-0.4530	-0.3549	-0.2764

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 3), 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 12: **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%	11.95***	10.16**	1.79**	1643
	(2.96)	(2.30)	(2.31)	
10%	11.87***	9.13*	2.75**	901
	(2.64)	(1.82)	(2.56)	
15%	12.16**	7.76	4.4***	524
	(2.47)	(1.44)	(3.16)	
20%	12.34**	6.94	5.4***	328
	(2.38)	(1.21)	(3.11)	
25%	12.61**	5.63	6.99***	220
	(2.36)	(0.96)	(3.20)	
30%	12.15**	4.99	7.16***	154
	(2.19)	(0.85)	(3.37)	
35%	12.96**	4.23	8.73***	113
	(2.25)	(0.71)	(3.71)	
	Panel B: *Precision long end: 0.001*			
5%	11.97***	10.59**	1.38**	1280
	(2.99)	(2.45)	(2.10)	
10%	11.79***	9.56**	2.23**	650
	(2.71)	(1.98)	(2.56)	
15%	12.09**	8.45	3.64***	355
	(2.53)	(1.59)	(2.80)	
20%	12.15**	7.76	4.39***	210
	(2.42)	(1.39)	(3.08)	
25%	12.46**	6.56	5.9***	134
	(2.38)	(1.15)	(3.50)	
30%	13.61**	6.64	6.97***	91
	(2.39)	(1.11)	(3.75)	
35%	11.64	7.14	4.5***	65
	(0.94)	(-0.12)	(3.12)	

Table continues on next page

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

Panel C: *Precision long end: no restriction*				
5%	12.41***	10.13*	2.28	2947
	(4.02)	(1.90)	(0.69)	
10%	12.43***	9.88*	2.55	2157
	(4.07)	(1.80)	(0.71)	
15%	12.44***	9.64*	2.79	1969
	(4.13)	(1.68)	(0.70)	
20%	12.41***	9.34	3.08	1763
	(4.17)	(1.57)	(0.70)	
25%	12.4***	9.02	3.38	1551
	(4.24)	(1.45)	(0.71)	
30%	12.38***	8.59	3.79	1347
	(4.31)	(1.33)	(0.74)	
35%	12.29***	8.18	4.11	1155
	(4.36)	(1.22)	(0.75)	

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.

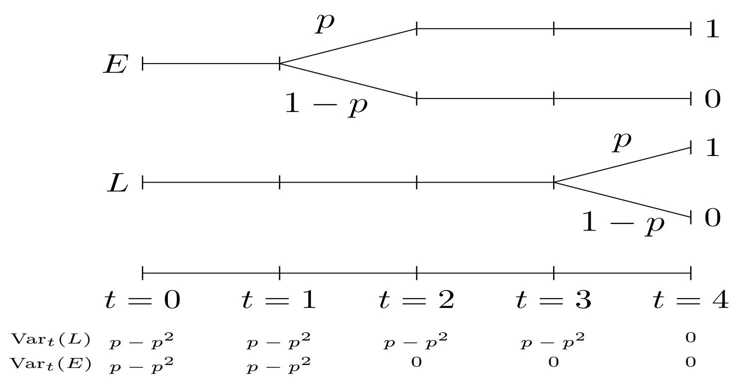

Figure 1: Stylized depiction of a late and early resolution claim

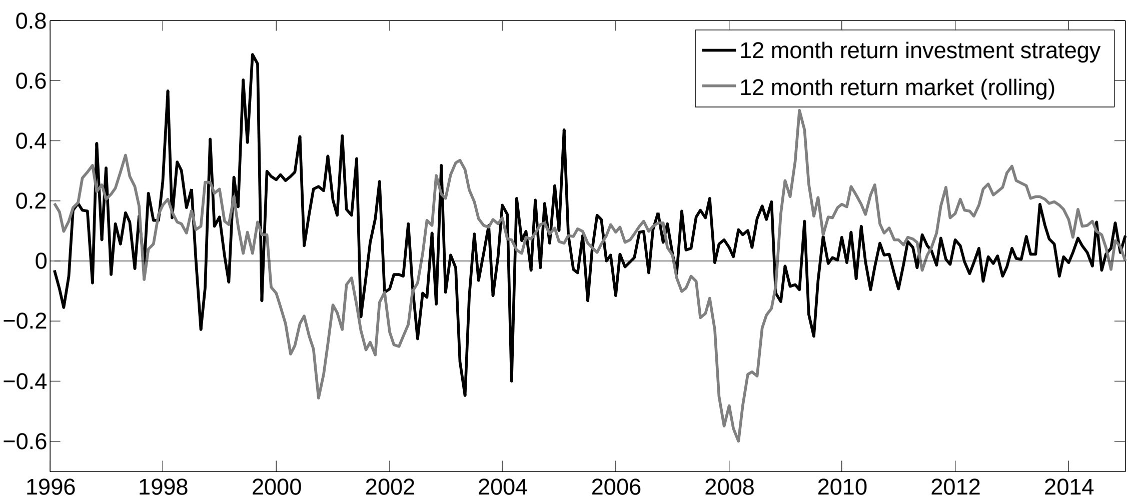

Figure 2: Twelve month returns on the market factor and the investment strategy based on pairs.

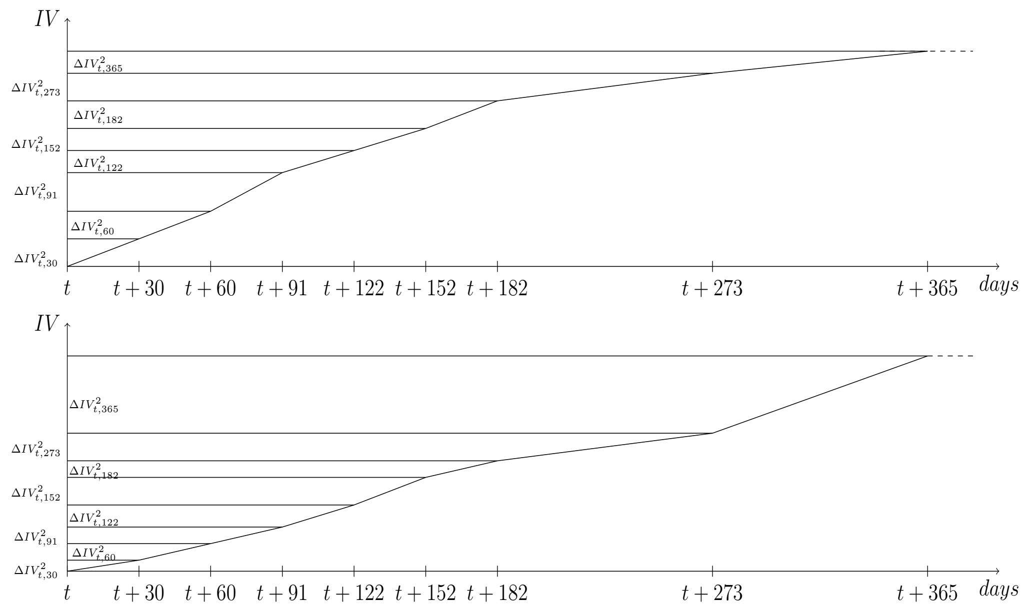

Figure 3: Stylized representation of the quantities involved in computing IVD with a early (low IVD, in the upper figure) and late (high IVD, in the lower figure) resolution claim.

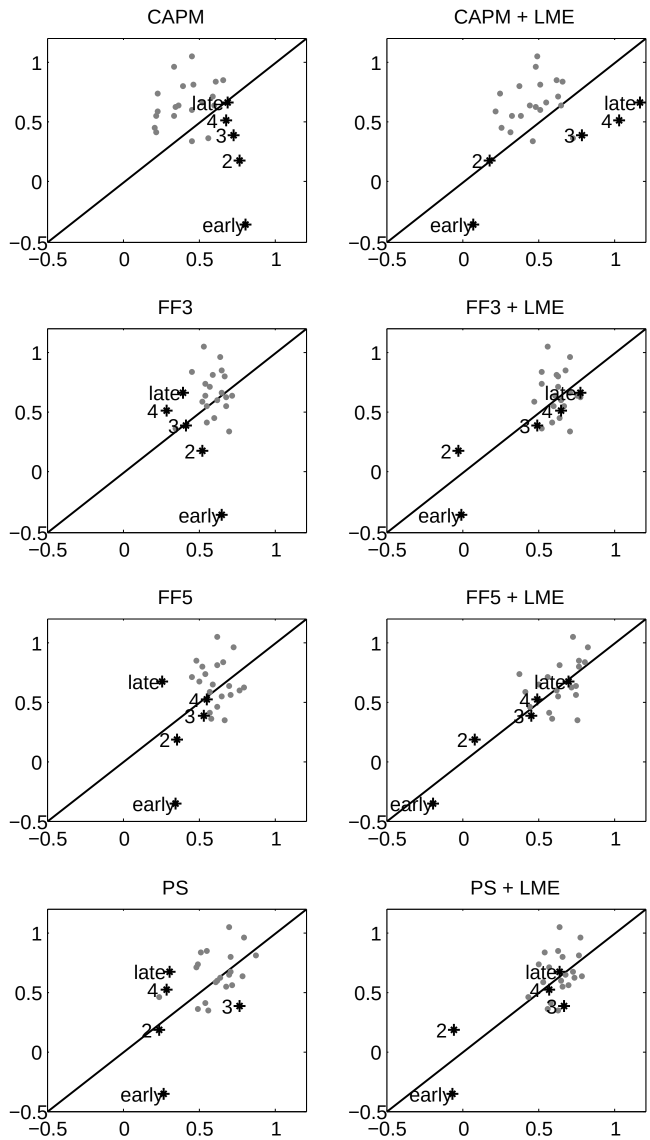

Figure 4: This figure plots model-implied expected returns (on the horizontal axis) against average realized returns (on the vertical axis) on 25 portfolios sorted independently based on IV_{365} and IVD. The left column of graphs shows the CAPM, the Fama and French (1993) three factor model, the Fama and French (2015) five factor model and the Pastor and Stambaugh (2003) 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.

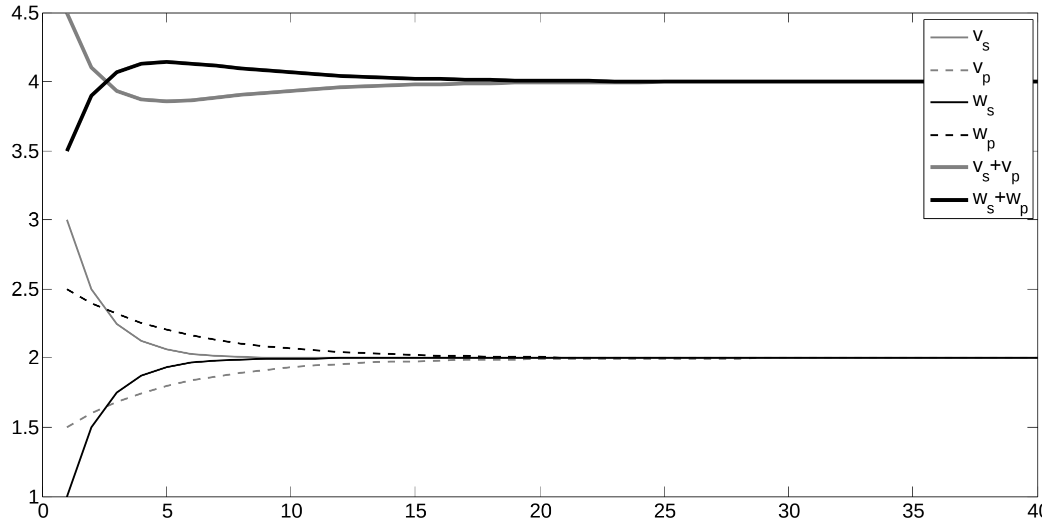

Figure 5: Stylized depiction of volatility processes with different persistence aggregating to an early and late uncertainty resolution profile

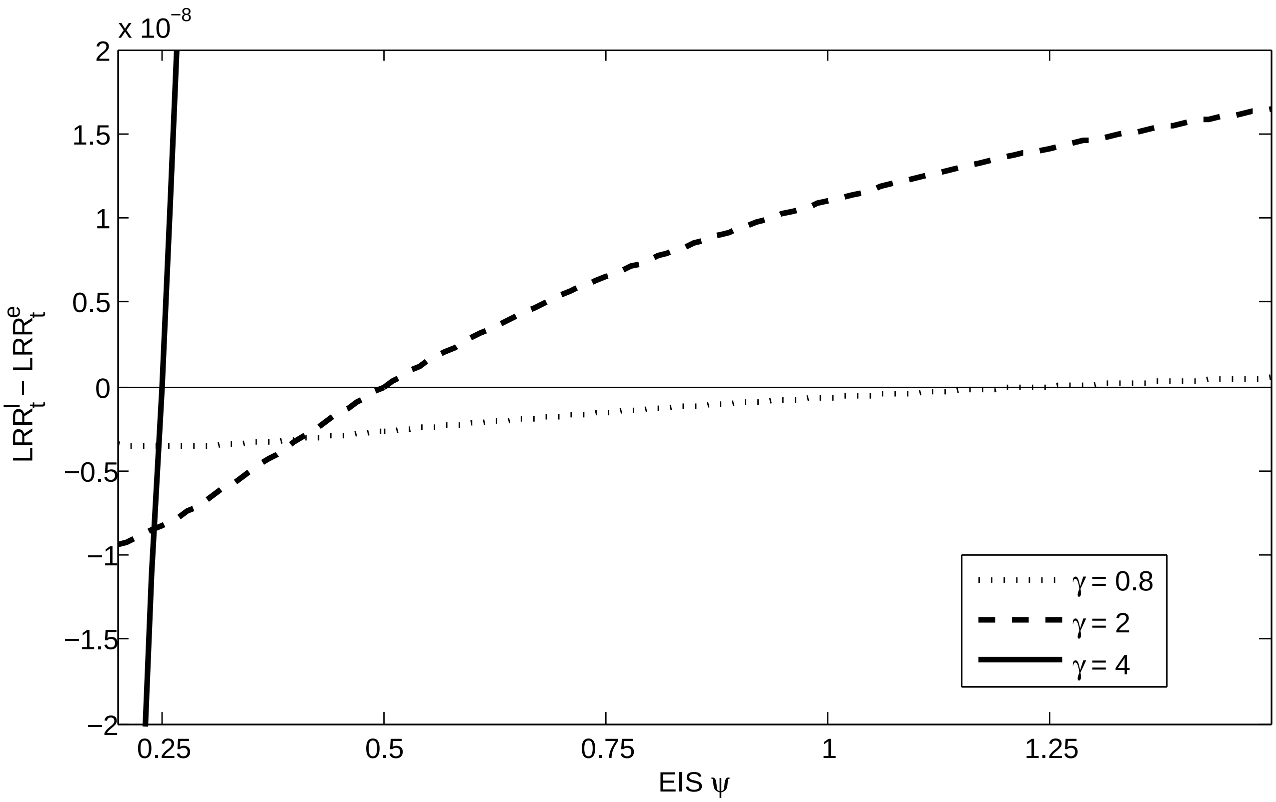

Figure 6: One-period expected return difference between the late and early resolution claim as described in Section 5 for different values of relative risk aversion γ and ψ. The other parameters are similar to Bansal and Yaron (2004) and Bansal et al. (2011): $\mu_u = 0.25 \cdot 0.0078^2$, $\rho_s = 0.95$, $\rho_p = 0.99$, $\sigma_u = 0.23 \cdot 10^{-5} \cdot \mu_u^{-\frac{1}{2}}$, $\rho_x = 0.979$, $\sigma_x = 0.044$, $\phi_e = \phi_l = 3$, $\sigma_e = \sigma_l = 3$, $\mu_c = \mu_e = \mu_l = 0.0015$, $\delta = -\ln 0.998$, $\zeta_e = 1$, and $\zeta_l = 0$. Initial volatility values are set symmetrically around the long-run means.