Model-Free Implied Dependence and the Cross-Section of Returns[*]

KOEN INGHELBRECHT
University of Ghent

DANIEL LINDERS
University of Amsterdam

GERTJAN VERDICKT
KU Leuven

YONG XIE
University of Illinois

First draft: May 11, 2022

This draft: September 5, 2022

Abstract

We document the asset-pricing implications of the model-free option-implied dependence (MFID); a measure that exhibits information on linear and non-linear dependence between random variables. We show that stocks with high exposure to MFID generate significantly higher risk-adjusted returns in bad times. This is consistent with time-varying preferences, implying an increase in the demand for stocks that provide a hedge against an increase in dependence in bad times. The MFID premium cannot be explained by common risk factors – implying that a risk-based theory is not likely an explanation of the result – and is robust when we condition on implied correlation.

KEYWORDS: correlation, return predictability, risk premia, comonotonicity
JEL CLASSIFICATION: G11, G12, G13, G14, G15

[*] We acknowledge all the helpful comments by Kris Boudt, Martijn Boons, Stephen Brown, Jan Dhaene, Lee Deville, Aleksy Leeuwenkamp, Hanno Lustig, Idan Hodor, Florian Hoffmann, Lyndon Moore, Thanh Huynh, Richard Sowers, and Florian Weigert and seminar participants at Auckland University of Technology, Deakin University, FMA Asia/Pacific Conference (Melbourne, 2022), KU Leuven, Monash Business School, Research in Behavioral Finance Conference (Amsterdam, 2022), the University of Ghent, and University of Illinois Urbana-Champaign. We acknowledge Turan Bali, Andrew Chen, Hanno Lustig, and Grigory Vilkov for sharing code and data. All errors are our own.

Corresponding author: gertjan.verdickt@kuleuven.be.

1. Introduction

Return dependence, generally measured by the correlation between asset returns, is a cornerstone in financial economics. If correlation is close to one, financial markets are strongly interconnected. This implies that assets are moving in unison, and diversification does not help to reduce the variability of the portfolio. The key issue with correlation, however, is that it only takes into account the linear dependence between assets. A correlation close to one only reflects that financial markets are strongly interconnected *linearly*. A correlation close to zero, therefore, does not imply weak dependence. A strongly dependent market could be the result of a high degree of non-linear dependence. In this paper, we fill a gap in the asset-pricing literature by taking into account both linear and non-linear dependence in the cross-section of returns.

We close this gap by measuring return dependencies through a model-free implied measure, which we define Model-Free Implied Dependence (MFID). MFID builds on comonotonicity theory, which describes a situation where random variables are only subject to a single systematic source of risk: assets' exposure to dependence.[1] Indeed, MFID is defined as a risk-neutral variance on a market index (observed index options) divided by the risk-neutral variance of the comonotonic market index (synthetic index options), that is, the situation in which index constituents move together in perfect unison. The synthetic index offers the upper bound on the degree of dependence that is present in the financial market. Hence, MFID assesses the distance of an observed market situation towards an extreme, comonotonic market situation. We find that MFID is closely related to important events (e.g., the outbreak of the Iraq War and COVID-19, and the bankruptcy of Lehman Brothers and LTCM), and exhibits a high co-movement with related metrics (e.g., disaster probability), while capturing idiosyncratic information over existing dependence metrics (e.g., implied correlation).

To estimate MFID, we use information implied by the Dow Jones Industrial Average (DJIA) index and options written on its constituents. We turn to the DJIA since it consists of 30 blue-chip stocks with more liquid options relative to other US indices. This has several advantages. First, MFID is a forward-looking measure. We extract the information contained in daily options so that the resulting measure is genuinely conditional. Second, and

[1] Comonotonicity was introduced in the finance literature by Roell (1987) and Yaari (1987), and developed further by Dhaene et al (2002).. In particular, MFID was first introduced by Dhaene et al. (2012) and originally labelled as the "herd behavior index" (HIX).

more importantly, the MFID can capture the nonlinear information in the return dependence structure, using comonotonicity theory. By accounting for nonlinear behavior, we improve over existing dependence measures (e.g. correlation). Finally, variation in MFID is not limited to behavior in the tails of the return distribution. For instance, disaster risk (Barro & Liao, 2020) and lower-tail dependence (Chabi-Yo et al., 2018) focus on extreme events, whereas MFID captures dependence in both an upward and downward market (although it generally increases in downward markets). Hence, MFID yields idiosyncratic information over existing measures, which we can exploit in standard asset-pricing tests.

We investigate the impact of MFID in the cross-section of returns. Sorting all stocks on the NYSE, Amex, and Nasdaq from January 1998 until December 2020 in deciles based on their exposure to MFID, we document that MFID carries a positive premium in bad times. That is, stocks with high exposure to MFID – those that increase together with the dependence measure – outperform those with low exposures – those that decrease when the dependence measure increase. We define a bad state as one in which the in-month daily stock market variance exceeds its median. This is consistent with the asset-pricing implications of the demand for stocks with a higher potential to hedge against dependence risk; highlighting time-varying preferences of investors. The difference between the high and low deciles yields an average risk-adjusted return of 1.4% per month. More interestingly, this return spread is not accounted for by the standard factors and other option-implied factors. It is also robust when we control for the COVID-19 pandemic, implied correlation, changes in the benchmark of bad economic states, firm-level cross-sectional regression, and bivariate regression. Moreover, we show that our conclusions hold in foreign exchange portfolios, mutual funds, risk factor premia, or international market indices.

To go beyond studying risk-adjusted returns, we test the underlying economic drivers of the MFID premium. In exploring the specific economic mechanisms behind MFID's pricing power, we turn to leverage constraints and behavioral theories (Adrian et al., 2014; Asness et al., 2020). For instance, we report the co-movement of long, short, and long-short returns and economic variables, option-implied factors, and risk aversion metrics. The results indicate that the observed stock return predictability is associated with these risk factors, implying that when economic variables (e.g., default spread and TED spread), risk aversion metrics (e.g., systematic risk and risk aversion index), and option-implied factors (e.g., disaster risk and implied correlation) increase, high-MFID-exposure stocks outperformed low-MFID-exposure counterparts. Differences in factor loadings among these risks are almost all statistically significant. This, again, highlights that MFID-sorted portfolios are a hedge against bad times. The findings, however, go against a risk-based theory, in which one predicts lower expected returns for assets that provide a hedge against bad times. Therefore, we argue a behavioral explanation is more likely, although it is not captured by standard behavioral factors (see Daniel et al., 2020).

Our paper contributes to multiple strands of the asset-pricing literature. First, it is related to the literature that focuses on (implied) correlation as a priced risk factor. Asness et al. (2020) create a Betting-Against-Correlation portfolio that generates significant *cross-sectional* risk-adjusted returns. Similarly, Buraschi et al. (2014) provide evidence of correlation risk in hedge fund returns. Driessen et al. (2009) offer return predictability evidence of option-implied correlation. Furthermore, there is a large number of articles studying the relationship between (implied) correlation and *aggregate* returns. Pollet and Wilson (2010) show that daily correlation among stocks predicts future stock returns. In line with this conclusion, Buss et al. (2019) document that implied correlation predicts future market returns up to 1 year ahead. We contribute to this literature by showing that correlation alone does not fully capture the dependence structure among asset returns. When holding implied correlation constant, the MFID-sorted long-short portfolio *still* produces significant risk-adjusted returns.[2]

Second, there is a growing literature that investigates the asset-pricing implications of option-implied metrics. Bali and Murray (2013) highlight a negative relationship between risk-neutral skewness and skewness returns. Amaya et al. (2015) confirm the strong *cross-sectional* relationship between realized skewness and stock returns, while not finding robust *time-series* relationships for kurtosis or volatility. Other papers that use similar metrics are Ang et al. (2006), Bardgett et al. (2019), Bekaert et al. (2013), Bekaert and Hoerova (2014), Chang et al. (2013), and Schlag et al. (2021). We add to this strand of the literature by investigating a model-free implied metric of the dependence structure that captures both linear and nonlinear components.

---

[2] In Appendix, we show that the results are robust for a wide range of alternative specifications (Table. A.1. to table A.10.)

Third, we contribute to the literature on time-varying preferences. For instance, Bansal et al. (2022) show that high socially-responsible investments earn higher (lower) risk-adjusted returns in good (bad) economic times. Similarly, Huynh and Xia (2021) document the investor preferences of climate change risk for corporate bonds. Gao et al. (2018) find the market-timing abilities of hedge funds in light of disaster concerns. Stambaugh et al. (2012) show that stock return anomalies are stronger in bad times. Finally, Kapadia et al. (2019) document that *ex-ante* firm characteristics allow investors to establish portfolios that provide insurance against a bear market. Consistent with this literature, we find that the MFID premium is statistically and economically significant in bad economic times, even when we control for *ex-ante* firm characteristics.

Finally, our paper is related to the literature on disaster risk (e.g., Barro, 2006; Cortes et al., 2022; Gabaix, 2012), tail risks (e.g., Bollerslev et al., 2015; Chabi-Yo et al., 2021; Chabi-Yo et al., 2018; Fan et al., 2022; Karagiannis & Tolikas, 2019; Kelly & Jiang, 2014), and risk aversion (e.g., Bekaert et al., 2021; Bekaert & Hoerova, 2016; Faccini et al., 2019; Weigert, 2015). In line with the papers, we document that MFID increases in bad times, such as an increase in the probability of disaster risk (Barro & Liao, 2020). Relative to these metrics, however, dependence risk can increase in upwards markets. Our metric, therefore, has the advantage of capturing potentially more uncertainty than those associated with disasters, the lower-tail of the return distribution, or time-varying risk aversion.

2. Model-free Implied Dependence

Correlation plays a main role in financial applications, such as in portfolio construction. However, correlation only employs information about the degree of linear dependence between variables. To capture the linear and nonlinear information between random variables, we rely on the comonotonicity methodology (Dhaene et al., 2002). Comonotonicity describes the perfect positive dependence between random variables. This translates to a financial market in which assets are moving perfectly together and it creates a one-dimensional market in that assets are not exposed to idiosyncratic elements, but to one systematic source. In this market, the following two statements are true. First, since asset prices are a function of a systematic factor (stochastic discount factor), the realization of this factor unambiguously determines all prices. Second, prices are a non-decreasing function of this factor, implying that they all move in the same direction.[3]

2.1.Definition

In reality, financial markets do not move in a *perfectly* dependent (or comonotonic) way. Through option prices, we can determine the comonotonic market situation, following Hobson et al. (2015) and Chen et al. (2015). In a comonotonic market, the distribution of returns is the same as in the observed market, but their dependence is different. Since dependence is stronger in a comontonic market, following the perfect positive dependence, comonotonic (synthetic) index options are more expensive than the observed index options. The gap between the observed and comonotonic market allows us to draw conclusions about the degree of comonotonicity. We label this gap the "model-free implied dependence measure". We define MFID at time t as follows,

$$MFID_t = \frac{2e^{rM}\sum_{i=-l}^{h}\Delta K_i Q[K_i] - (\mathbb{E}[S] - K_0)^2}{2e^{rM}\sum_{i=-l}^{h}\Delta K_i \bar{Q}^c[K_i] - (\mathbb{E}[S] - K_0)^2}, \tag{1}$$

where $Q[K_i]$ denotes the price of an out-of-the-money (OTM) index option with strike K_i and time-to-maturity m, and $\bar{Q}^c[K_i]$ is an appropriate linear combination of the available constituents' options with time-to-maturity M. The price $\bar{Q}^c[K_i]$ can then be interpreted as the price of comonotonic index options with strike K_i. The index M-year forward rate is denoted by $\mathbb{E}[S]$, and r is the risk-free rate. Then, $\Delta K_i = \frac{K_{i+1}-K_{i-1}}{2}$ for $i = -l+1, \ldots, h-1$, $\Delta K_i = K_{-l+1} - K_{-l}$, and $\Delta K_h = K_h - K_{h-1}$. The first strike below the forward rate $\mathbb{E}[S]$ is denoted by K_0 and $K_l < K_{l+1} < \cdots < K_0 < \cdots < K_h$.

In Equation (1), the nominator is an approximation for the realized risk-neutral variance of the time-m market index price S, which is determined through the prices of index options.[4] The denominator is an approximation for the risk-neutral index variance in a comonotonic market. It can be determined by using appropriate linear combinations of constituent's option prices (Dhaene et al., 2002). We then compare the realized implied index

[3] If stocks follow $S_{i,t} = f_t(U)$, where f_t is a non-decreasing function. In a comonotonic market, where we have two assets, the price of these assets could either go up or down together. In a non-comonotonic market, where there is not a single systematic source, the price of asset 1 could go up, when the price of assets 2 goes down, and vice versa.

[4] It relies on Carr and Madan (2002) and Carr and Wu (2006), who show that the risk-neutral variance of an index can be determined in a model-free way using a linear combination of OTM options; the focus of these papers is on the volatility index, VIX.

variance with its upper bound, the comonotonic index variance. A small gap between these measures indicates a strong degree of dependence between stocks. By defining MFID as the relative distance between the realized market and a synthetic market, we limit the range of MFID to be between zero and one (with one as the upper bound).

By definition, an option price is the sum of its intrinsic and time value. Information about the future behavior of asset prices should only affect their time value. Hence, we focus on OTM options (as in Carr & Madan, 2002; Carr & Wu, 2006) when extracting information about the degree of return dependence.

Measuring implied dependence by comparing the realized market situation (the nominator) with the extreme market situation (the denominator) has three advantages. First, we capture the information not embedded in existing dependence measures, such as (implied) correlation. Second, our approach is model-free. The index options are observed in the market and the comonontonic index options are determined using traded options. Finally, we use all information in the option curve to calculate MFID. In contrast, implied correlation is based on a particular choice of stocks and uses mainly at-the-money (ATM) index options.

2.2. Empirical calculation

As indicated in Equation (1), MFID consists of two elements: the numerator is the realized risk-neutral variance of the market index, which could be expressed as a linear combination of traded OTM index options (e.g., Carr & Madan (2001)). The price $Q[K_i]$ is then given by

$$Q[K_i] = \begin{cases} P[K_i], & if K_i < K_0 \\ \frac{P[K_i] + C[K_i]}{2}, & if K_i = K_0 \\ C[K_i], & if K_i > K_0 \end{cases}$$

where *P[K]* and *C[K]* denote the price of an index put and call with maturity M and strike K, respectively.

For the denominator, we determine the comonotonic index variance. Once the comonotonic index option price $\bar{Q}^c[K_i]$ is determined for a traded strike price K_i, the calculation for the denominator is similar to the numerator. The price $\bar{Q}^c[K_i]$ is given by

$$\bar{Q}^c[K_i] = \begin{cases} \bar{P}^c[K_i], & if K_i < K_0 \\ \dfrac{\bar{P}^c[K_i] + \bar{C}^c[K_i]}{2}, & if K_i = K_0 \\ C^c[K_i], & if K_i > K_0 \end{cases}$$

In the next section, we detail how to estimate the comonotonic index options prices $\bar{Q}^c[K_i]$.

2.2.1. Comonotonic option prices

Breeden and Litzenberger (1978) show that the option curve of assets characterizes the risk-neutral distribution via the following relationship:

$$F_{S_i}(K) = 1 + e^{rM} C'_i[K+], \tag{2}$$

where F_{S_i} denotes the risk-neutral distribution function of the time-*t* stock price of asset *i* and $C'_i[K+]$ denotes the right derivative of the corresponding call option curve. However, the right-hand side of Equation (2) only leads to the risk-neutral distribution function of stock *i* if the full option curve can be observed. In other words, for each possible strike, we need the corresponding market call price. Since only a finite number of strike prices are traded, the option curve C_i is only known on a discrete strike price grid. The available strike prices for stock *i* are denoted by $K_{i,j}$, for $j = 0, \ldots, m_i + 1$. We define the approximate risk-neutral distribution function for stock i as follows,

$$\bar{F}_{S_i}(\mathrm{x}) = \begin{cases} 0, & if x < 0 \\ 1 + e^{rM} \dfrac{C_i[K_{i,j+1}] + C_i[K_{i,j}]}{K_{i,j+1} - K_{i,j}}, & if K_{i,j} \leq x < K_{i,j+1},\ j = 0,1,\ldots,m_i \\ 1, & if x > K_{i,m_i+1} \end{cases} \tag{3}$$

where we assume that the traded strike prices are ordered $K_{i,j} < K_{i,j+1}$. Moreover, we assume that K_{i,m_1+1} is such that $\bar{F}_{S_i}(K_{i,m_1+1}) = 1$. Through the put-call parity, one could determine the distribution function of stock *i* by using the corresponding put option curve.

The approximation $\bar{F}_{S_i}$ is a reasonable approximation in that model prices for call and put options correspond to the available traded option prices. The cumulative distribution function $\bar{F}_{S_i}$ can be used to approximate non-traded options. Instead of using the approximation $\bar{F}_{S_i}$, one can impose strong assumptions on the underlying return dynamics to determine the alternative approximation for the risk-neutral distribution functions, using available options. Overall, it is shown by Chen et al. (2005) that using the approximate risk-neutral distribution functions $\bar{F}_{S_i}, i = 1,2, \dots, n$, the approximate comonotonic index option price is defined as follows,

$$\bar{C}^C[K] = e^{-rM} E\left[\left(\sum_{i=1}^{n} w_i \bar{F}_{S_i}{}^{-1}(U) - K\right)_+\right], \tag{4}$$

where $(x)_+ = max(x, 0)$ and $E[.]$ is an expectation under the risk-neutral probability measure. Then $\bar{C}^C[K]$ can be interpreted as the price of an index option written on a comonotonic index. Indeed, the components in the index $\sum_{i=1}^{n} w_i \bar{F}_{S_i}{}^{-1}(U)$ are comonotonic, since they are non-decreasing functions of the systematic component U. The distribution function of the comonotonic index price $\sum_{i=1}^{n} w_i \bar{F}_{S_i}{}^{-1}(U)$ is denoted by$F_{S^c}(K)$.

The comonotonic index option price can be determined as follows,

$$\bar{C}^C[K] = \sum_{i \epsilon N_K} w_i C_i[K_{i,j}] + \sum_{i \epsilon \bar{N}_K} w_i\left(\alpha_K C_i[K_{i,j}] + (1 - \alpha_K) C_i[K_{i,j+1}]\right), \tag{5}$$

where α_K is any element in [0,1] such that $K = \sum_{i \epsilon N_K} w_i K_{i,j_i} + \sum_{i \epsilon \bar{N}_K} w_i\left(\alpha_K K_{i,j_i} + (1 - \alpha_K) K_{i,j_i+1}\right)$ in which N_K is defined as $N_K = \{i \,\epsilon\, (1,2, \dots, n) \mid \bar{F}_{S_i}(K_{i,j_i-1}) < F_{S^c}(K) < \bar{F}_{S_i}(K_{i,j_i})\}$.

A discrete set of option prices for each index constituent is necessary to build the marginal distributions, while no additional assumptions are required to determine comonotonic index option prices (Dhaene et al., 2000)). Equation (4) says that we need to select a linear combination of underlying options such that the corresponding combination of strike prices equals the index strike price. This follows Jamshidian (1989), who documents that such a linear combination of options results in a super-replicating portfolio of the index option. Equation (5), thus, is only one element in a set of super-replicating portfolios. Using the no-arbitrage condition, the price of the comonotonic call option always exceeds the price of the index option, $C[K] \leq \bar{C}[K]$.

By using the comonotonic combination of strike prices, one could find the cheapest super-replicating portfolio. If we use options with a maturity of one month to determine the MFID, we can study the dependence of stock prices within one month, i.e. M = 1/12. To compare MFID over time, we have to determine the value of MFID at each trading day for any given maturity. However, on any given day, only a finite number of maturities are traded. When M is not traded, we perform the calculations on maturity M_1, which is closest to but smaller than M, resulting in $MFID_{M_1}$.[5] We call this near-term maturity. The next-term maturity is the maturity M_2, which is the traded maturity closest to but larger than the maturity M. This gives us a definition of the constant-maturity MFID,

$$MFID_t = MFID_{M_1} \frac{M_2 - M}{M_2 - M_1} + MFID_{M_2} \frac{M - M_1}{M_2 - M_1}, \tag{6}$$

[INSERT FIGURE 1]

Figure 1 illustrates the gap between the realized (green) and the comonotonic (blue) option curve for two days, using DJIA as our example. The left panel plots October 1st, 2007 when MFID equaled 0.47. The right panel, in turn, plots October 1st, 2008 when MFID topped 0.60. These two trading days depict the differences in the gap between the nominator (the realized market) and the denominator (the synthetic market). Indeed, the smaller the gap is, the closer the actual financial market behaves as a comonotonic market.

2.2.2. Constructing the MFID

The model-free implied dependence metric is extracted from the DJIA, which is a price-weighted market index consisting of 30 blue-chip stocks. The advantage of the DJIA is that its options and its constituents' options are relatively liquid compared to other indices, such as the S&P100 and the S&P500. This liquidity is advantageous when calculating MFID, since we use the full option curve to determine the gap between realized and synthetic markets, as shown in Figure 1.

We use daily option prices for the index and constituents from OptionMetrics. From January 1998 to December 2020, we link the option prices with Compustat (e.g. the historical DJIA constituents) and CRSP (e.g. firm-level information). As in Driessen et al. (2009), we use American options. Given that we focus on shorter-term OTM options, differences between American and European option prices are relatively small. In line with the option literature, we excluded options that have non-positive volumes and bid prices, and where either no bid or ask

[5] More technical details are in Appendix 2.

is available. In the case there is no reliable data for specific constituents, we remove this stock from the index and adjust index weights accordingly. However, we always have option data for at least 95% of trading days. Finally, we use zero-coupon rates, which are available for a discrete set of maturities, as the risk-free rate.

[INSERT FIGURE 2]

In Figure 2, we plot the time series of daily (top) and monthly (bottom) values for the MFID from January 1998 to December 2020. The largest values of MFID occurred in March 2020, which coincides with the outbreak of COVID-19 and the subsequent stock market decrease. Other key events are the bankruptcies of LTCM (August 1998) or Lehman Brothers (September 2008), the start of the Iraq War (March 2013) or COVID-19 (March 2020), and Greece's downgrade (July 2011), which saw elevated levels of MFID. This implies that MFID corresponds to key downturns in financial markets.

2.3.Economic significance

In the previous sections, we showed both theoretically and empirically that there is information embedded in MFID. MFID, however, is not the only metric that proxies dependence (e.g., implied correlation) or tail events (e.g., implied skewness). In this section, we study the economic significance of MFID versus other measures.

2.3.1. Implied correlation

Similar to MFID, correlation measures the degree of (linear) dependence by comparing the observed situation with an extreme dependence situation, in which correlation equals one. Since in this case, the extreme situation only captures perfect *linear* dependence among asset returns, correlation only describes a subset of all possible dependence structures and is therefore only a crude approximation of the actual co-movement.

[INSERT FIGURE 3]

Figure 3 documents four scenarios where two random variables are moving perfectly together, i.e. in all four cases the random variables are comonotonic. The difference between the scenarios is the correlation coefficient, ranging from 0.9975 to 0.033. We observe that correlation can be misleading in that low values cannot always be interpreted as a sign of weak dependence. Indeed, if two random variables are comonotonic, the correlation is not necessarily equal to one. One should not compare the dependence between random variables against a (maximum) correlation of 1, but instead to the comonotonic correlation, which can be strictly smaller than one and even be close to zero.

More recently, researchers have focused on implied correlation (IC), which is an option-implied index for the degree of linear dependence (e.g., Buss et al. (2017, 2019); Driessen et al. (2009); Skintzi & Refenes (2005)). The IC can be determined using the implied volatility on the market index and its constituents, that is,

$$IC_t = \frac{\sigma^2 - \sum_{i=n}^{n} w_i^2 \sigma_i^2}{\sum_{i-1}^{n} \sum_{j \neq i} w_i w_j \sigma_i \sigma_j}, \tag{7}$$

where is σ the implied volatility of the market index and σ_i are the implied volatilities of its constituents. The implied volatilities are determined using available options with the same maturity M and therefore the implied correlation reflects the expectation of the market about future correlation up to time M.

In general, there are three main fallacies of implied correlation. First, the IC only measures linear dependencies between variables. This implies that a value close to one coincides with a highly dependent linear stock market, but a small value does not necessarily relate to a stock market where one can diversify by investing in a large number of stocks, as shown in Figure 2. Additionally, volatility has a different impact on (implied) correlation relative to MFID. To illustrate this point, we consider an example with two assets that exhibit an average return of 3%, a volatility of 20%, and a correlation coefficient of 0.95, as in Dhaene et al. (2012).

[INSERT FIGURE 4]

Figure 4 plots the effect of an increase in the volatility of one of the assets on both correlation and MFID. When volatility increases, the gap between MFID and correlation increases. MFID tends to one, whereas correlation goes to zero. This suggests that (1) the non-linear dependence becomes more important when volatility is high, and (2) correlation can fail to capture the underlying dependence structure adequately. Since volatility mainly increases in market downturns, non-linear dependence is arguably more prevalent in bad economic times.

Second, implied correlation is not a model-free measure. It assumes that stock returns are driven by correlated normal distributions. Returns are known to be leptokurtic, resulting in volatility skews or smiles (Chang et al. (2012, 2013)), which can influence the *real* dependence structure among assets. Finally, the IC does not use all available option data, instead, one needs to select the appropriate strike for index and constituents, and derive the corresponding implied volatilities. MFID goes beyond the set of linear dependence structures. It is a model-free metric that captures non-linear co-movement (as well as linear dependence) and uses all available options' information.

[INSERT FIGURE 5]

[INSERT TABLE 1]

Figure 5 shows that the co-movement between implied correlation and MFID is relatively high. Importantly, there is distinct variation between the two metrics that can be exploited in asset-pricing tests. Indeed, Table 1 confirms that there is high co-movement between the two dependence measures (above 0.8).

2.3.2. Option-implied higher moments

We are not the first to introduce an option-implied measure. Among others, Chang et al. (2012) define option-implied indices for the variance, skewness, and excess kurtosis of assets. The difference between the measures and MFID is that option-implied measures for variance, skewness, and excess kurtosis are univariate measures and therefore they contain information about the stock market index and the constituents. The MFID, on the other hand, is a multivariate metric that uses option data of the index and its constituents to separate marginal information from dependence information. Option-implied metrics for the variance (*MFIV*), skewness (*MFIS*), and excess kurtosis (MFIK) are defined as follows:

$$MFIV = \frac{e^{rM}V - \mu^2}{\tau} \tag{8}$$

$$MFIS = \frac{e^{rM}W - 3\mu e^{rM}V + 2\mu^3}{(e^{rT}V - \mu^2)^{3/2}} \tag{9}$$

$$MFIK = \frac{e^{rM}X - 4\mu e^{rM}W + 6e^{rT}\mu^2 V + 3\mu^4}{(e^{rM}V - \mu^2)^2} - 3 \tag{10}$$

where $\mu = e^{rM} - 1 - \frac{e^{rM}}{2}V - \frac{e^{rM}}{6}W - \frac{e^{rM}}{24}X$ and r is the continuously-compounded risk-free rate from period from m to time M, and V, W, and X are given by,

$$V = \int_{K=S}^{\infty} \frac{2 - \left(1 - \ln\left(\frac{K}{S}\right)\right)}{K^2} C[K]dK + \int_{K=0}^{S} \frac{2 - \left(1 + \ln\left(\frac{S}{K}\right)\right)}{K^2} P[K]dK$$

$$W = \int_{K=S}^{\infty} \frac{6\ln\left(\frac{K}{S}\right) - 3\left(\ln\left(\frac{K}{S}\right)\right)^2}{K^2} C[K]dK + \int_{K=0}^{S} \frac{6\ln\left(\frac{S}{K}\right) - 3\left(\ln\left(\frac{S}{K}\right)\right)^2}{K^2} P[K]dK$$

$$X = \int_{K=S}^{\infty} \frac{12\left(ln\left(\frac{K}{S}\right)\right)^2 - 4\left(\ln\left(\frac{K}{S}\right)\right)^3}{K^2} C[K]dK + \int_{K=0}^{S} \frac{12\left(ln\left(\frac{S}{K}\right)\right)^2 - 4\left(\ln\left(\frac{S}{K}\right)\right)^3}{K^2} P[K]dK$$

where $C[K]$ and $P[K]$ are the prices of call and put options with strike $K$and S is the stock price.

[INSERT TABLE 1]

Additionally, we calculate Aggregate Tail Risk (*ATR*; Kelly et al., 2016), Corridor Model-Free Implied Variance (*CIX*; Andersen & Bondarenko, 2007), option-implied disaster risk (*Disaster*; Barro & Liuo, 2020), Risk Aversion index (*RA*; Bekaert et al., 2021), *SVIX* (Martin, 2012), and *VIX*. Table 1 reports the co-movement between MFID and the option-implied metrics. We show that the co-movement between MFIV and MFID is high and positive (0.490). Similarly, *SVIX*, *VIX*, and *CIX* strongly co-move, and hence exhibit a similar co-movement with MFID. In turn, the co-movement between MFID and MFIK or MFIS is negative and smaller in magnitude, -0.176 and -0.165 respectively.[6]

3. Empirical results

In this section, we conduct multiple tests to assess the impact of MFID in the cross-section of returns. Following Figure 4, we entertain the possibility that the MFID anomaly varies across different states of the world. To test this hypothesis, we use a portfolio approach and firm-level analysis. Moreover, to show that our findings do not hinge on our empirical design, we provide ample robustness tests.

[6] In Figure A.1. to A.4., we document the co-movement between MFID and other risk measures.

3.1.Data and methodology

Our stock sample includes all U.S. common stocks traded on the NYSE, Amex, and Nasdaq from January 1998 through December 2020. Monthly returns are taken from CRSP. Similar to Bali et al. (2017), we exclude stocks below $5 and above $1,000. To avoid survivorship bias, we adjust the returns for stock delistings. Since we use rolling regressions, we require at least 60 monthly observations per stock. Accounting data are obtained from the merged CRSP-Compustat database.

For each stock in our sample, we estimate the monthly exposure of excess returns to MFID in a fixed 60-month rolling regression. We also control for the market index (MKT) and risk factors on size (SMB), book-to-market (HML), investment (CMA), and operating profitability (RMW) from the Fama and French Five-Factor Model (2015), momentum (UMD) from Carhart (1997), and the illiquidity risk factor from Amihud (2000). We run the following regression:

$$R_{i,t} = a_{i,t} + \beta_{i,t}^{MFID} \cdot MFID_t + \gamma_{i,t} \cdot X_t + \varepsilon_{i,t}, \tag{11}$$

where $R_{t,i}$ is the monthly excess return of stock *i* at time *t*, $MFID_t$ is the model-free implied dependence at time *t*, and X_t is a vector of risk factors, defined above. This procedure gives us a monthly exposure to MFID (MFID beta) starting from January 2003.

Additionally, we introduce several cross-sectional return predictors. First, we calculate co-skewness following Harvey and Siddique (2000) as

$$COSKEW_{i,t} = \frac{E\left[\epsilon_{i,t} R_{m,t}^2\right]}{\sqrt{E\left[\epsilon_{i,t}^2\right]} E\left[R_{m,t}^2\right]},$$

where $\epsilon_{i,t} = R_{i,t} - \left(a_{i,t} + b_{i,t} \cdot R_{m,t}\right)$ are the residuals from the regression of the excess stock return ($R_{i,t}$) against the contemporaneous market return ($R_{m,t}$) using monthly observations over the last 60 months.

We estimate idiosyncratic volatility of stock *i* (IVOL) as the standard deviation of residuals from the regression

$$R_{i,t} = a_{i,t} + \gamma_{i,t} \cdot X_t + \varepsilon_{i,t},$$

where X_t are a set of risk factors, including the Fama and French five factors, momentum, and liquidity.

Following Hou et al. (2021), we calculate the growth rate of total assets (I/A), which is measured as the change in book assets (AT), and operating profitability (ROE), which is measured as the income before extraordinary items (IBQ) divided by one-quarter lagged book equity.

3.2. Univariate portfolio-level analysis

[INSERT FIGURE 6]

We construct ten portfolios by sorting individual stocks based on the MFID beta (β^{MFID}) in each month, where decile 1 (10) and contains stocks with the lowest (highest) β^{MFID}. In Figure 6, we plot the variation in exposure to MFID over time. During the entire sample, decile 1 (P1) has a negative beta and decile 10 (P10) has a positive beta. In other words, the return of the average stock in decile 10 increases when MFID increases, hence, it does offer a hedge against bad times. In fact, we show that the difference in MFID exposure peaks around the onset of the Iraq War (March 2003), Greece's downgrade (August 2012), and the outbreak of COVID-19 (March 2020). Around these crises, the gap between the beta of the lowest and highest decile portfolio increases remarkably. This indicates a distinct hedging potential in bad economic states.

For every decile, we calculate value-weighted portfolio returns. We then construct a long-short portfolio using the extreme deciles, 10 (long) and 1 (short). The long-short difference portfolio captures information embedded in the MFID beta, as highlighted above. Subsequently, we classify each month as either a bad or good state of the world. A bad state is defined as any month in which the in-month daily stock's standard deviation is above its median, and vice versa. Following Stambaugh et al. (2012), we run the following regression:

$$R_{i,t} = \alpha_{i,t}^{H} \cdot d_t^{H} + \alpha_{i,t}^{L} \cdot d_t^{L} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}, \quad (12)$$

where $R_{i,t}$ is the monthly return on decile 10 (long), decile 1 (short), and the difference (long-short), d_t^H (d_t^L) is a dummy variable that equals one if the daily in-month stock market variance in month *t* is above (below) the median, and zero otherwise; and X_t is a vector of common risk factors: Fama and French Five-Factors (*FF5F*)

(2015), momentum (*UMD*), short- and long-run reversal (*SLR*), short- and long-run behavioral factors (*DHS*) (Daniel et al., 2020), and Q5 factor model (Hou et al., 2021).

[INSERT TABLE 2]

Panel A of Table 2 reports value-weighted (risk-adjusted) returns with Newey-West *t*-statistics in parentheses. The main finding from this table is that there is a positive significant relationship between MFID exposure and stock returns in a bad state of the world. We document that the unconditional return of the long-short portfolio equals 0.7% per month in a bad state of the world, significant at the 1% confidence level. In contrast, the return of the long-short portfolio is -0.2% per month in good economic times, although statistically insignificant. More importantly, the difference between these two unconditional returns totals 0.9%, statistically significant at the 1% confidence level.

For the risk-adjusted returns, we highlight that the long-short alphas equal around 1.2% per month, significant at the 5% confidence level. This result is mainly driven by the stocks with the highest exposure towards MFID, the long leg. In good states of the world, when variance is below its median, the long-short risk-adjusted return is negative (although statistically insignificant). Overall, the findings imply that the performance of stocks that co-move positively with MFID persists in the month after the portfolio formation and that this performance is not explained by other risk factor models, which is in line with related results from implied correlation (Asness et al., 2020).

The evidence in Panel B of Table 2 confirms the robustness of the result by presenting equally-weighted alphas. Overall, the economic significance of our findings remains the same, which varies around 1.1% per month, but the statistical significance decreases slightly (the *t*-statistics is 1.905 in the Fama and Frech Five-Factor Model). Nevertheless, other risk factors are not able to capture the information embedded in MFID (see Figure A.5.).

In Panel C, we detail the risk loadings from the value-weighted risk-adjusted long-short returns. We document that the returns are mainly driven by the negative exposure to momentum (UMD), betting-against beta (BAB), and operating profitability (ROE). In particular, the result of momentum and BAB is intuitive. Stocks with a low exposure to MFID are those that perform well when MFID is low (good state) and bad when MFID is high (bad state). In other words, stocks with high exposure to MFID are those that outperform when the rest of the market is doing poorly.

In conclusion, the results imply that higher-exposure stocks are a hedge against bad times. This, however, goes against a risk-based theory of asset pricing, in which one predicts low expected returns for stocks that provide a hedge against bad times. One could imagine that investors switch their portfolios in a bad state of the world and buy assets that performed well; assets that increase in value when MFID increases. Therefore, we conclude that the best possible explanation for the observed variation in returns is a behavioral story. However, the risk-adjusted returns are significant even after controlling for short- and long-term behavioral factors (Daniel et al., 2020). This implies that MFID captures a behavioral-style factor that is not captured by established measures.

One of the issues of asset-pricing models is the practical implementations. This revolves around the question of how certain investors can be that a specific stock in a specific decile sorted on exposure to MFID remains in that decile one year later. High persistence is also important when interpreting the evidence in an equilibrium model, they are a good proxy for conditional betas, such as in the ICAPM (see Merton, 1973). We calculate the transition matrix in Figure 7.

[INSERT FIGURE 7]

Figure 7 shows that an individual stock in decile 1 has a 49.52% probability of remaining in its decile after one year, and a 19.04% probability of ending up in decile 2, etc. In turn, stocks that were in decile 10 have a 50.42% probability of remaining in its decile after one year. This highlights the persistence of MFID beta for individual stocks.

3.3.Bivariate portfolio analysis

Among the most important questions that remain is what information is actually embedded in MFID; whether MFID contains new information over implied correlation. One way to credibly distinguish between linear and non-linear dependence is to create a portfolio that captures non-linear-dependence aspects (MFID) while being relatively unrelated to linear-dependence aspects (implied correlation). To accomplish this, we decompose the MFID-sorted portfolio into a new strategy: one that goes long stocks with a high exposure to MFID and shorts those with low exposures to MFID, while seeking to match the exposure to implied correlation. Additionally, we create a similar strategy by matching information relating to (model-free implied) variance, skewness, and kurtosis. Similar to Equation (12), we calculate the exposure of individual stocks to the four measures. We test these four bivariate portfolios relative to classic risk factor models (Fama & French, 2015). Table 3 presents the alpha of these portfolios.

[INSERT TABLE 3]

This table shows that the risk-adjusted returns of the long-short portfolio remain statistically significant across all bivariate sorts. Similar to the univariate regressions, we show the alphas in the bad states vary around 1.3% per month, significant at the 1% confidence level. This highlights that there is information in MFID that is not yet captured by other measures. For instance, the significant MFID premium over implied correlation indicates that the non-linear component contains information for investors in bad states of the world. Hence, one could use the information in MFID as a hedge against bad times.

3.4. Robustness checks

Having demonstrated the strong positive cross-sectional relation between MFID beta and stock returns in bad states of the world that is not explained by standard risk factors, we continue to study the possibility that this relation can be explained through other drivers. In this section, we study (1) changes to our definition of states of the world, (2) the impact of COVID-19 on our evidence, (3) the use of other test assets, and (4) asset classes. Overall, this section shows that the findings are robust to changes in our empirical design.

3.4.1. Stock level cross-sectional analysis

One of the advantages of using portfolios is the reduction of residual variance. The drawback, however, is that we throw out important firm-level information. Moreover, using portfolio-level analysis, we can only test for information in the aggregate variation by a limited number of variables. In this section, we apply a multivariate approach to paint a comprehensive picture of MFID within the cross-section of stock returns. We apply a Fama and Macbeth (1973) cross-sectional regression with contemporaneous firm-level stock returns (Panel A) or one to three-month ahead returns (Panel B) as the dependent variable, and MFID beta and firm-level characteristics as independent variables, that is,

$$R_{i,t+h} = \lambda_{i,t}^{1}\left(d_t^H \cdot \beta_{i,t}^{MFID}\right) + \lambda_{i,t}^{2}\left(d_t^L \cdot \beta_{i,t}^{MFID}\right) + \lambda_{i,t} X_{i,t} + \epsilon_{i,t+h}, \tag{13}$$

where $R_{i,t+h}$ is the realized excess return on stock *i* from month *t* to *t+h*, $\beta_{i,t}^{MFID}$ is the MFID beta of stock *i* in month *t*, d_t^H (d_t^L) is a dummy variable that equals one if the daily in-month variance in month *t* is above (below) its median, and $X_{i,t}$ is a vector of firm-specific characteristics, defined in section 3.1.

[INSERT TABLE 4]

Panel A of Table 4 reports the time-series averages of slope coefficients and Newey-West *t*-statistics. We show that there is a positive significant relation between $d_t^H \cdot \beta_{i,t}^{MFID}$ and asset returns. In other words, an increase in MFID beta leads to a significant increase in stock returns in a bad state. This, therefore, is in line with the main conclusion from Table 2. The average slope coefficient from the regression with $d_t^H \cdot \beta_{i,t}^{MFID}$ alone equals 2.039 (i.e., column 1), significant at the 1% confidence level. This slope coefficient corresponds to an increase of 0.46% per month in average returns for moving from the first to tenth decile.[7] This result is robust when controlling for firm characteristics (Columns 2 to 7). For instance, even if we control for $\beta_{i,t}^{IC}$, the long-short portfolio still yields an average return in the following month of 0,47%, significant at the 5% confidence level. This indicates that our findings are orthogonal to Kapadia et al. (2019), who find a portfolio constructed based on *ex-ante* firm characteristics (e.g., firm size and leverage) outperforms in bear markets. In fact, we show that even controlling for these firm characteristics, we still observe outperformance in bad economic times.

Panel B of Table 4 studies the predictive ability of the MFID beta. There are two takeaways. First, we document that $d_t^H \cdot \beta_{i,t}^{MFID}$ is a significant predictor for expected stock returns. This relationship, however, vanishes after two months. Instead, the coefficient for $d_t^L \cdot \beta_{i,t}^{MFID}$ – the MFID beta in good states of the world – is significant from month three onwards. The average slope coefficient equaled -1.664, which equals an average decrease of

[7] The difference in β^{MFID} between deciles 10 and 1 equals 0.226 (see Table A.2.).

0.37% in expected returns. We argue that there is an asymmetric relationship between MFID and stock returns depending on the economic state. In bad states, a higher dependence implies that stocks move down in unison, and, hence, is not something investors would desire.

3.4.2. State-dependent abnormal returns

Although return dependence among asset prices generally increases in bad times, it can also increase in a good state of the world. This suggests that there can be four different states of the world: one in which MFID is high (low) when the stock market is low (high) – which we already documented extensively – but also one in which MFID is low (high) when the stock market is low (high). One way to distinguish between these scenarios is to run a regression model in which we further decompose the regression intercept to accommodate to investigate their informational contributions. More specifically, we use the following regression framework,

$$R_{i,t} = \alpha_{i,t}^{HH} \cdot d_t^{HH} + \alpha_{i,t}^{HL} \cdot d_t^{HL} + \alpha_{i,t}^{LH} \cdot d_t^{LH} + \alpha_{i,t}^{LL} \cdot d_t^{LL} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}, \quad (14)$$

where d_t^{HH} and d_t^{HL} are dummy variables indicating high-variance period and high- and low- MFID periods, d_t^{LH} and ad_t^{LL}re dummy variables indicating low-variance periods and high- and low- MFID periods, $R_{i,t}$ is the excess return in month *t* on the long or short leg, and the difference of MFID-sorted value-weighted portfolios, X_t refers to risk factors used in asset-pricing models.

[INSERT TABLE 5]

Table 5 reports the results from the analysis. There are three takeaways from this table. First, when both MFID and variance are high, the risk-adjusted returns are statistically significant at the 1% confidence level. They are also economically meaningful, as they vary between 1.9% and 2.4% per month. This suggests that in the worst states of the world, investors demand stocks with high potential to hedge against dependence risks; those that increase when return dependence increases. This result is in line with the rest of our conclusion. Second, when both MFID and variance are low – arguably the best state of the world – the alphas are negative and statistically significant at the 5% confidence level. Indeed, we show that the performance wedge between stocks with high and low MFID exposure is time-varying: with highly-exposed stocks outperforming low-exposed ones during bad economic times, while underperforming during good economic times. Finally, when there is a disconnect between MFID and stock market variance, these strategies do not generate any risk premia for investors. This re-confirms that the information embedded in MFID is confined to market stress since a high MFID in a stock market with low volatility does not contain important information for investors.

3.4.3. Horse race

To bring home the point that MFID contains information over and above other (model-free implied) measures, we run a horse race. We consider strategies conditional on implied correlation, MFIK, MFIS, and MFIV relative to MFID. First, we test the power and importance of the strategy on a classic risk factor. Second, we add MFID as an additional risk factor to examine the economic and statistical significance of the risk-adjusted returns on these strategies. Finally, we test whether the alphas remain significant in our MFID strategy when we include the four new strategies in our risk factor model.

[INSERT TABLE 6]

Panel A of Table 6 reports the risk-adjusted returns across all the strategies. Column 1 shows the benchmark, the MFID-sorted strategy with the Fama and French five factors including BAB. In Columns 2, 4, 6, and 8, we present the alphas of the strategy sorting on implied correlation, MFIK, MFIS, and MFIV, respectively. In line with the evidence of Asness et al. (2020), we find that the implied correlation strategy has a positive significant alpha in a bad state of the world. The regression magnitude, while smaller than the benchmark, is economically meaningful at 1.3% per month. However, once we add MFID as a risk factor, the risk-adjusted returns become zero in bad states. For MFIV, we document the same phenomenon: a significant alpha without MFID as a risk factor, but insignificant alpha once we include MFID in the regression framework. MFIK and MFIS, in contrast, behave differently. Sorting on MFIK, for instance, does not appear to be a profitable strategy in good and bad states of the world. Sorting on MFIS, in turn, generates a negative risk premium, which is in line with previous research (e.g., Bali & Murray, 2013; Chang et al., 2012, 2013). Adding MFID to the factor model does not alter this result.

Panel B shows the evidence of the MFID-sorting portfolio when we include these four strategies as a risk factor. In line with the bivariate regression results in Table 5, MFID does contain information for the cross-section of returns, as indicated by the statistically significant alphas. The magnitude decreases, however, by around 40% in the case of implied correlation (Column 1) to 0.9% per month. This confirms there is a small overlap between the measures, but that the non-linear correlation components outweigh the linear correlation.

3.4.4. Benchmark variation

One key parameter in our empirical design is the choice of benchmark. So far, we have focused on variance as our breakpoint to determine a certain month's good or bad state of the world. Table 7 highlights the robustness of the results by using the cyclically-adjusted price-earnings ratio (CAPE), disaster probability, dividend yield, economic policy uncertainty, implied and realized correlation, MFID, risk aversion, and VIX as the benchmark of interest.[8] Similar to the main analysis, we use the median as the breakpoint. Additionally, we add the flight-to-safety dummy of Baele et al. (2021) and the NBER recessions indicator as the additional benchmark. If there has been at least one flight-to-safety episode (or recession) in a given month, the indicator variable yields one.

[INSERT TABLE 7]

Table 7 shows that the MFID premium is significant in a bad state, regardless of how we characterize bad. The regression intercepts are always statistically significant, although it varies at which confidence level. Using the disaster probability, for instance, generates an alpha of 2.8% per month, significant at the 1% confidence level. Nevertheless, the main driver of the premium is the long leg, similar to our main findings. There are, however, two good states which generate a negative MFID premium. For Disaster probability and VIX, the MFID-sorted long-short portfolio generates an alpha around -1%, significant at the 5% confidence level.

3.4.5. COVID-19

Baker et al. (2020) highlight that the outbreak of the COVID-19 pandemic leads to a significant increase in stock market volatility. This can bias our results in two ways. First, since we use the median of stock market variance

[8] CAPE is obtained from Robert Shiller's website. Economic policy uncertainty is obtained from Baker et al. (2016).

as the breakpoint to characterize bad and good states of the world, it could be that the increased volatility (due to COVID-19) distorts our benchmark. Second, if the MFID premium is a hedge against bad times – as we have argued – most of the risk-adjusted returns can be earned in this period with unprecedented levels of volatility. If this premium is predominately earned in this relatively short period, then our results are not robust. Hence, we should see an increase in the alpha during this period. To test the impact of COVID-19 on our findings, we adjust our empirical design in two ways. First, we re-calculate the median stock market variance up to March 2020 and use this as our main benchmark. Second, we include a third dummy variable in our regression,

$$R_{i,t} = \alpha_{i,t}^{H} \cdot d_t^{H} + \alpha_{i,t}^{L} \cdot d_t^{L} + \alpha_{i,t}^{COVID} \cdot d_t^{COVID} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}, \tag{15}$$

where d_t^H (d_t^L) is a dummy variable that equals one if the daily in-month variance in monthly t is above (below) its median up until February 2020, and zero otherwise, d_t^{COVID} is a dummy variable that equals one from March 2020 onwards, and zero otherwise, and X_t refers to risk factors used in asset-pricing models.

[INSERT TABLE 8]

Table 8 reports the results. This table makes two important points. First, MFID is priced in the cross-section of stock returns even in the period before the outbreak of COVID-19. The magnitude of the risk-adjusted returns decreases slightly from 1.4% to 1.2%, although they remain economically meaningful. Second, there is a surge in the alpha for the long-short portfolio in the COVID-19 period. Depending on the risk factor model, we show that the alpha equals around 4.2%. This confirms that MFID premium indeed is a hedge against bad times for investors.

3.4.6. Quantile regressions

So far, we sorted every stock based on the conditional average relationship between MFID and excess returns and found that stocks with a high MFID exposure outperformed low-exposure counterparts in a bad economic state. If this were true, one would expect that this finding becomes stronger if we only take into account higher values of MFID. To test this hypothesis, we estimate the monthly exposure to MFID in a fixed 60-month rolling quantile regression, in which we use threshold values of MFID – obtained as the percentiles of MFID over that

60-month period. Once we obtained the threshold-adjusted monthly exposures, we follow the rest of our main analysis, that is, we sort stocks into deciles based on their MFID-adjusted exposure, and regress the long, short, and long-short difference portfolio against risk factor models. Table 9 presents the evidence from this analysis.

[INSERT TABLE 9]

Overall, this table documents a positive relationship between the threshold value and the risk-adjusted returns from long-short portfolios. When MFID is at the first quantile, the alpha of the long-short portfolio is equal to 1.2%, although statistically insignificant. In turn, when MFID is above its median, the returns range from 3.5% to 4.2% per month, significant at the 1% confidence level. How do we reconcile these findings? At lower levels of MFID, it is arguably very hard to distinguish those stocks that provide a hedge when dependence increases. It confirms the results from Table 2, that there is no cross-sectional variation in stock returns in good economic times. Since alphas increase monotonically with the threshold, it suggests that stocks react more strongly when the level of MFID is relatively higher. This is also in line with the main conclusions from Table 2.

3.4.7. Other test assets

We proceed by testing its impact among three types of test assets. First, we focus on a cross-section of portfolios by obtaining Kenneth French's monthly returns on 100 portfolios formed on size and book-to-market, size and profitability, and size and investments, as well as 49-sector portfolios. Next, we use Chen and Zimmermann's (2022) long-short factor portfolios to investigate MFID's impact. Finally, we collect data on international equity indices, in line with Gao and Song (2013).

[INSERT TABLE 10]

Panel A of Table 10 presents the magnitude and statistical significance of the alphas from the factor portfolios. We show that the risk-adjusted returns of the long-short portfolios are statistically significant in a bad state of the world. Similar to the cross-section of stock returns, the long leg drives these findings. In contrast, in a good state of the world, we do not document a significant alpha. Similarly, in Panel B and C, we find that the results hold for risk factor portfolios and international indices respectively. To conclude, MFID beta is priced not only in the cross-section of individual stock returns, but also in the cross-section of equity, factor, and international portfolios. This shows the robustness of our results, suggesting that investors can use MFID as a hedge against bad times.

3.4.8. Mutual funds

We next test for the presence of an MFID premium in the cross-section of mutual fund returns. In particular, we turn to actively-managed US equity mutual funds, as many researchers have shown that the aggregate risk realizations matter for mutual fund investors (e.g., Berk & van Binsbergen, 2016; Karagiannis & Tolikas, 2019). An essential question, therefore, remains whether MFID is also an important risk factor in this asset class.

We obtain the fund returns, total net assets (TNA), and other characteristics from the CRSP Survivorship-Bias-Free Mutual Fund Database. We select domestic equity open-end mutual funds and exclude funds before they pass the $5 million threshold. In line with our analyses, we apply the 60-month rolling regression framework, as in Equation (12). Each month, we sort mutual funds into quintile portfolios based on their MFID betas. We calculate value-weighted portfolio returns (with TNA as weights) and test the risk-adjusted return of quintiles 5 (long) and 1 (short), as well as the long-short portfolio.

[INSERT TABLE 11]

We report the risk-adjusted returns relative to various asset-pricing models in Table 11. These findings indicate that the regression intercepts in a bad state of the world (when the variance is above its median) are statistically significant around the 5% confidence level. The average monthly risk-adjusted return totals 0.3% for the long-short portfolio; which is robust in all asset-pricing models. In a good state of the world, however, the intercepts are statistically indifferent from zero. Overall, the evidence supports the main conclusions of our paper: assets that co-move with MFID are a hedge in bad times since such assets have a significantly higher return, which cannot be explained by other risk factors.

3.4.9. Currency markets

We turn to formal tests of another asset class, foreign exchange rates. If a currency appreciates with respect to the US dollar when MFID increases, this currency is considered a hedge against dependence risk. This makes the currency interesting to investors seeking to hedge this risk. To test this hypothesis, we obtain the spot and one-month forward exchange rates relative to the US dollar from WM/Reuters Datastream for 37 countries, as in Fan et al. (2022). Monthly excess returns for holding foreign currency k from the perspective of US investors are calculated as follows,

$$rx_{i,t+1} = (i_{i,t} - i_t) + (fx_{k,t} - fx_{k,t+t}) \approx f_{k,t} - fx_{k,t+t}, \tag{16}$$

where f and fx denote the log of forward rate and spot exchange rates, respectively, and $rx_{i,t+1}$ is the monthly excess return.

To assess whether MFID is priced in the cross-section of currency returns, we run a 60-month rolling regression framework, in the spirit of Equation (12),

$$rx_{i,t} = a_{i,t} + \beta_{i,t}^{DOL} \cdot DOL_t + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{MFID} \cdot MFID + \varepsilon_{i,t}, \tag{17}$$

where *DOL* is the Dollar factor (Lustig et al., 2011), *MTK* is the value-weighted excess market return, and *MFID* is the model-free implied (stock market) dependence. Each month, we sort currencies into five portfolios based on their MFID beta. MFID-sorted portfolio returns are equally-weighted. To calculate the risk-adjusted returns of the long-short portfolio, we run the following regression:

$$rx_{i,t}^{LS} = \alpha_{i,t}^{H} \cdot d_t^{H} + \alpha_{i,t}^{L} \cdot d_t^{L} + \beta_{i,t}^{DOL} \cdot DOL_t + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{CAR} \cdot CAR_t + \beta_{i,t}^{ATR} \cdot ATR_t + \varepsilon_{i,t}, \tag{18}$$

where $rx_{i,t}^{LS}$ is quintile 5 (Long), quintile 1 (Short), or the difference (Long-Short), *CAR* is the Carry factor (Lustig et al, 2011), *DOL* is the Dollar factor (Lustig et al., 2011), and *ATR* is defined above.

[INSERT TABLE 12]

Table 12 reports the findings of this analysis, for the full sample and developed-market currencies. In line with the stock market evidence, we find that the long-short portfolio yields a significant risk-adjusted return in a bad state of the world. The portfolio's alpha equals 0.2%, which is statistically significant at the 1% confidence level. This return differential mainly comes from the long leg, significant at the 10% confidence level. In a good state of the world, however, the risk-adjusted return on the long-short portfolio is insignificant. In Panel B, we show that these conclusions hold for developed-market currencies. The findings are comparable in magnitude. Overall, Table 12 shows that the MFID beta portfolios are not fully spanned by standard currency risk factors. Currencies with higher exposures to MFID are a hedge against bad times, while not generating lower returns.

4. Economic channels

Having highlighted strong positive cross-sectional relationships between MFID and asset returns, we continue analyzing the economic drivers of this premium. First, we study characteristics impacting MFID betas through a cross-sectional regression. Second, we analyze theories relating to leverage constraints and investor behavior to better understand the MFID premia dynamics. Finally, we test other potential drivers by focusing on money illusion and skewness effects.

4.1.MFID exposure

To exploit the cross-sectional variation of the MFID beta, we run a Fama-MacBeth (1973) regression with MFID betas as the dependent variable, and the state factors as independent variables. Additionally, we apply a fixed-effects model to account for unobserved heterogeneity between firms, industries, and months.

[INSERT TABLE 13]

Table 13 presents the regression coefficients of the two methods. There are three key takeaways from this table. First, MFID beta has a strong positive correlation with market beta. Assets with high MFID betas are generally also stocks with high market betas. The findings are in line with the evidence on risk loadings from the trading strategy (cfr. Table 2). Second, there is a negative association between momentum and MFID beta. Indeed, the stocks that have performed well over the last 12 months (minus 1 month) are generally those with a low MFID beta. Stocks with higher MFID betas are those that performed well when MFID is high (bad states of the world) and bad when MFID is low (good states of the world). However, in a bad state, the rest of the market generally underperforms, and hence, has generally a lower momentum return. These results are robust across methods. This is in line with the evidence from Ang and Chen (2002), who document that underperforming stocks have greater correlation asymmetries. Finally, depending on the regression method, implied correlation beta, size, book-to-market, and co-skewness are significant. This, again, is in line with the conclusion from Ang and Chen (2002). However, since these are not robust, we do not dig deeper into this finding.

4.2. Economic drivers

If MFID is a hedge against the bad times, as we have argued, this should be reflected in the loadings on various risk factors. We add three types of risk factors. First, following the disaster risk literature, we include economic variables from Goyal and Welch (2008) and the Federal Reserve Economic Data (Fed. St. Louis).

- *Default spread* is the yield difference between Moody's Baa and Aaa corporate bonds.
- *Term spread* is the difference between the 10-year US treasury yield and the 3-month T-bill rate.
- *Dividend yield* is the 12-month sum of dividends to the stock market index's price.
- *Inflation* is the monthly year-on-year change of the CPI index.
- *TED spread* is the difference between the 3-month T-bill rate and the 3-month LIBOR in US dollars.

Second, we add option-implied variables: implied correlation, MFIK, MFIS, MFIV, and VIX, as defined above. Finally, we add various risk aversion measures:

- *Casino* is defined as US casino profits scaled by nominal gross domestic product (Asness et al, 2020).
- *Disaster* is the option-implied disaster probability of Barro and Liu (2020).
- *Capital ratio* is the aggregate primary dealer equity capital ratio of He et al. (2017).
- *Risk aversion* is the time-varying relative risk aversion coefficient of Bekaert et al. (2020).
- *Systematic risk* is a risk measure defined by and obtained from Allen et al. (2012).

[INSERT TABLE 14]

Table 14 reports the findings from regressing the returns of decile 10 (long), decile 1 (short), and the long-short portfolio on the reported variables together with the market excess return. Panel A presents the coefficients of the economic variables. There are two takeaways. First, the long portfolio has a significant positive regression coefficient for default spread, dividend yield, and TED spread. This indicates that the portfolio performs well in bad times. Indeed, the long-short portfolio also shows significant positive factor loadings. This confirms the conclusion that the MFID-sorted portfolio is a strategy that outperforms in bad times, and therefore serves as a hedge for the investors. Second, inflation does not have a significant impact on the strategy of both long and short legs. This suggests that money illusion is less likely to be a driver of the MFID premium, in line with the evidence from Asness et al. (2020).

Panel B confirms this conclusion. The long-short portfolio has a positive risk loading with implied correlation, MFIV, MFIK, and VIX. If these measures correctly point to disaster risks, the MFID premium is higher in these bad states. Similarly, in Panel C, we document that Disaster, Risk Aversion, and Systematic Risk point toward a similar result. The long-short MFID portfolio outperforms in times when measures indicate market distress, which implies that MFID is a valuable hedging strategy during market downturns. This, however, goes against the conventional wisdom of risk-based asset pricing, which forecasts that assets that offer a hedge against bad times generated lower expected returns.

Finally, Panel C offers two additional insights. First, Column 3 reports that the MFID premium increases when the intermediary equity capital ratio decreases. Since this capital ratio is procyclical, a high value for the metric implies a good state of the world. The negative relationship between the MFID premium and the capital ratio, therefore, indicates that investors shift their portfolios toward high-MFID stocks when intermediary leverage increases. Indeed, the relationship between the long (short) leg's return and capital ratio is negative (positive), consistent with the results in Asness et al. (2020). Second, the lottery demand seems to be positively associated with the MFID premium; an increase in casino profits goes along with an increase in the MFID premium. This confirms that there may be a behavioral explanation for our evidence.

5. Conclusion

In finance, return dependence is predominately measured by the correlation between returns. The main issue with correlation is that it only captures the *linear* dependence, and neglects non-linear correlation components. In this paper, we use the Dow Jones Industrial Average to estimate a measure that captures both components, MFID. Borrowing from the literature on comonotonicity theory, MFID is defined as the ratio between the risk-neutral variance of a (realized) index option and model-free risk-neutral variance of a comonotonic (synthetic) index option. Using this measure, we investigate the impact of MFID in the cross-section of asset returns.

Our main contribution to the literature is by showing that MFID is a hedge against bad economic times. Stocks with higher exposure to our measure – those that increase together with the increase in implied dependence – *outperform* those with a lower exposure. This suggests that investors demand those assets with a high potential to hedge against dependence risk in bad times. Overall, the findings hold in a battery of robustness tests, such as bivariate regression with implied correlation, currency portfolios, and mutual funds. The results, however, go against risk-based theories, in which one anticipates *lower* expected returns for those assets that offer hedges against bad times. Therefore, we conclude a behavioral explanation of our results is more likely, although it is not captured by standard behavioral asset-pricing factors.

Since MFID conveys information that is not captured by more standard dependence metrics (e.g., correlation), we argue that these current measures underestimate the true extent of the co-movement between asset returns. This implies that financial applications that rely on dependence (e.g., hedging, risk management, and portfolio allocation) severely undervalue this type of risk. We leave such applications for future research.

References

Adrian, T., Etula, E., & Muir, T. (2014). Financial Intermediaries and the Cross-Section of Asset Returns. *Journal of Finance*, *69*(6), 2557–2596. https://doi.org/10.1111/jofi.12189

Allen, L., Bali, T. G., & Tang, Y. (2012). Does Systemic Risk in the Financial Sector Predict Future Economic Downturns? *Review of Financial Studies*, *25*(10), 3000–3036. https://doi.org/10.1093/rfs/hhs094

Amaya, D., Christoffersen, P., Jacobs, K., & Vasquez, A. (2015). Does realized skewness predict the cross-section of equity returns? *Journal of Financial Economics*, *118*(1), 135–167.

Amihud, Y. (2000). Cross-Section and Time-Series Effects Cross-Section and Time-Series Effects. *Journal of Financial Markets*, *5*(1), 31–56.

Andersen, T. G., & Bondarenko, O. (2007). *Construction and Interpretation of Model-Free Implied Volatility* (No. 13449).

Ang, A., Chen, J., & Xing, Y. (2006). Downside risk. *Review of Financial Studies*, *19*(4), 1191–1239.

Asness, C., Frazzini, A., Gormsen, N. J., & Pedersen, L. H. (2020). Betting against correlation: Testing theories of the low-risk effect. *Journal of Financial Economics*, *135*(3), 629–652.

Baele, L., Bekaert, G., Inghelbrecht, K., & Wei, M. (2020). Flights to Safety. *The Review of Financial Studies*, *33*(2), 689–746. https://doi.org/10.1093/rfs/hhz055

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636.

Bali, T. G., Brown, S. J., & Tang, Y. (2017). Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics*, *126*, 471–489.

Bali, T. G., & Murray, S. (2013). Does Risk-Neutral Skewness Predict the Cross Section of Equity Option Portfolio Returns? *Journal of Financial and Quantitative Analysis*, *48*(4), 1145–1171.

Bansal, R., Wu, D. A., & Israel, B. (2022). Socially Responsible Investing in Good and Bad Times. *Review of Financial Studies*.

Bardgett, C., Gourier, E., & Leippold, M. (2019). Inferring volatility dynamics and risk premia from the S&P 500 and VIX markets. *Journal of Financial Economics*, *131*(3), 593–618.

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

Barro, R. J., & Liao, G. Y. (2020). Rare disaster probability and options pricing. *Journal of Financial Economics*.

Bekaert, G., Engstrom, E., & Xu, N. R. (2021). The Time Variation in Risk Appetite and Uncertainty. *Management Science*, *1*(617).

Bekaert, G., & Hoerova, M. (2014). The VIX, the variance premium, and stock market volatility. *Journal of Econometrics*, *183*(2), 181–192. https://doi.org/10.1016/j.jeconom.2014.05.008

Bekaert, G., & Hoerova, M. (2016). What do asset prices have to say about risk appetite and uncertainty? *Journal of Banking and Finance*, *67*, 103–118. https://doi.org/10.1016/j.jbankfin.2015.06.015

Bekaert, G., Hoerova, M., & Lo Duca, M. (2013). Risk, uncertainty, and monetary policy. *Journal of Monetary Economics*, *60*(7), 771–788. https://doi.org/10.1016/j.jmoneco.2013.06.003

Berk, J. B., & van Binsbergen, J. H. (2016). Assessing asset pricing models using revealed preference. *Journal of Financial Economics*, *119*(1), 1–23. https://doi.org/10.1016/j.jfineco.2015.08.010

Bollerslev, T., Todorov, V., & Xu, L. (2015). Tail risk premia and return predictability. *Journal of Financial Economics*, *118*(1), 113–134.

Buraschi, A., Kosowski, R., & Trojani, F. (2014). When there is no place to hide: Correlation risk and the cross-section of hedge fund returns. *Review of Financial Studies*, *27*(2), 581–616.

Buss, A., Schoenleber, L., & Vilkov, G. (2017). Option-Implied Correlations, Factor Models, and Market Risk. *SSRN Electronic Journal*.

Buss, A., Schoenleber, L., & Vilkov, G. (2019). Expected Correlation and Future Market Returns. *SSRN Electronic Journal*.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. In *The Journal of Finance* (Vol. 52, Issue 1, pp. 57–82).

Carr, P., & Madan, D. (2002). Towards a Theory of Volatility Trading. In *Option Pricing, Interest Rates and Risk Management* (pp. 458–476). Cambridge University.

Carr, P., & Wu, L. (2006). A Tale of Two Indices. *Journal of Derivatives*, 13–29.

Chabi-Yo, F., Huggenberger, M., & Weigert, F. (2021). Multivariate crash risk. *Journal of Financial Economics*.

Chabi-Yo, F., Ruenzi, S., & Weigert, F. (2018). Crash Sensitivity and the Cross Section of Expected Stock Returns. *Journal of Financial and Quantitative Analysis*, *53*(3), 1059–1100.

Chang, B. Y., Christoffersen, P., & Jacobs, K. (2013). Market skewness risk and the cross-section of stock returns. *Journal of Financial Economics*, *107*(1), 46–68.

Chang, B. Y., Christoffersen, P., Jacobs, K., & Vainberg, G. (2012). Option-implied measures of equity risk. *Review of Finance*, *16*(2), 385–428. https://doi.org/10.1093/rof/rfq029

Chen, A. Y., & Zimmermann, T. (2022). Open Source Cross-Sectional Asset Pricing. *Critical Finance Review*, *11*(2), 207–264.

Cortes, G. S., Gao, G. P., Silva, F. B. G., & Song, Z. (2022). Unconventional monetary policy and disaster risk: Evidence from the subprime and COVID-19 crises. *Journal of International Money and Finance*, *122*.

Daniel, K., Hirshleifer, D., & Sun, L. (2020). Short- and Long-Horizon Behavioral Factors. *Review of Financial Studies*, *33*(4), 1673–1736.

Dhaene, J., Denuit, M., Goovaerts, M. J., Kaas, R., & Vyncke, D. (2002). The concept of comonotonicity in actuarial science and finance: theory. *Insurance Mathematics and Economics*, *31*, 3-33,133-161.

Driessen, J., Maenhout, P. J., & Vilkov, G. (2009). The price of correlation risk: Evidence from equity options. *Journal of Finance*, *64*(3), 1377–1406. https://doi.org/10.1111/j.1540-6261.2009.01467.x

Faccini, R., Konstantinidi, E., Skiadopoulos, G., & Sarantopoulou-Chiourea, S. (2019). A new predictor of U.S. Real economic activity: The S&P 500 option implied risk aversion. *Management Science*, *65*(10).

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22.

Fama, E. F., & Macbeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*(3), 607–636.

Fan, Z., Londono, J. M., & Xiao, X. (2022). Equity tail risk and currency risk premiums. *Journal of Financial Economics*, *143*(1), 484–503. https://doi.org/10.1016/j.jfineco.2021.05.020

Gabaix, X. (2012). Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance. *Quarterly Journal of Economics*, *127*(2), 645–700.

Gao, G. P., Gao, P., & Song, Z. (2018). Do Hedge Funds Exploit Rare Disaster Concerns? *Review of Financial Studies*, *31*(7), 2650–2692.

Goyal, A., & Welch, I. (2008). A Comprehensive Look at the Empirical Performance of Equity Premium Prediction. *The Review of Financial Studies*, *21*(4), 1455–1508.

He, Z., Kelly, B. T., & Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, *126*(1), 1–35. https://doi.org/10.1016/j.jfineco.2017.08.002

Hou, K., Mo, H., Xue, C., & Zhang, L. (2021). An Augmented q -Factor Model with Expected Growth *. *Review of Finance*, *February 2020*, 1–41. https://doi.org/10.1093/rof/rfaa004

Huynh, T. D., & Xia, Y. (2021). Climate Change News Risk and Corporate Bond Returns. *Journal of Financial and Quantitative Analysis*, *56*(6), 1985–2009. https://doi.org/10.1017/S0022109020000757

Kapadia, N., Ostdiek, B. B., & Weston, J. P. (2019). Getting Paid to Hedge: Why Don't Investors Pay a Premium to Hedge Downturns? *Journal of Financial and Quantitative Analysis*, *54*(3), 1157–1192.

Karagiannis, N., & Tolikas, K. (2019). Tail risk and the cross-section of mutual fund expected returns. *Journal of Financial and Quantitative Analysis*, *54*(1), 425–447. https://doi.org/10.1017/S0022109018000650

Kelly, B. T., & Jiang, H. (2014). Tail risk and asset prices. *The Review of Financial Studies*, *27*(10), 2841–2871.

Kelly, B. T., Lustig, H. N., & Van Nieuwerburgh, S. (2016). Too-Systemic-to-Fail: What Option Markets Imply about Sector-Wide Government Guarantees. *American Economic Review*, *106*(6), 1278–1319.

Lustig, H. N., Roussanov, N., & Verdelhan, A. (2011). Common risk factors in currency markets. *Review of Financial Studies*, *24*(11), 3731–3777. https://doi.org/10.1093/rfs/hhr068

Martin, I. (2017). What is the expected return on the market? *Quarterly Journal of Economics*, *132*(1), 367–433.

Merton, R. C. (1973). An Intertemporal Capital Asset Pricing Model. *Econometrica*, *41*(5), 867–887.

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703.

Pollet, J. M., & Wilson, M. (2010). Average correlation and stock market returns. *Journal of Financial Economics*, *96*(3), 364–380. https://doi.org/10.1016/j.jfineco.2010.02.011

Roell, A. (1987). Risk Aversion in Quiggin and Yaari's Rank-Order Model of Choice Under Uncertainty. *The Economic Journal*, *97*, 143–159.

Schlag, C., Thimme, J., & Weber, R. (2021). Implied volatility duration : A measure for the timing of uncertainty resolution. *Journal of Financial Economics*, *140*(1), 127–144.

Skintzi, V. D., & Refenes, A. (2005). Implied Correlation Index : A New Measure of Diversification. *Journal of Futures Markets*, *25*(2), 171–197.

Stambaugh, R. F., Yu, J., Yuan, Y., Frank, M., Hwang, B., Irvine, P., Novy-marx, R., & Panageas, S. (2012). The short of it : Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(4), 288–302.

Weigert, F. (2015). Crash Aversion and the Cross-Section of Expected Stock Returns Worldwide. *Review of Asset Pricing Studies*, *6*(1), 135–178. https://doi.org/10.1093/rapstu/rav019

Yaari, M. E. (1987). The Dual Theory of Choice under Risk. *Econometrica*, *55*(1), 95–115.

Figures

Figure 1. Model-Free Implied Dependence

This figure plots the realized (green) and comontonic (blue) option prices of the Dow Jones Industrial Average (DJIA) on October 1st, 2007 (Left Panel) and October 1st, 2008 (Right Panel) for different strike prices.

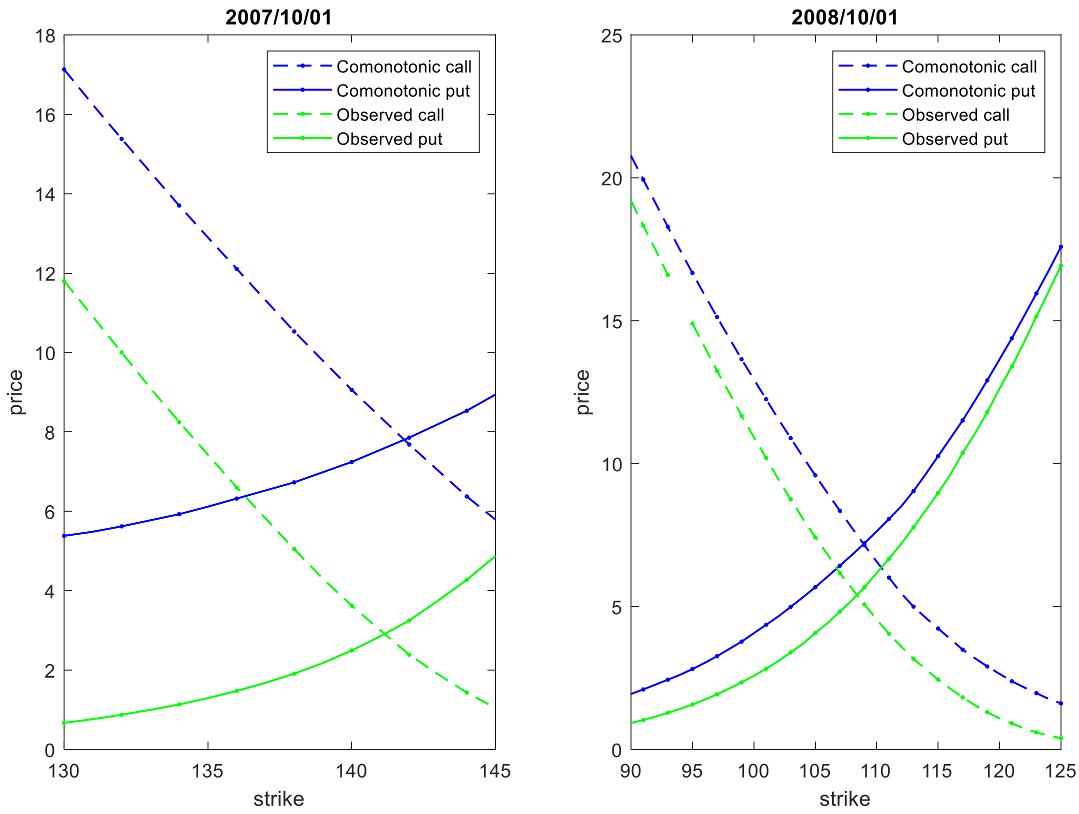


Figure 2. Model-Free Implied Dependence

This figure shows the time series of Model-Free Implied Dependence (MFID) at daily (top panel) and monthly (bottom panel) frequency. We list several important moments in the stock market that correspond with a large value for MFID: the bankruptcy of LTCM (blue) and Lehman Brothers (purple), 9/11 (orange), the outbreak of the Iraq War (yellow) and COVID-19 pandemic (red), and Greece's bond downgrade (green). The sample runs from January 1998 to December 2020.

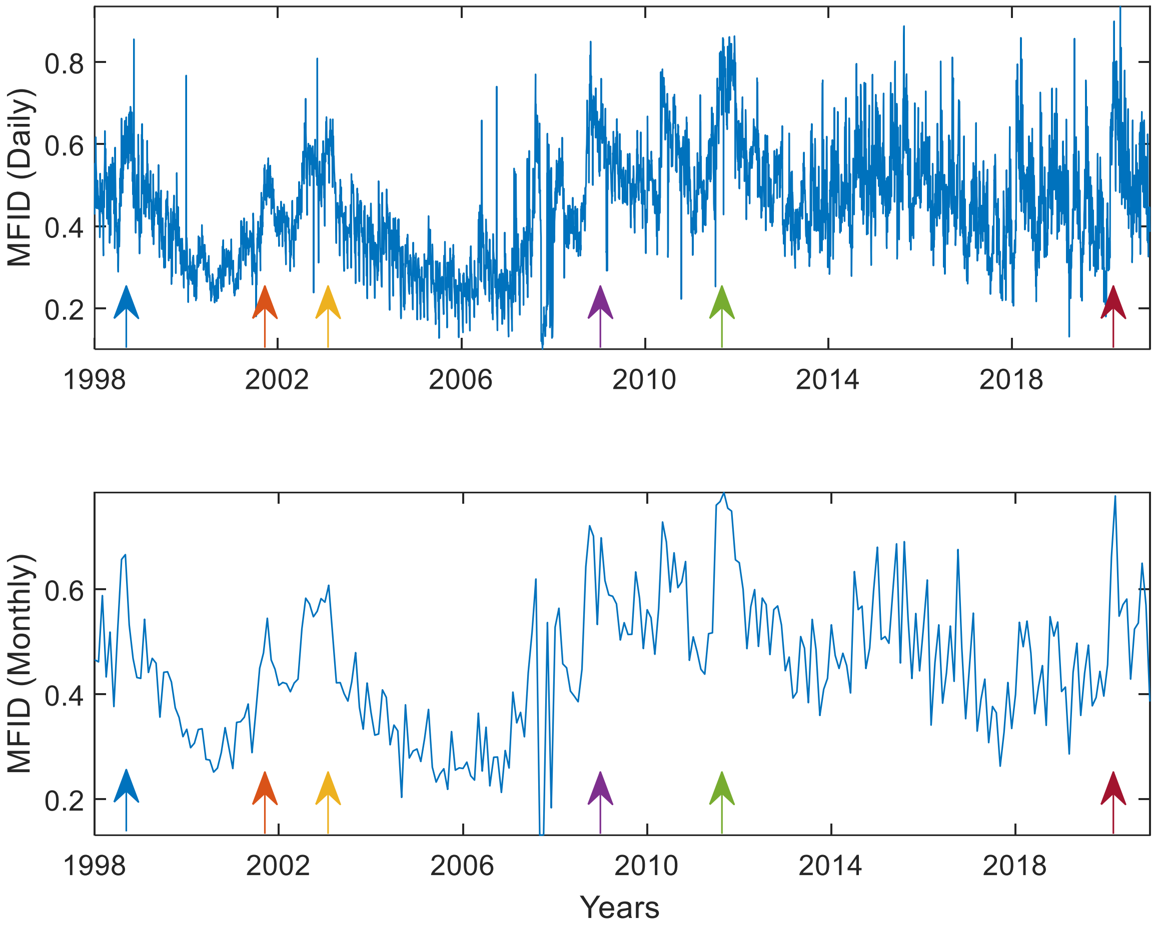


Figure 3. Comonotonicity versus correlation: the role of dependence

This figure shows the support of a bivariate random variable in four scenarios. In every scenario, the variables are comonotonic while the degree of linear dependence (correlation) is different in each scenario, ranging from 0.9975 to 0.0333.

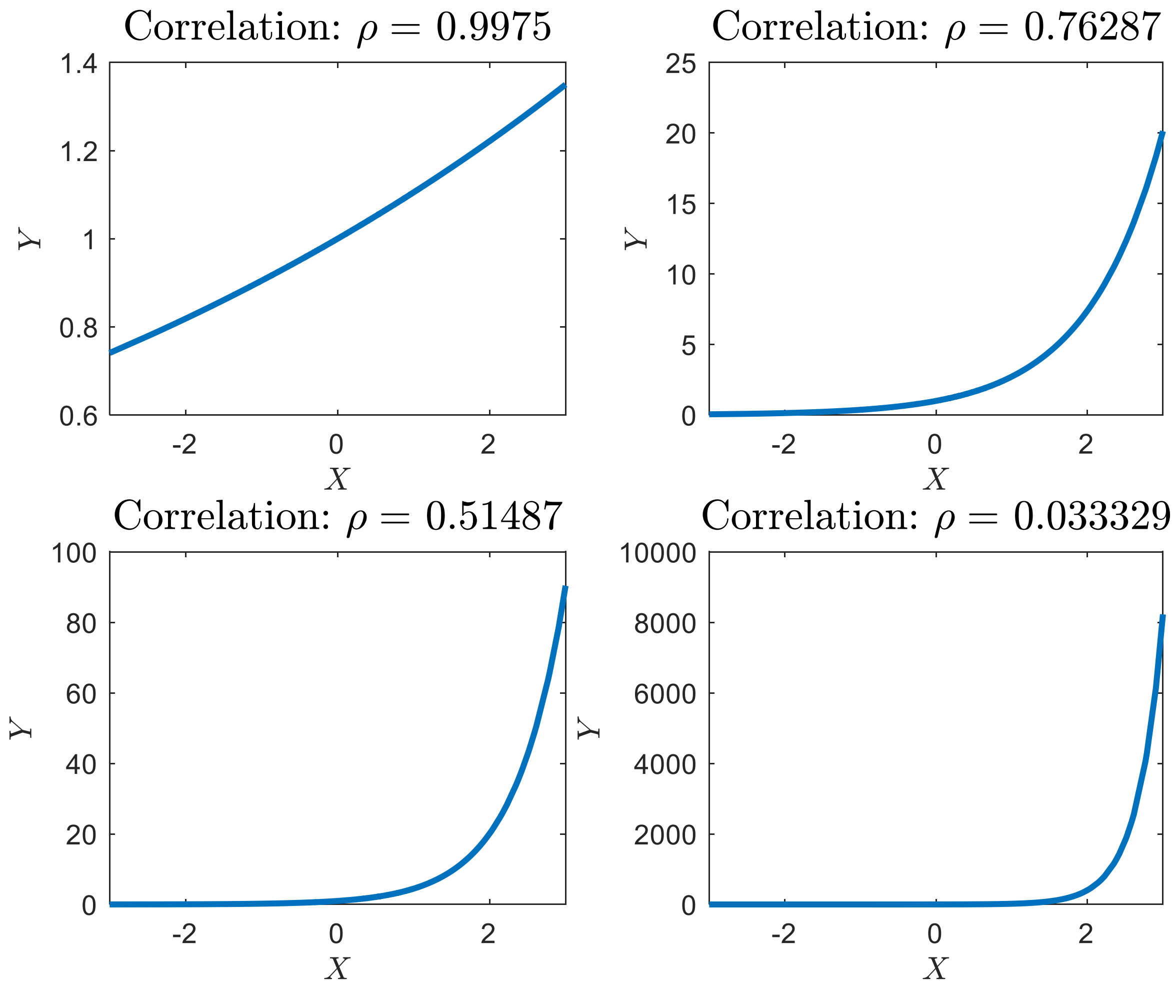


Figure 4. Comonotonicity versus correlation: the role of volatility

This figure shows the effects on correlation and MFID when one of two assets has an increase in volatility. The initial scenario comprises two assets with a return of 3%, a variance of 20%, and a correlation of 0.95.

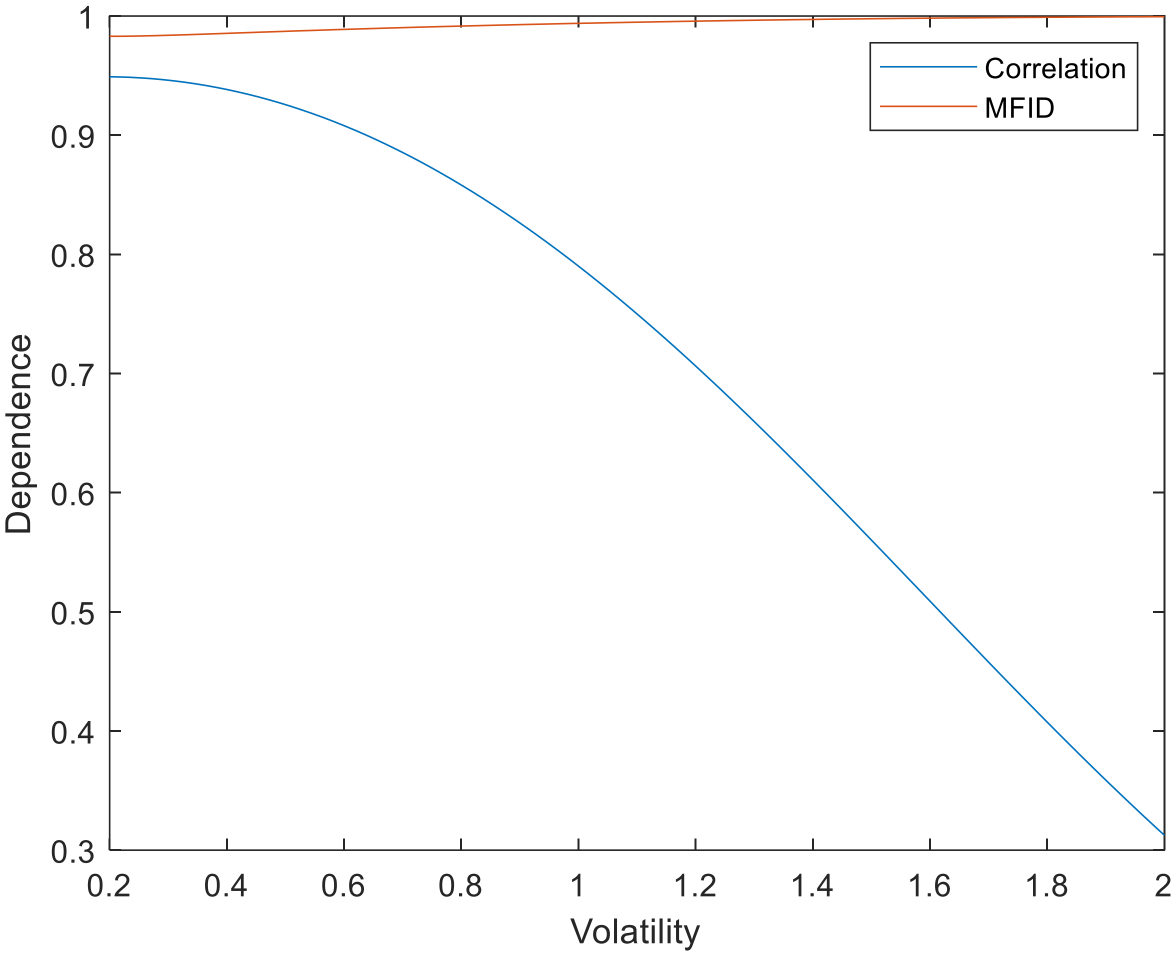


Figure 5. MFID versus implied correlation

This figure shows the model-free implied dependence (MFID) and implied correlation (IC) (Panel A) and the difference between MFID and IC (Panel B). The sample runs from January 1998 to December 2020.

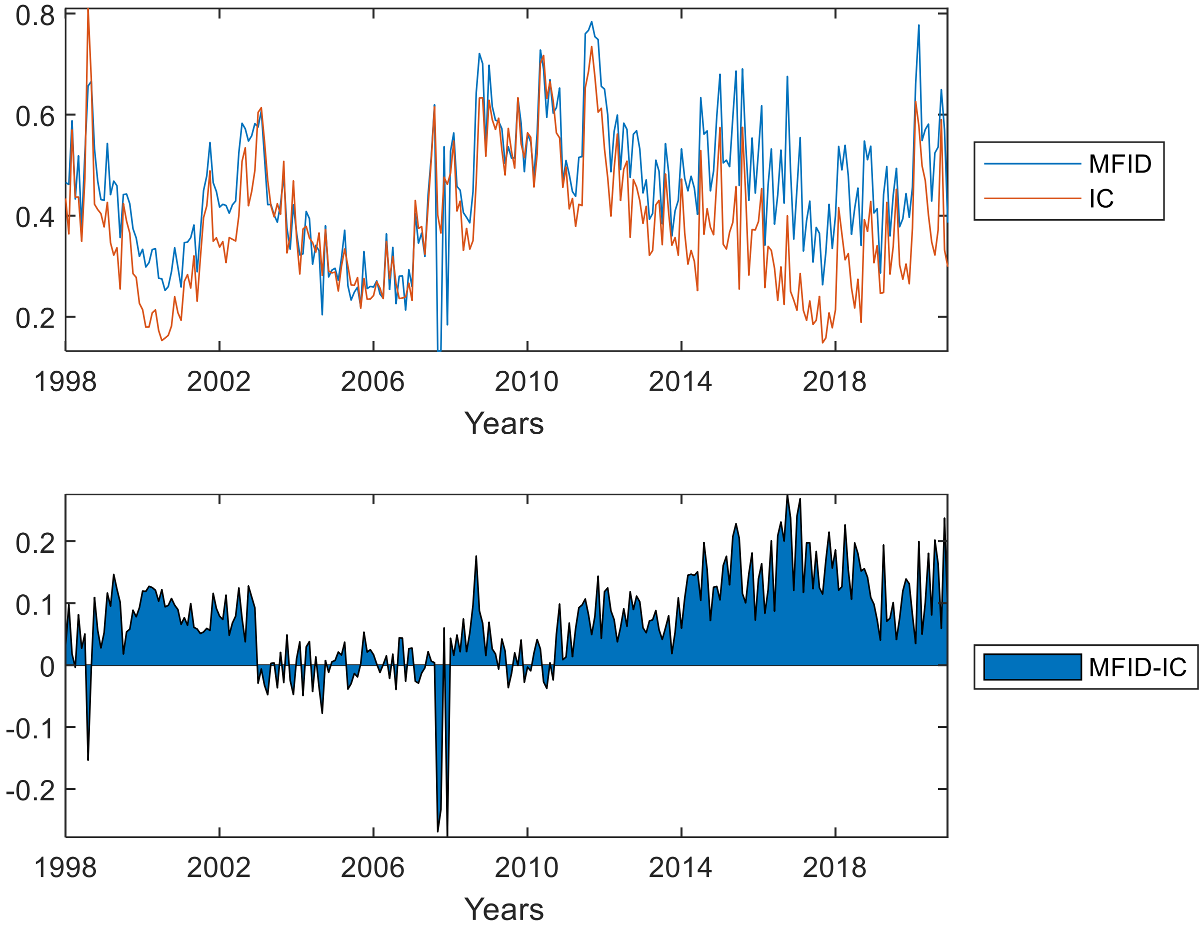


Figure 6. MFID Exposure

This figure shows the time series of MFID-betas for the MFID-sorted portfolios. The MFID betas are estimated using the following 60-month rolling regression: $R_{i,t} = \alpha_i + \beta_i MFID_t + \gamma X_t + \epsilon_{i,t}$, where $R_{i,t}$ is the excess return of stock i over month t, $MFID_t$ is the model-free implied dependence measure, and X_t is a vector of risk factors, that includes the excess market return, size, value, profitability, investment, momentum, and liquidity factors. The sample runs from January 1998 to December 2020.

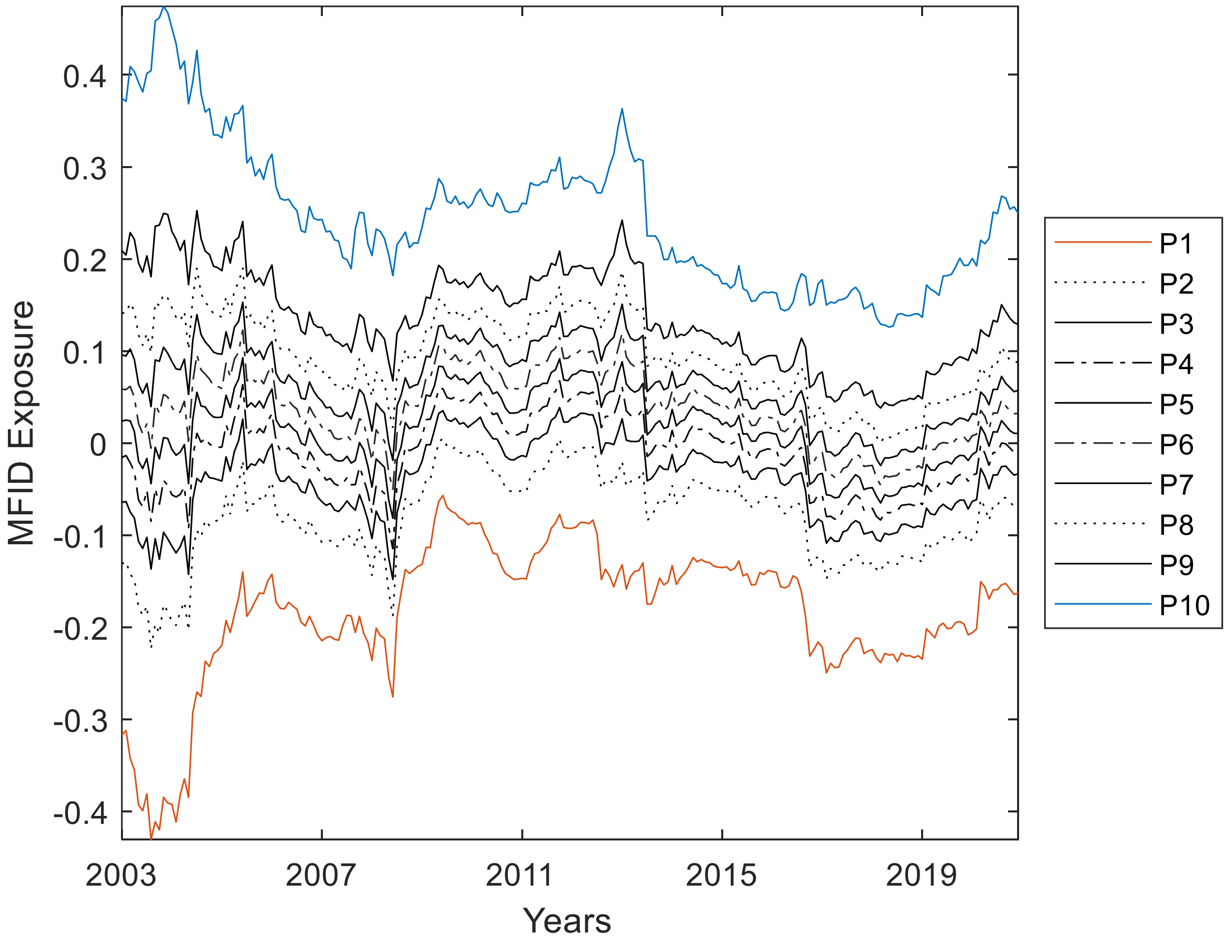
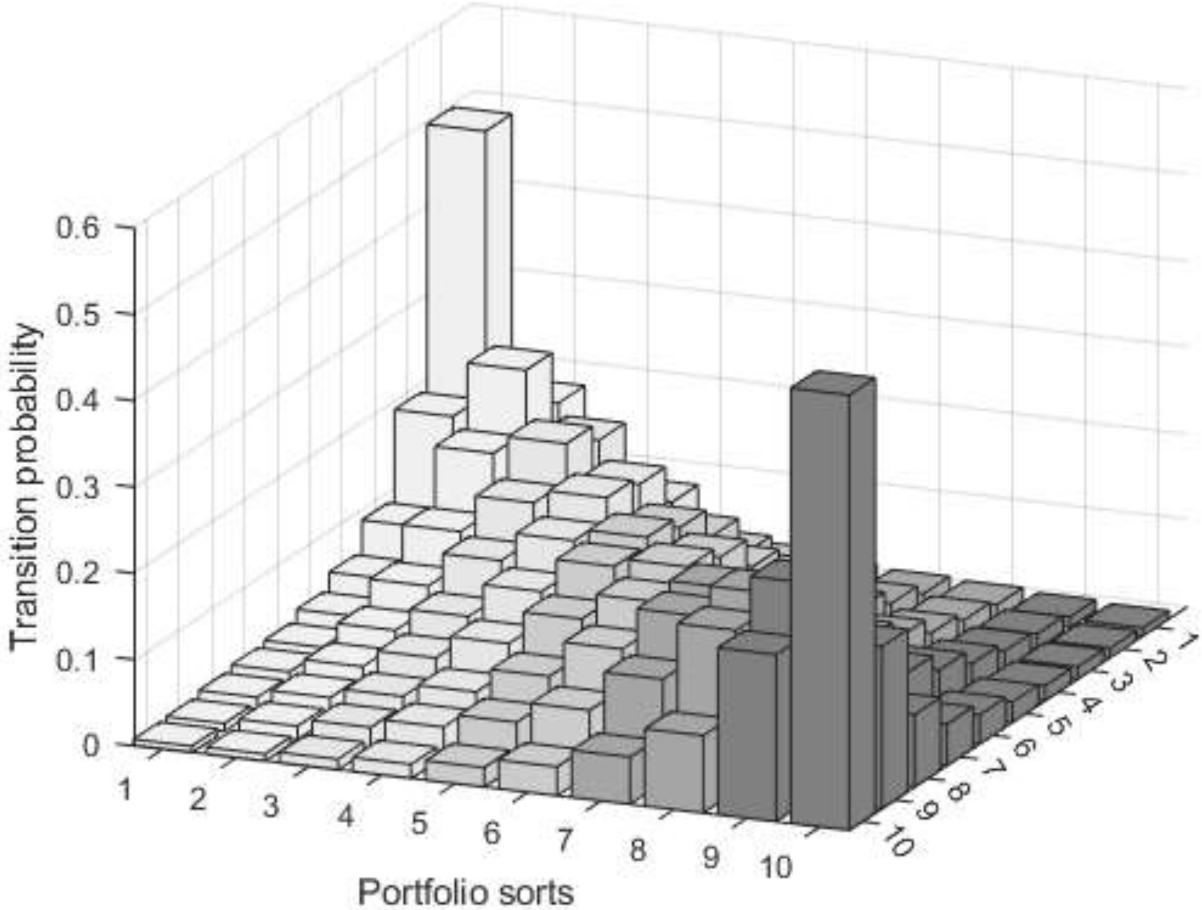


Figure 7. Transition probability

This figure shows the MFID-transition matrix, which equals the relative frequency at which any stock is sorted into MFID decile portfolio *i* in year *t* given that it was in MFID decile portfolio *j* in year *t-1*. The sample covers all U.S. common stocks traded on the NYSE, AMEX, and NASDAQ. The sample period is from January 1998 to December 2020.



Tables

Table 1. Correlation matrix

This table reports the correlation matrix between the MFID and option-implied metrics. The variables include aggregate tail risk of Kelly et al. (2016) (*ATR*), the corridor implied variance (*CIX*), disaster probability of Barro and Liao (2020) (*Disaster*), implied correlation (*IC*), model-free implied kurtosis (*MFIK*), skewness (*MFIS*), and variance of Chang et al. (2012) (*MFIV*), risk aversion of Bekaert et al. (2017) (*RA*), lower-bound volatility index of Martin (2017) (*SVIX*), and the volatility index (*VIX*). The sample is from January 1998 to December 2020.

	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. MFID	-0.156	0.498	0.580	0.818	-0.176	-0.165	0.498	0.541	0.526	0.533
2. ATR	1									
3. CIX	0.199	1								
4. Disaster	0.194	0.871	1							
5. IC	-0.137	0.528	0.638	1						
6. MFIK	0.131	0.171	0.211	0.059	1					
7. MFIS	0.343	-0.007	0.063	0.036	0.317	1				
8. MFIV	0.190	0.995	0.857	0.511	-0.021	0.137	1			
9. RA	0.279	0.865	0.916	0.598	0.011	0.189	0.847	1		
10. SVIX	0.234	0.959	0.897	0.550	0.017	0.229	0.923	0.904	1	
11. VIX	0.233	0.958	0.900	0.553	0.013	0.217	0.934	0.911	0.998	1

Table 2. Benchmark-adjusted returns during high and low variance: classic risk factors

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily in-month stock market variance. The average returns in the high- and low-variance periods are estimates of α_{i,t_H}^{H} and $\alpha_{i,t}^{L}$ in the regression:

$$R_{i,t} = \alpha_{i,t}^{H} \cdot d_t^H + \alpha_{i,t}^{L} \cdot d_t^L + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d_t^H and d_t^L are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month *t* on the long and short leg, and the difference between long and short of MFID-sorted value-weighted (Panel A and C) and equally-weighted (Panel B) portfolios. X_t refers to all risk factors used in the asset-pricing model; Fama & French 5 Factors (FF5F), *Betting-against beta* (BAB), *Short and long-term reversal* (SLR), *Momentum* (UMD), *Short and long-term behavioral* factors of Daniel et al. (2018) (DHS), and *Q-5 factor* model (Q5). *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta over 60 months during the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Variance > Median			Variance < Median		
	Long	Short	Long-Short	Long	Short	Long-Short
Panel A: Value-weighted returns						
Returns	0.005*	-0.003*	0.007***	0.017***	0.019***	-0.002
	(1.718)	(-1.749)	(3.029)	(5.270)	(6.569)	(-0.782)
FF5F	0.017***	0.005	0.012**	0.004	0.010***	-0.006
	(4.844)	(1.503)	(2.115)	(0.854)	(4.027)	(-0.934)
+ BAB	0.020***	0.004	0.016***	0.006	0.009***	-0.004
	(6.495)	(1.345)	(2.920)	(1.490)	(3.900)	(-0.639)
+ SLR	0.018***	0.005	0.013**	0.005	0.010***	-0.005
	(4.924)	(1.575)	(2.167)	(1.046)	(3.940)	(-0.834)
+ UMD	0.018***	0.004	0.014**	0.003	0.010***	-0.006
	(5.285)	(1.442)	(2.397)	(0.944)	(4.273)	(-1.293)
DHS	0.034***	0.005	0.014**	0.006	0.010***	-0.005
	(5.476)	(1.505)	(2.488)	(1.267)	(4.789)	(-0.773)
Q5	0.017***	0.005*	0.012**	0.004	0.011***	-0.007
	(5.009)	(1.685)	(2.027)	(0.945)	(4.550)	(-1.341)
Panel B: Equally-weighted returns						
Returns	0.003	-0.003**	0.006***	0.014***	0.017***	-0.003
	(1.058)	(-2.008)	(2.846)	(4.303)	(5.965)	(-1.336)
FF5F	0.010***	-0.000	0.011*	0.002	0.011***	-0.009
	(3.330)	(-0.100)	(1.905)	(0.428)	(4.419)	(-1.519)
+ BAB	0.013***	-0.001	0.014**	0.003	0.010***	-0.007
	(4.424)	(-0.454)	(2.644)	(0.845)	(4.286)	(-1.279)
+ SLR	0.010***	-0.000	0.010*	0.003	0.010***	-0.008
	(3.138)	(-0.060)	(1.788)	(0.731)	(4.335)	(-1.322)
+ UMD	0.011***	-0.001	0.012**	0.001	0.011***	-0.010*
	(3.547)	(-0.188)	(2.078)	(0.405)	(4.785)	(-1.811)
DHS	0.019***	0.005	0.011**	0.006	0.010***	-0.007
	(5.476)	(1.505)	(1.990)	(1.267)	(4.789)	(-1.280)
Q5	0.011***	0.001	0.011*	0.002	0.012***	-0.010*
	(3.558)	(0.324)	(1.886)	(0.448)	(5.379)	(-1.929)

Table 2 (continued)

Panel C: Trading strategy: Long-short

	1.	2.	3.	4.	5.	6.
Alpha · d^H	0.012**	0.016***	0.013**	0.014**	0.014**	0.012**
	(2.115)	(2.920)	(2.167)	(2.397)	(2.488)	(2.027)
Alpha · d^L	-0.006	-0.004	-0.005	-0.007	-0.005	-0.007
	(-0.934)	(-0.639)	(-0.834)	(-1.293)	(-0.773)	(-1.341)
MKT	0.122	0.125	0.091	0.012	0.074	0.088
	(0.866)	(1.018)	(0.568)	(0.089)	(0.589)	(0.679)
SMB	0.070	0.016	0.033	0.088		
	(0.428)	(0.097)	(0.226)	(0.522)		
HML	0.161	0.146	0.075	-0.063		
	(0.689)	(0.760)	(0.265)	(-0.329)		
CMA	-0.025	0.084	0019	0.045		
	(-0.126)	(0.429)	(0.092)	(0.230)		
RMW	-0.668*	-0.805**	-0.777*	-0.635**		
	(-1.916)	(-2.279)	(-1.943)	(-1.994)		
BAB		-0.510***				
		(-5.091)				
STR			0.033			
			(0.150)			
LTR			0.245			
			(1.004)			
UMD				-0.372***		
				(-2.988)		
SHB					-0.373*	
					(-1.721)	
LHB					-0.207	
					(-1.308)	
ME						0.175
						(0.959)
ROE						-0.464*
						(-1.962)
I/A						-0.483
						(-1.651)
EG						0.407
						(1.457)
R^2 (%)	6.09	13.73	5.91	13.94	6.88	8.44

Table 3. Bivariate risk factors

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily in-month stock market variance. The average returns in the high- and low-variance periods are estimates of α^{H}_{i,t_H} and $\alpha^{L}_{i,t}$ in the regression:

$$R_{i,t} = \alpha^{H}_{i,t} \cdot d^{H}_{t} + \alpha^{L}_{i,t} \cdot d^{L}_{t} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d^{H}_{t} and d^{L}_{t} are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month *t* on long-short difference MFID-sorted value-weighted portfolios while matching implied correlation, MFIK, MFIS, and MFIK, X_t refers to risk factors used in the asset-pricing model, which is the Fama and French five-factor model including betting-against-beta. *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta and bivariate sort over 60 months, in the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Bivariate sort	Implied correlation	MFIK	MFIS	MFIV
Alpha · d^H	0.013***	0.013***	0.015***	0.013***
	(4.243)	(3.647)	(4.301)	(3.604)
Alpha · d^L	0.001	0.002	0.002	0.003
	(0.151)	(0.417)	(0.445)	(0.701)
MKT	-0.179**	0.166**	-0.091	-0.046
	(-2.409)	(2.093)	(-0.913)	(-0.570)
SMB	0.307***	0.0324**	0.356***	0.292***
	(2.966)	(2.391)	(2.824)	(2.423)
HML	-0.098	-0.171	-0.079	0.012
	(-0.945)	(-1.519)	(-0.581)	(0.125)
CMA	-0.259	-0.109	0.057	-0.114
	(-1.460)	(-0.565)	(0.305)	(-0.648)
RMW	-0.437**	-0.399*	-0.409**	-0.618***
	(-2.354)	(-1.872)	(-2.019)	(-3.171)
BAB	-0.304***	-0.238***	-0.280***	-0.269***
	(-3.192)	(-2.957)	(-3.142)	(-3.413)
R^2 (%)	16.15	20.42	13.04	14.93

Table 4. Fama-MacBeth Cross-sectional Regression

This table reports time-series average of the slope coefficients obtained from regressing monthly excess returns (in percentage) on MFID beta (β^{MFID}) interacted with a dummy variable (d_H) that yields one if the stock market variance is above its median, and 0 otherwise; and a set of lagged variables using Fama-MacBeth methodology. Control variables are the market beta (β^{MKT}), implied correlation beta (β^{IC}), book-to-market (BM), market cap. measured in hundred thousand dollars (*Size*), momentum (*MOM*), short-term-reversal (*REV*), co-skewness (*COSKEW*), idiosyncratic volatility (*IVOL*), the annual growth of book assets (I/A), and operating profitability (*ROE*). In Panel A, we use the one-month ahead stock returns. In Panel B, we use t-month ahead returns, where t ranges from one to four. T-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Firm-level stock returns

	1.	2.	3.	4.	5.	6.	7.	8.
$\beta^{MFID} \cdot d^H$	2.039***	2.122***	1.877**	1.975**	2.093**	2.119**	2.085**	2.112**
	(2.690)	(2.708)	(2.452)	(2.512)	(2.311)	(2.304)	(2.302)	(2.299)
$\beta^{MFID} \cdot d^L$	-0.634	-0.593	-0.878	-0.815	-0.612	-0.617	-0.589	-0.598
	(-0.942)	(-0.856)	(-1.324)	(-1.252)	(-0.751)	(-0.742)	(-0.722)	(-0.722)
β^{IC}		-0.162**		-0.144*		0.020		0.014
		(-2.144)		(-1.982)		(0.321)		(0.221)
β^{MKT}			0.221*	0.213*	0.009	0.015	0.003	0.008
			(1.789)	(1.730)	(0.090)	(0.089)	(0.029)	(0.083)
Size			-3.746***	-3.907***	-1.936**	-2.005**	-5.671***	-5.629***
			(-2.922)	(-3.033)	(-2.030)	(-2.111)	(-3.135)	(-3.155)
BM			0.026	0.031	-0.005	-0.004	-0.005	-0.005
			(0.521)	(0.632)	(-0.011)	(-0.091)	(-0.109)	(-0.016)
MOM					-1.756***	-1.781***	-1.762***	-1.787***
					(-4.777)	(-4.851)	(-4.811)	(-4.887)
REV					-0.037***	-0.036***	-0.037***	-0.036***
					(-5.631)	(-5.481)	(-5.659)	(-5.510)
COSKEW					-0.930	-0.914	-0.938	-0.917
					(-1.119)	(-1.113)	(-1.147)	(-1.112)
IVOL					7.439***	7.686***	7.569***	7.818***
					(3.501)	(3.612)	(3.581)	(3.698)
I/A							0.275**	0.264**
							(2.131)	(2.091)
ROE							-0.006	-0.005
							(-0.781)	(-0.672)
Intercept	1.147***	1.170***	0.994***	1.009***	0.552***	0.543**	0.587***	0.572***
	(3.662)	(3.723)	(3.637)	(3.682)	(2.612)	(2.581)	(2.741)	(2.681)
R^2 (%)	2.33	2.71	4.66	4.99	9.09	9.32	9.34	9.56

Table 4 (continued)

Panel B: Long-term predictive power

	h = 0	h = 0	h = 1	h = 1	h = 2	h = 2	h = 3	h = 3
$\beta^{MFID} \cdot d^H$	2.085**	2.112**	1.722*	1.757**	1.295	1.350	0.274	0.304
	(2.302)	(2.299)	(1.926)	(1.961)	(0.935)	(1.043)	(0.288)	(0.316)
$\beta^{MFID} \cdot d^L$	-0.589	-0.598	-1.033	-0.943	-1.664*	-1.544*	-1.753**	-1.561*
	(-0.722)	(-0.722)	(-1.341)	(-1.201)	(-1.873)	(-1.777)	(-1.998)	(-1.726)
β^{MKT}	0.003	0.008	0.086	0.062	0.147	0.111	0.199	0.146
	(0.029)	(0.083)	(0.577)	(0.428)	(0.535)	(0.446)	(0.914)	(0.684)
Size	-5.671***	-5.629***	-10.662***	-10.393***	-14.950***	-14.622***	-22.719***	-22.155***
	(-3.135)	(-3.155)	(-3.981)	(-3.872)	(-2.904)	(-3.023)	(-5.321)	(-5.170)
BM	-0.005	-0.005	-0.019	-0.018	-0.037	-0.031	-0.078	-0.068
	(-0.109)	(-0.016)	(-0.314)	(-0.299)	(-0.408)	(-0.343)	(-0.925)	(-0.824)
β^{IC}		0.014		0.865		1.533		1.899**
		(0.221)		(1.411)		(1.434)		(2.193)
MOM	-1.762***	-1.787***	-2.682***	-2.698***	-3.419***	-3.432***	-4.600***	-4.531***
	(-4.811)	(-4.887)	(-5.191)	(-5.300)	(-3.722)	(-4.055)	(-6.261)	(-6.381)
REV	-0.037***	-0.036***	-0.043***	-0.046***	-0.041***	-0.045***	-0.062***	-0.065***
	(-5.659)	(-5.510)	(-5.262)	(-5.586)	(-3.891)	(-4.288)	(-4.951)	(-5.181)
COSKEW	-0.938	-0.917	-1.457	-1.504	-2.029	-2.182	-2.664	-2.798
	(-1.147)	(-1.112)	(-1.303)	(-1.366)	(-0.967)	(-1.104)	(-1.484)	(-1.551)
IVOL	7.569***	7.818***	15.962***	15.735***	22.847***	22.454***	35.734***	35.158***
	(3.581)	(3.698)	(5.333)	(5.330)	(3.852)	(4.121)	(7.051)	(7.040)
I/A	0.275**	0.264**	0.523***	0.502**	0.750**	0.724**	1.133***	1.092***
	(2.131)	(2.091)	(2.639)	(2.523)	(2.033)	(2.074)	(3.681)	(3.541)
ROE	-0.006	-0.005	-0.008	-0.009	-0.011	-0.013	-0.019	-0.021
	(-0.781)	(-0.672)	(-0.765)	(-0.892)	(-0.584)	(-0.722)	(-1.201)	(-1.358)
Intercept	0.587***	1.147***	1.243***	1.368***	1.815***	2.008***	2.095***	3.234***
	(2.741)	(3.662)	(3.892)	(4.160)	(2.806)	(3.241)	(5.651)	(5.971)
R^2 (%)	9.34	2.33	7.93	8.21	7.62	7.91	7.61	7.86

Table 5. State-dependent adjusted returns: variance conditional on MFID

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily in-month stock market variance. The risk-adjusted returns are estimates in the regression

$$R_{i,t} = \alpha_{i,t}^{HH} \cdot d_t^{HH} + \alpha_{i,t}^{HL} \cdot d_t^{HL} + \alpha_{i,t}^{LH} \cdot d_t^{LH} + \alpha_{i,t}^{LL} \cdot d_t^{LL} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d_t^{HH} and d_t^{HL} are dummy variables indicating high-variance period and high- and low- MFID periods, d_t^{LH} and d_t^{LL} are dummy variables indicating low-variance periods and high- and low- MFID periods, $R_{i,t}$ is the excess return in month *t* on the long and short leg, and the difference between long and short leg of MFID-sorted value-weighted portfolios, X_t refers to risk factors used in asset-pricing models. *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta during the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

		Variance > Median			Variance < Median		
	MFID	Long	Short	Long-Short	Long	Short	Long-Short
FF5F	> Median	0.021***	0.001	0.020***	0.011	0.007*	0.004
		(4.881)	(0.232)	(2.752)	(1.341)	(1.871)	(0.343)
	< Median	0.011**	0.009**	0.002	-0.016***	-0.004	-0.019**
		(2.579)	(2.325)	(0.239)	(-3.263)	(0.810)	(-2.485)
+ BAB	> Median	0.024***	0.000	0.024***	0.010	0.007*	0.003
		(5.808)	(0.115)	(3.279)	(1.436)	(1.943)	(0.298)
	< Median	0.014***	0.009**	0.005	-0.014***	0.003	-0.017**
		(3.809)	(2.222)	(0.814)	(-2.928)	(0.747)	(-2.246)
+ SLR	> Median	0.022***	0.001	0.021***	0.011	0.007*	0.004
		(4.675)	(0.322)	(2.724)	(1.375)	(1.829)	(0.355)
	< Median	0.011***	0.009**	0.004	-0.015***	0.004	-0.018**
		(2.695)	(2.330)	(0.355)	(-3.019)	(0.766)	(-2.346)
+ UMD	> Median	0.024***	0.000	0.024***	0.007	0.007**	-0.000
		(5.808)	(0.115)	(3.279)	(1.242)	(2.072)	(-0.020)
	< Median	0.014***	0.009**	0.005	-0.014***	0.004	-0.017**
		(3.809)	(2.222)	(0.814)	(-2.928)	(0.757)	(-2.179)
DHS	> Median	0.032***	0.010	0.023***	0.007	0.004	0.003
		(5.215)	(1.515)	(3.138)	(0.771)	(0.573)	(0.352)
	< Median	0.036***	0.030***	0.007	-0.021***	-0.001	-0.020***
		(7.157)	(6.499)	(1.124)	(-2.895)	(-0.114)	(-2.645)
Q5	> Median	0.020***	0.001	0.019**	0.010	0.009**	0.001
		(5.004)	(0.371)	(2.593)	(1.564)	(2.455)	(0.155)
	< Median	0.012***	0.010**	0.002	-0.017***	0.003	-0.020***
		(2.786)	(2.541)	(0.307)	(-3.365)	(0.751)	(-2.645)

Table 6. Horse race

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily in-month stock market variance. The average returns in the high- and low-variance periods are estimates of α_{i,t_H}^{H} and $\alpha_{i,t}^{L}$ in the regression:

$$R_{i,t} = \alpha_{i,t}^{H} \cdot d_t^H + \alpha_{i,t}^{L} \cdot d_t^L + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d_t^H and d_t^L are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month *t* on long-short difference MFID-sorted, implied correlation-sorted, MFIK, MFIS, MFIV value-weighted portfolios, X_t refers to the Fama and French five-factor model including betting-against-beta (BAB). *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta and bivariate sort over 60 months, in the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Long-short portfolio

	MFID	IC		MFIK		MFIS		MFIV	
	1.	2.	3.	4.	5.	6.	7.	8.	9.
Alpha · d^H	0.016***	0.013*	0.000	-0.007	-0.006	-0.011**	-0.009**	0.017*	0.006
	(2.920)	(1.888)	(0.044)	(-1.505)	(-1.370)	(-2.193)	(-1.991)	(1.861)	(0.971)
Alpha · d^L	-0.004	0.001	0.004	-0.006	-0.006	-0.004	-0.005	-0.004	-0.002
	(-0.639)	(0.179)	(1.039)	(-1.334)	(-1.357)	(-0.783)	(-0.825)	(-0.729)	(-0.348)
MKT	0.125	-0.053	-0.155*	0.040	0.047	0.215*	0.223*	-0.068	-0.156
	(1.018)	(-0.334)	(-1.727)	(0.481)	(0.554)	(1.746)	(1.824)	(-0.368)	(-1.080)
SMB	0.016	0.089	0.076	-0.230*	-0.229*	0.159	0.161	0.107	0.095
	(0.097)	(0.442)	(0.555)	(-1.709)	(-1.725)	(0.933)	(0.943)	(0.488)	(0.527)
HML	0.146	0.459*	0.340**	-0.106	-0.099	-0.419	-0.409	0.201	0.098
	(0.760)	(1.701)	(2.159)	(-0.625)	(-0.583)	(-1.629)	(-1.644)	(0.884)	(0.664)
CMA	0.084	0.164	0.095	-0.025	-0.021	0.457*	0.462*	0.094	0.035
	(0.429)	(0.616)	(0.553)	(-0.159)	(-0.131)	(1.682)	(1.692)	(0.278)	(0.123)
RMW	-0.805**	-0.489	0.168	0.163	0.122	0.417	0.368	-0.377	0.190
	(-2.279)	(-1.192)	(0.781)	(0.555)	(0.428)	(1.124)	(1.068)	(-1.131)	(0.826)
BAB	-0.510***	-0.478**	-0.062	-0.111	-0.137	0.116	0.085	-0.589**	-0.230
	(-5.091)	(-2.336)	(-0.254)	(-0.626)	(-0.806)	(0.929)	(0.674)	(-2.582)	(-1.353)
MFID			0.816***		-0.051		-0.060		0.704***
			(10.773)		(-0.683)		(-0.604)		(7.909)
R^2 (%)	13.73	8.82	57.57	-1.05	-1.25	3.32	3.17	8.50	39.33

Table 6 (continued)

Panel B: MFID portfolio benchmark

	1.	2.	3.	4.
Alpha · d^H	0.007***	0.014**	0.013**	0.007**
	(2.809)	(2.368)	(2.330)	(2.124)
Alpha · d^L	-0.004	-0.007	-0.007	-0.003
	(-1.035)	(-1.267)	(-1.371)	(-0.841)
IC	0.658***			
	(14.965)			
MFIK		-0.056		
		(-0.651)		
MFIS			-0.055	
			(-0.593)	
MFIV				0.483***
				(7.194)
MKT	0.159***	0.127	0.137	0.158*
	(2.667)	(1.039)	(1.127)	(1.807)
SMB	-0.042	0.003	0.025	-0.035
	(-0.378)	(0.019)	(0.149)	(-0.259)
HML	-0.156	0.140	0.123	0.049
	(-1.533)	(0.726)	(0.725)	(0.384)
CMA	-0.024	0.083	0.109	0.039
	(-0.193)	(0.421)	(0.572)	(0.225)
RMW	-0.483**	-0.796**	-0.783**	-0.623**
	(-2.553	(-2.239)	(-2.360)	(-2.377)
BAB	-0.196**	-0.516***	-0.504***	-0.225***
	(-2.121)	(-5.152)	(-5.368)	(-2.772)
R^2 (%)	59.98	13.57	13.61	42.80

Table 7. Benchmark variation

The table reports average benchmark-adjusted returns following good and bad economic states, based on the median level of market stress variables, for which we use the option-implied disaster probability (Barro & Liu, 2020), dividend yield, economic policy uncertainty (EPU), flight-to-safety of Baele et al. (2020), option-implied implied correlation of DJIA, MFID, realized correlation of DJIA, risk aversion of Bekaert et al. (2021), and VIX. The average returns in the bad and good economic states are estimates of α_{i,t_H}^{H} and $\alpha_{i,t}^{L}$ in the regression:

$$R_{i,t} = \alpha_{i,t}^{H} \cdot d_t^H + \alpha_{i,t}^{L} \cdot d_t^L + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d_t^H and d_t^L are dummy variables indicating bad and good states, $R_{i,t}$ is the excess return in month t on the long and short leg, and the difference between the long and short leg of MFID-sorted value-weighted portfolios, X_t refers to the Fama and French Five-Factor model with the momentum factor. T-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Bad state			Good state		
Benchmark	Long	Short	Long-Short	Long	Short	Long-Short
CAPE	0.017***	0.000	0.016**	0.010***	0.009***	0.001
	(4.436)	(0.087)	(2.110)	(2.722)	(4.325)	(0.175)
Disaster probability	0.026***	-0.002	0.028***	0.003	0.013***	-0.010**
	(4.536)	(-0.732)	(3.486)	(1.095)	(5.531)	(2.533)
Dividend yield	0.016***	0.005*	0.012*	0.003	0.011***	-0.008
	(4.056)	(1.843)	(1.965)	(0.923)	(3.798)	(-1.383)
EPU	0.016***	0.002	0.014**	0.006*	0.012***	-0.006
	(3.789)	(0.615)	(2.122)	(1.861)	(5.950)	(-1.290)
Flight-to-Safety	0.036***	0.002	0.034***	0.008***	0.008***	0.000
	(4.165)	(0.328)	(2.549)	(3.045)	(3.514)	(0.081)
Implied correlation	0.016***	0.004	0.013**	0.005	0.011***	-0.006
	(4.063)	(1.383)	(2.078)	(1.483)	(4.462)	(-1.129)
MFID	0.016***	0.004	0.012**	0.006	0.011***	-0.005
	(4.010)	(1.385)	(1.993)	(1.584)	(4.120)	(-1.016)
Realized correlation	0.013***	0.002	0.011*	0.008**	0.014***	-0.005
	(3.195)	(0.802)	(1.702)	(2.491)	(5.729)	(-1.184)
Recession	0.066***	-0.009	0.075***	0.005**	0.009***	-0.004
	(14.528)	(-1.169)	(7.198)	(2.104)	(3.998)	(-1.012)
Risk aversion	0.021***	0.002	0.020***	0.005*	0.011***	-0.006
	(3.843)	(0.500)	(2.522)	(1.720)	(3.861)	(-1.243)
VIX	0.025***	-0.003	0.029***	0.003	0.013***	-0.010***
	(4.476)	(-0.878)	(3.361)	(1.147)	(5.851)	(-2.652)

Table 8. COVID-19 period

The table reports average the benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily in-month stock market variance, and the COVID-19 pandemic period. The average returns estimates in the regression

$$R_{i,t} = \alpha_{i,t}^{H} \cdot d_t^{H} + \alpha_{i,t}^{L} \cdot d_t^{L} + \alpha_{i,t}^{COVID} \cdot d_t^{COVID} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d_t^H and d_t^L are dummy variables indicating high- and low-variance periods before March 2020, and d_t^{COVID} is a dummy variable equal to one in the period after March 2020, $R_{i,t}$ is the excess return in month *t* on the long and short leg, and the difference between the long and short leg of MFID-sorted value-weighted portfolios, X_t refers to all risk factors used in the asset-pricing model. *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta during the previous month.

	Variance > Median			Variance < Median			COVID-19		
Risk factor model	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
FF5F	0.017***	0.006*	0.011*	0.003	0.010***	-0.007	0.033***	-0.014	0.047**
	(4.767)	(1.826)	(1.919)	(0.666)	(4.123)	(-1.219)	(3.410)	(-1.077)	(2.440)
+ BAB	0.020***	0.005*	0.015***	0.005	0.010**	-0.005	0.029***	-0.013	0.042**
	(6.123)	(1.677)	(2.669)	(1.361)	(4.004)	(-0.964)	(3.321)	(-1.001)	(2.040)
+ Short & long reversal	0.017***	0.006*	0.011*	0.003	0.010***	-0.006	0.032***	-0.014	0.046**
	(4.743)	(1.924)	(1.920)	(0.857)	(4.027)	(-1.128)	(3.375)	(-1.101)	(2.463)
+ UMD	0.018***	0.005*	0.012**	0.003	0.010***	-0.007	0.030***	-0.013	0.043**
	(5.167)	(1.178)	(2.147)	0.787)	(4.278)	(-1.456)	(3.387)	(-1.030)	(2.113)
DHS	0.018***	0.006**	0.012**	0.005	0.011***	-0.008	0.035***	-0.011	0.046***
	(5.483)	(2.000)	(2.315)	(1.121))	(4.762)	(-1.455)	(5.123)	(-0.829)	(2.645)
Q5	0.017***	0.007**	0.010*	0.003	0.011***	-0.006	0.027***	-0.008	0.036**
	(4.945)	(2.102)	(1.799)	(0.726)	(4.316)	(-1.003)	(3.051)	(-0.705)	(1.994)

Table 9. Quantile regression

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily in-month stock market variance. The average returns in the high- and low-variance periods are estimates of α^{H}_{i,t_H} and $\alpha^{L}_{i,t}$ in the regression:

$$R_{i,t} = \alpha^{H}_{i,t} \cdot d^{H}_{t} + \alpha^{L}_{i,t} \cdot d^{L}_{t} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d^{H}_{t} and d^{L}_{t} are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month t on the long and short leg, and the difference between the long and short leg of MFID-sorted value-weighted portfolios. X_t refers to all risk factors used in the asset-pricing model; Fama & French 5 Factors (FF5F), *Betting-against beta* (BAB), *Short and long-term reversal* (SLR), *Momentum* (UMD), *Short and long-term behavioral* factors of Daniel et al. (2018) (DHS), and *Q-5 factor* model (Q5). *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta over 60 months during the previous month, using a quantile regression (based on the thresholds in its respective row) *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Variance > Median			Variance < Median		
Threshold	Long	Short	Long-Short	Long	Short	Long-Short
0.10	0.025***	0.013**	0.012	0.004**	0.010***	-0.006**
	(5.826)	(1.990)	(1.316)	(2.342)	(6.141)	(-2.231)
0.25	0.025***	0.006	0.019	0.007***	0.006***	0.001
	(3.595)	(0.941)	(1.631)	(3.509)	(3.545)	(0.244)
0.40	0.025***	0.002	0.023*	0.006***	0.006***	-0.001
	(3.098)	(0.456)	(1.936)	(2.807)	(3.284)	(-0.251)
0.50	0.029***	0.001	0.028**	0.006***	0.007***	-0.002
	(3.948)	(0.164)	(2.541)	(2.663)	(3.675)	(-0.490)
0.60	0.035***	-0.000	0.035***	0.004**	0.007***	-0.002
	(5.566)	(-0.064)	(3.387)	(2.094)	(3.421)	(-0.605)
0.75	0.038***	-0.002	0.040***	0.005**	0.007***	-0.002
	(6.714)	(-0.355)	(4.390)	(2.438)	(4.163)	(-0.753)
0.90	0.041***	-0.001	0.042***	0.005***	0.009***	-0.004
	(7.032)	(-0.139)	(4.880)	(2.791)	(4.892)	(-1.352)

Table 10. Other test portfolios

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily in-month stock market variance. The average returns in the high- and low-variance periods are estimates of α_{i,t_H}^{H} and $\alpha_{i,t}^{L}$ in the regression:

$$R_{i,t} = \alpha_{i,t}^{H} \cdot d_t^H + \alpha_{i,t}^{L} \cdot d_t^L + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d_t^H and d_t^L are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month t on the long and short leg, and the difference between the long and short leg of MFID-sorted value-weighted portfolios, X_t refers to all risk factors used in the asset-pricing model. T-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting, each month, 100 portfolios formed on size and book-to-market, operating profitability, and investments, and 49 industry portfolios (349 portfolios, Panel A), value-weighted long-short portfolios of Chen and Zimmermann (2021) (205 portfolios, Panel B), and country indices measured in US dollars (50 portfolios, Panel C). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Variance > Median			Variance < Median		
Risk factor model	Long	Short	Long-Short	Long	Short	Long-Short
Panel A. Portfolio evidence (349 Portfolios)						
FF5F	0.029**	-0.011	0.040*	-0.006	0.023**	-0.029*
	(2.650)	(-0.820)	(1.976)	(-0.547)	(2.282)	(-1.724)
+ BAB	0.031***	-0.015	0.046**	-0.004	0.020*	-0.025
	(2.834)	(-1.012)	(2.176)	(-0.422)	(1.901)	(-1.428)
+ SLR	0.028**	-0.014	0.042*	-0.001	0.019*	-0.021
	(2.454)	(-1.016)	(1.989)	(-0.133)	(1.845)	(-1.330)
+ UMD	0.030***	-0.009	0.039*	-0.006	0.022**	-0.028
	(2.734)	(-0.652)	(1.889)	(-0.582)	(2.061)	(-1.611)
DHS	0.196***	0.150***	0.046*	0.076	0.102*	-0.027*
	(4.831)	(3.934)	(1.921)	(1.525)	(1.855)	(-1.714)
Q5	0.042***	-0.001	0.043**	0.003	0.038***	-0.035**
	(3.352)	(-0.065)	(2.033)	(0.283)	(4.164)	(2.264)
Panel B. Factor evidence (205 Factors)						
FF5F	0.009***	-0.001	0.012**	0.004	0.004	0.001
	(3.629)	(-0.500)	(2.599)	(1.446)	(1.011)	(0.218)
+ BAB	0.009***	-0.002	0.011**	0.004	0.003	0.001
	(2.902)	(-0.752)	(2.322)	(1.194)	(0.843)	(0.189)
+ SLR	0.010***	-0.002	0.014***	0.004	0.005	0.000
	(3.727)	(-0.923)	(2.825)	(1.360)	(1.442)	(0.046)
+ UMD	0.009***	-0.002	0.013***	0.004	0.003	0.001
	(3.426)	(-1.042)	(2.734)	(1.194)	(0.843)	(0.163)
DHS	0.006**	-0.001	0.006*	0.003	0.004	-0.000
	(2.641)	(-0.303)	(1.662)	(0.919)	(0.749)	(-0.043)
Q5	0.009***	0.000	0.008**	0.004	0.004	-0.001
	(3.815)	(0.204)	(2.428)	(1.207)	(1.324)	(-0.148)

Table 9 (Continued)

Panel C. International evidence (50 Indices)

FF5F	0.004	-0.003	0.006***	0.006	0.005	0.000
	(0.865)	(-0.499)	(2.781)	(1.161)	(1.046)	(0.092)
+ BAB	0.001	-0.005	0.006***	0.004	0.004	0.000
	(0.185)	(-1.069)	(2.665)	(0.821)	(0.729)	(0.043)
+ SLR	0.003	-0.003	0.006***	0.006	0.006	-0.000
	(0.779)	(-0.476)	(2.632)	(1.189)	(1.179)	(-0.126)
+ UMD	0.004	-0.002	0.006***	0.005	0.005	0.000
	(1.034)	(-0.326)	(2.684)	(1.062)	(0.943)	(0.126)
DHS	0.004	-0.002	0.006**	0.006	0.006	0.001
	(0.866)	(-0.287)	(2.468)	(1.190)	(1.049)	(0.241)
Q5	0.005	-0.002	0.007***	0.006	0.006	0.000
	(1.195)	(-0.331)	(3.087)	(1.298)	(1.180)	(0.132)

Table 11. Mutual funds

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily in-month stock market variance. The average returns in the high- and low-variance periods are estimates of α^{H}_{i,t_H} and $\alpha^{L}_{i,t}$ in the regression:

$$R_{i,t} = \alpha^{H}_{i,t} \cdot d^{H}_{t} + \alpha^{L}_{i,t} \cdot d^{L}_{t} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d^{H}_{t} and d^{L}_{t} are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month t on the long and short leg, and the difference between the long and short leg of MFID-sorted value-weighted mutual fund portfolios, X_t refers to all risk factors used in the asset-pricing model. T-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual mutual funds each month based on their MFID beta during the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Variance > Median			Variance < Median		
	Long	Short	Long-Short	Long	Short	Long-Short
FF5F	0.001	-0.002	0.003*	-0.000	0.001	-0.001
	(0.132)	(-1.196)	(1.777)	(-0.376)	(0.842)	(-0.849)
+ BAB	0.001	-0.002*	0.003**	-0.001	0.000	-0.001
	(1.322)	(-1.674)	(2.028)	(-0.506)	(0.510)	(-0.753)
+ SLR	0.001	-0.002*	0.003**	-0.001	0.001	-0.001
	(1.344)	(-1.680)	(2.165)	(-0.486)	(0.503)	(-0.748)
+ UMD	0.001	-0.002	0.003*	-0.000	0.001	-0.001
	(1.326)	(-1.287)	(1.864)	(-0.388)	(0.929)	(-0.933)
DHS	0.002**	-0.002	0.004**	0.001	0.001	-0.001
	(2.087)	(-1.380)	(2.205)	(0.570)	(1.333)	(-0.557)
Q5	0.002**	-0.001	0.003*	0.000	0.002	-0.001
	(2.192)	(-0.914)	(1.980)	(0.299)	(1.477)	(-0.924)

Table 12. Currency market

The table reports average benchmark-adjusted currency returns following high- and low levels of stock market variance, based on the median level of daily in-month stock market variance. The average returns in the high- and low-variance periods are estimates of α_{i,t_H}^{H} and $\alpha_{i,t}^{L}$ in the regression:

$$R_{i,t} = \alpha_{i,t}^{H} \cdot d_t^H + \alpha_{i,t}^{L} \cdot d_t^L + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d_t^H and d_t^L are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month *t* on the long and short leg, and the difference between the long and short leg of MFID-sorted equally-weighted currency portfolios. Currency returns for holding foreign currency k_i from the perspective of US investors are calculated as follows: $rx_{k,t+1} = (i_{k,t} - i_t) + (fx_{k,t} - fx_{k,t+1})$, where f and fx denote the log of the forward and spot exchange rate of 37 currencies against the US dollar, as in Fan et al. (2022). X_t refers to risk factors used in the asset pricing model; *DOL* and *CAR* refer to the Dollar and Carry factor in Lustig et al. (2011), *ATR* is the aggregate tail risk of Kelly et al. (2019), and *MKT* is the value-weighted CRSP stock market return. *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual currencies each month based on their MFID beta during the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Variance > Median			Variance < Median		
	Long	Short	Long-Short	Long	Short	Long-Short
Panel A: All currencies						
DOL	0.001	-0.001	0.002*	-0.000	0.001	-0.001
	(1.628)	(-0.910)	(1.911)	(-0.215)	(0.753)	(-0.874)
+ ATR	0.001**	-0.001	0.002**	-0.000	0.001	-0.001
	(2.068)	(-1.090)	(2.522)	(-0.325)	(0.827)	(-1.076)
+ CAR	0.001*	-0.001	0.002**	-0.000	0.001	-0.001
	(1.769)	(-1.074)	(2.327)	(-0.043)	(0.594)	(-0.637)
+ MKT	0.001*	-0.001	0.002**	-0.000	0.001	-0.001
	(1.656)	(-1.093)	(2.325)	(-0.173)	(0.688)	(-0.809)
Full Model	0.001*	-0.001	0.003***	-0.000	0.001	-0.001
	(1.914)	(-1.230)	(2.843)	(-0.215)	(0.664)	(-0.869)
Panel B: Developed currencies						
DOL	0.001	-0.001	0.002**	0.000	0.000	-0.000
	(1.423)	(-1.187)	(2.402)	(0.605)	(0.426)	(-0.012)
+ ATR	0.001*	-0.001	0.002***	0.000	0.001	-0.000
	(1.801)	(-1.427)	(3.120)	(0.531)	(0.489)	(-0.138)
+ CAR	0.001	-0.001	0.002***	0.001	0.000	0.000
	(1.589)	(-1.300)	(2.812)	(0.775)	(0.310)	(0.206)
+ MKT	0.001	-0.001	0.002***	0.000	0.000	0.000
	(1.513)	(-1.320)	(2.759)	(0.669)	(0.379)	(0.065)
Full Model	0.001*	-0.001	0.002***	0.000	0.000	0.000
	(1.764)	(-1.499)	(3.371)	(0.644)	(0.387)	(0.033)

Table 13. Cross-sectional Regression: MFID exposure

This table reports time-series average of the slope coefficients obtained from regressing MFID beta (β^{MFID}) on a vector of variables using a Fama-MacBeth (FM; Columns 1 to 3) or fixed-effects OLS regression (FE; Columns 4 to 7). The control variables are the market beta (β^{MKT}), implied correlation beta (β^{IC}), market capitalization measured in millions of dollars (Size), book-to-market (BM), momentum (MOM), short-term-reversal (REV), co-skewness (COSKEW), idiosyncratic volatility (IVOL), the annual growth of book assets (I/A), and operating profitability (ROE). T-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	1.	2.	3.	4.	5.	6.	7.
β^{MKT}	0.021***	0.023***	0.022***	0.023***	0.025***	0.025***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^{IC}	0.009*	0.020	0.019	0.005***	0.005***	0.005***	0.005***
	(0.082)	(0.123)	(0.168)	(0.000)	(0.000)	(0.000)	(0.000)
Size		-0.000***	-0.000***	-0.000	0.000	0.000*	0.000
		(0.000)	(0.000)	(0.130)	(0.332)	(0.100)	(0.364)
BM		-0.000	-0.000	-0.002***	-0.002	-0.006***	-0.001**
		(0.562)	(0.749)	(0.010)	(0.336)	(-0.007)	(0.028)
MOM		-0.028**	-0.031**	-0.027**	-0.017***	-0.017***	-0.017***
		(0.030)	(0.024)	(0.031)	(0.000)	(0.000)	(0.000)
REV			-0.000		0.017***		0.020***
			(0.653)		(0.000)		(0.000)
COSKEW			0.002		-0.021***		-0.202***
			(0.715)		(0.001)		(0.000)
IVOL			0.042		-0.148		-0.285**
			(0.396)		(0.234)		(0.015)
I/A			-0.001		-0.001		-0.000
			(0.186)		(0.224)		(0.987)
ROE			0.003		0.001		0.001
			(0.249)		(0.861)		(0.815)
Intercept	-0.014***	0.031***	0.023***	-0.021***	0.091***	0.072***	0.099***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2 (%)	7.43	14.04	17.64	3.65	4.29	4.17	5.33
Firm FE	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	Yes
Specification	FM	FM	FM	FE	FE	FE	FE

Table 14. Risk Exposure of MFID-sorted portfolios

This table reports the portfolio loadings on economic variables (Panel A), option-implied factors (Panel B), and risk aversion (Panel C) of the top (Long) and bottom decile (Short) MFID-sorted portfolios, as well as the Long-Short portfolio. Loadings are estimated using time series regression of portfolio returns on one of the factors together with the market return. Economic variables include (1) *default spread*, between the difference between Moody's Aaa and Baa corporate bond yields, (2) *dividend yield*, which is the 12-month dividends divided by price, (3) *inflation*, the monthly year-on-year changes of the consumer price index (CPI), (4) *TED spread*, which is difference between 3-month T-bill rates and 3-month LIBOR index and (5) *term spread*, which is the difference between 10-year T-bond yield and 3-month T-bill rate. The option-implied factors include model-free implied variance (*MFIV*), skewness (*MFIS)* and kurtosis (*MFIK*) from S&P500 index options as in Bakshi, Kapadia, and Madan (2003), and correlation (*IC*), and *VIX* is the CBOE volatility index. The risk aversion metrics include (1) *Casino*, which is the profits in the casino industry in the previous quarter dividend by GDP, (2) *Disaster*, which we obtain from Barro and Liao (2021), (3) *Capital ratio*, which is the intermediary capital ratio from Kelly et al. (2018), (4) *Risk aversion*, taken from Bekaert et al. (2021), and (5) *Systematic risk* from Bali et al. (2012). *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Economic variables

	Default spread	Dividend yield	Inflation	TED spread	Term spread
Long	3.448***	4.697***	-0.675	3.466***	-0.077
	(4.720)	(5.327)	(-1.048)	(3.666)	(-0.335)
Short	-0.946*	-1.089	0.352	-0.580	0.304**
	(-1.631)	(-1.559)	(0.601)	(-1.007)	(2.209)
Long-Short	4.394***	5.786***	-1.027	4.047***	-0.381
	(3.723)	(4.053)	(-1.185)	(2.871)	(-1.152)

Panel B: Option-implied factors

	IC	MFIV	MFIS	MFIK	VIX
Long	0.068***	0.308***	0.003	0.001*	0.368***
	(3.007)	(4.342)	(0.818)	(1.831)	(4.484)
Short	-0.031**	-0.082	-0.001	-0.000	-0.104
	(-2.227)	(-1.256)	(-0.478)	(-0.574)	(-1.302)
Long-Short	0.099***	0.390***	0.004	0.002*	0.472***
	(3.095)	(3.276)	(0.772)	(1.752)	(3.297)

Panel C: Risk aversion metrics

	Casino	Disaster	Capital ratio	Risk aversion	Systematic risk
Long	2.264**	0.224***	-0.682***	0.018***	0.103***
	(2.039)	(4.565)	(-3.171)	(4.470)	(3.332)
Short	-1.076	-0.078	0.268**	-0.004	-0.034**
	(-0.858)	(-1.618)	(2.320)	(-0.999)	(-2.037)
Long-Short	3.341*	0.302***	-0.950***	0.023***	0.137***
	(1.820)	(3.542)	(-3.371)	(2.922)	(3.440)

Appendix 1: Additional Information

Figure A.1. MFID vs. Realized Correlation

This figure shows the time series of the Model-Free Implied Dependence (MFID) and Realized Correlation (RC) (Panel A) and the difference between MFID and RC (Panel B). The sample runs from January 1998 to December 2020.

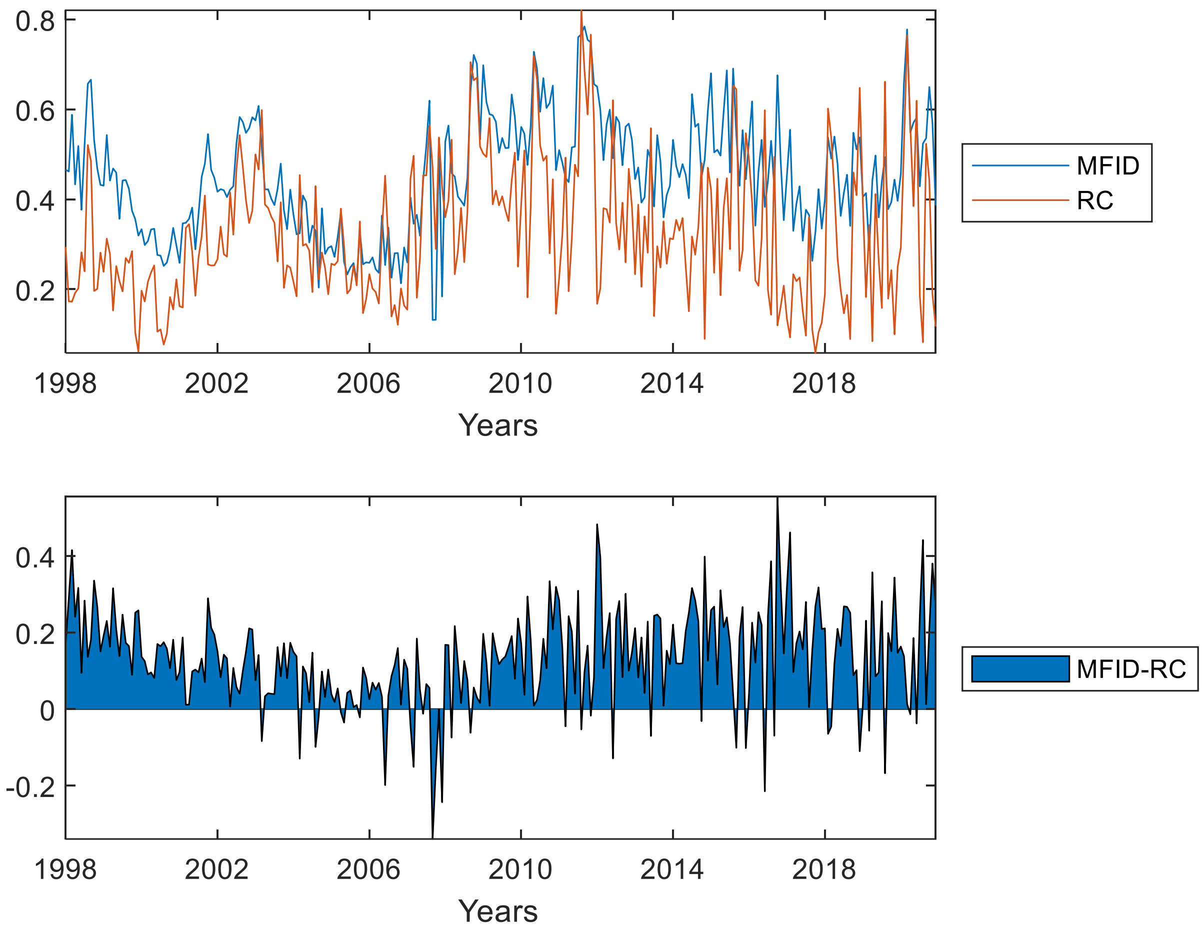


Figure A.2. MFID and Flight-to-Safety Episodes

This figure shows the time series of the model-free implied dependence (MFID) and Flight-to-Safety (FTS) episodes. The sample runs from January 1998 to December 2020.

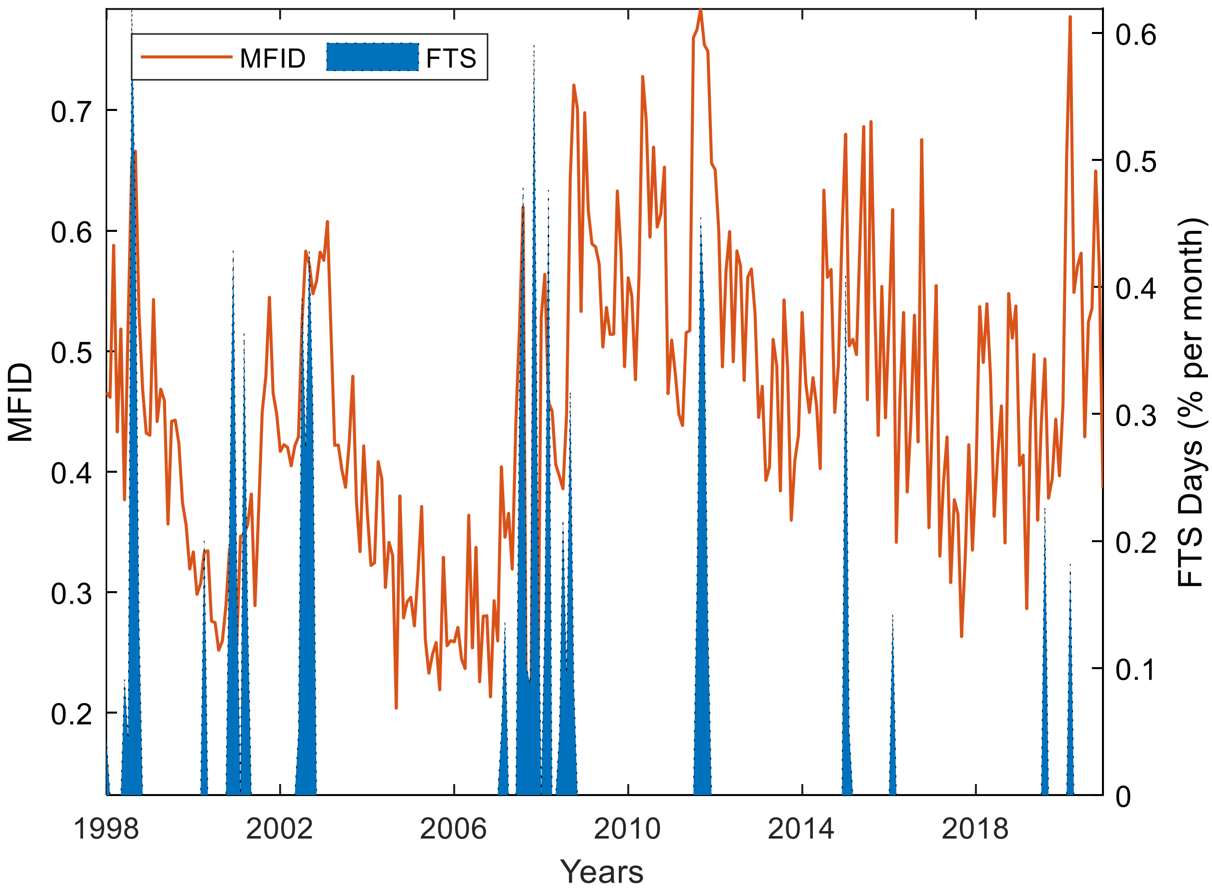


Figure A.3. MFID vs. Disaster probability

This figure shows the time series of the model-free implied dependence (MFID) and option-implied disaster probability (Disaster probability) episodes. The sample runs from January 1998 to December 2020.

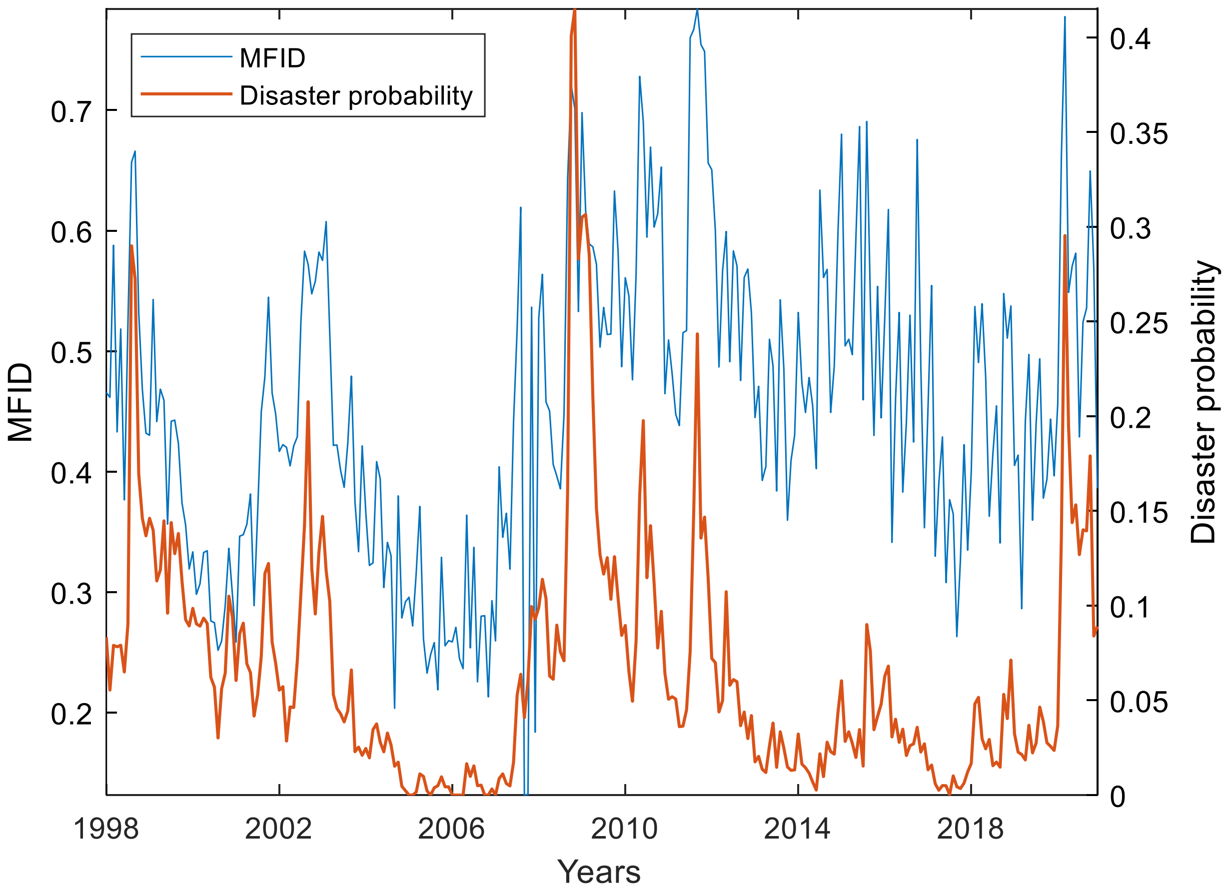


Figure A.4. Performance of MFID Long-Short portfolio

This figure shows the cumulative returns for the long-short portfolio sorted on MFID in event time. The event time is months after the characteristics were last refreshed.

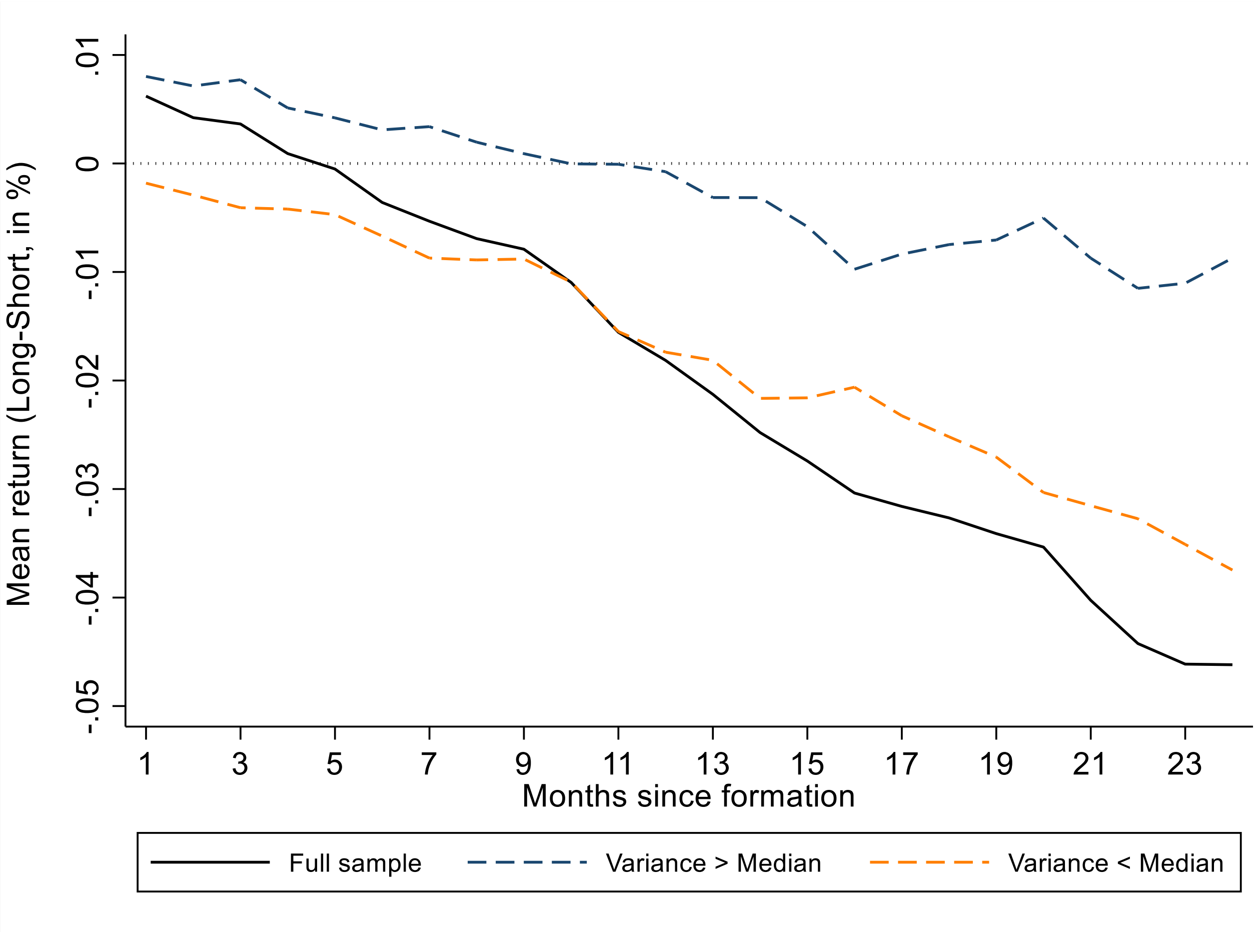


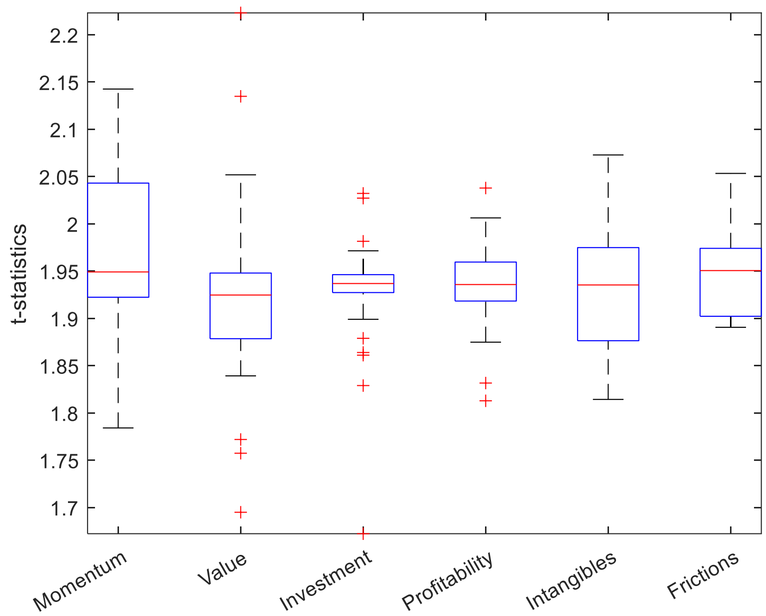
Figure A.5. Factor Zoo

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily in-month stock market variance. The average returns in the high- and low-variance periods are estimates of α^H_{i,t_H} and $\alpha^L_{i,t}$ in the regression:

$$R_{i,t} = \alpha^H_{i,t} \cdot d^H_t + \alpha^L_{i,t} \cdot d^L_t + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d^H_t and d^L_t are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month t on either the long or short leg, and the difference of MFID-sorted value-weighted portfolios, X_t refers to the individual risk factors used in the asset-pricing model, following Chen and Zimmermann (2021).

Panel A. Variance > Median



Panel B. Variance < Median

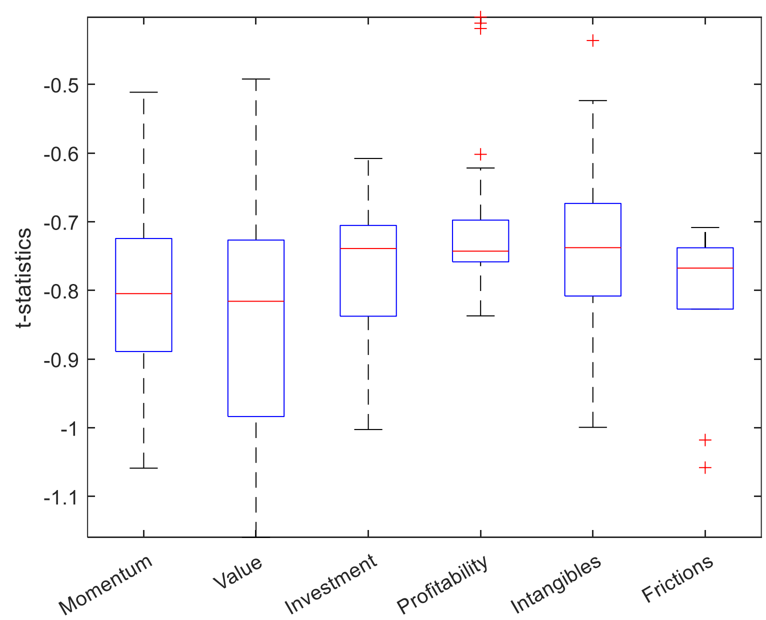


Table A.1. Benchmark-adjusted returns: classic risk factors

The table reports average benchmark-adjusted returns. The average returns are estimates in the regression:

$$R_{i,t} = \alpha_t + \gamma X_t + \epsilon_{i,t}$$

where $R_{i,t}$ is the excess return in month t on the long and short leg, and the difference between long and short of MFID-sorted value-weighted (Panel A and C) and equally-weighted (Panel B) portfolios. X_t refers to all risk factors used in the asset-pricing model; Fama & French 5 Factors (FF5F), *Betting-against beta* (BAB), *Short and long-term reversal* (SLR), *Momentum* (UMD), *Short and long-term behavioral* factors of Daniel et al. (2018) (DHS), and *Q-5 factor* model (Q5). *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta over 60 months during the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Risk factor model	Long	Short	Long-Short
FF5F	0.011***	0.007***	0.004
	(3.206)	(3.336)	(0.778)
+ BAB	0.013***	0.007***	0.007
	(4.581)	(3.197)	(1.489)
+ SLR	0.011***	0.007***	0.004
	(3.420)	(3.373)	(0.906)
+ UMD	0.011***	0.007***	0.004
	(3.657)	(3.371)	(0.943)
DHS	0.013***	0.007***	0.005
	(3.906)	(3.622)	(1.181)
Q5	0.011***	0.008***	0.003
	(3.690)	(3.674)	(0.669)

Table A.2. Benchmark-adjusted returns

The table reports average benchmark-adjusted returns following high and low levels of stock market variance. The average returns in the high- and low-variance periods are estimates α^H_{i,t_H} and $\alpha^L_{i,t}$ in the regression:

$$R_{i,t} = \alpha^H_{i,t} \cdot d^H_t + \alpha^L_{i,t} \cdot d^L_t + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d^H_t and d^L_t are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month *t* on decile MFID-sorted value-weighted portfolios. *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta over 60 months during the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Short	2.	3.	4.	5.	6.	7	8.	9.	Long
					Panel A: Fama-French 5 Factor + UMD					
> Median	0.004	0.003	0.002*	0.004***	0.002*	0.002**	0.006***	0.008***	0.012***	0.016***
	(1.611)	(1.520)	(1.676)	(3.893)	(1.813)	(2.038)	(5.267)	(4.545)	(4.932)	(4.485)
< Median	0.013***	0.008***	0.008***	0.005***	0.006***	0.002	0.005***	0.004**	0.005**	0.003
	(4.670)	(4.411)	(4.894)	(3.524)	(4.690)	(1.562)	(3.156)	(2.247)	(2.397)	(0.944)
					Panel B: Q5 Factor Model					
> Median	0.005*	0.005**	0.004***	0.004***	0.003**	0.003*	0.006***	0.007***	0.010***	0.017***
	(1.685)	(2.291)	(2.784)	(3.530)	(2.288)	(1.862)	(4.518)	(3.997)	(4.678)	(5.009)
< Median	0.011***	0.009***	0.009***	0.005***	0.007***	0.002	0.005***	0.003**	0.003	0.004
	(4.550)	(5.021)	(5.238)	(3.416)	(5.216)	(1.440)	((3.129)	(2.053)	(1.426)	(0.945)

Table A.3. Quintile splits

The table reports average benchmark-adjusted returns following high and low levels of stock market variance. The average returns in the high- and low-variance periods are estimates of α_{i,t_H}^H and $\alpha_{i,t}^L$ in the regression:

$$R_{i,t} = \alpha_{i,t}^H \cdot d_t^H + \alpha_{i,t}^L \cdot d_t^L + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d_t^H and d_t^L are dummy variables indicating high and low-variance periods, $R_{i,t}$ is the excess return in month *t* on the top (long) and bottom (short) quintile and the long-short difference value-weighted portfolios. *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta over 60 months during the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Variance > Median			Variance < Median		
	Long	Short	Long-Short	Long	Short	Long-Short
CAPM	0.012***	0.003	0.009**	0.004	0.009***	-0.005
	(4.182)	(1.261)	(2.037)	(1.583)	(5.531)	(-1.551)
FF3F	0.012***	0.003	0.009**	0.004	0.009***	-0.005
	(4.093)	(1.184)	(2.097)	(1.419)	(5.339)	(-1.497)
FF5F	0.013***	0.002	0.011**	0.004	0.009***	-0.005
	(4.389)	(0.850)	(2.375)	(1.483)	(5.158)	(-1.261)
+ BAB	0.014***	0.001	0.014***	0.005**	0.008***	-0.003
	(5.812)	(0.545)	(3.311)	(2.414)	(4.911)	(-0.875)
+ ILLIQ	0.014***	0.001	0.013***	0.005**	0.008***	-0.004
	(5.134)	(0.602)	(2.973)	(2.185)	(5.041)	(-1.171)
+ INT	0.013***	0.002	0.012**	0.004	0.009***	-0.005
	(4.714)	(0.758)	(2.599)	(1.647)	(5.301)	(-1.562)
+ SLR	0.013***	0.002	0.011**	0.004*	0.009***	-0.005
	(4.495)	(0.950)	(2.395)	(1.748)	(5.347)	(-1.253)
+ UMD	0.013***	0.002	0.012**	0.004*	0.009***	-0.005
	(4.702)	(0.791)	(2.605)	(1.682)	(5.422)	(-1.602)
Q5	0.011***	0.003	0.008**	0.003	0.010***	-0.007**
	(4.285)	(1.376)	(1.997)	(1.321)	(5.740)	(-2.269)

Table A.4. Daily data

The table reports average benchmark-adjusted returns following days of positive and negative stock market returns. The average returns in the high- and low-variance periods are estimates α_{i,t_H}^{H} and $\alpha_{i,t}^{L}$ in the regression:

$$R_{i,t} = \alpha_{i,t}^{H} \cdot d_t^H + \alpha_{i,t}^{L} \cdot d_t^L + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d_t^H and d_t^L are dummy variables indicating positive and negative-variance periods, $R_{i,t}$ is the excess return in month t on all decile MFID-sorted value-weighted portfolios. To calculate the MFID beta, we use a 60-month rolling window using either the DHS factor model or the Q5 factor model. *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Return < 0		Return > 0	
	Long-Short (VW)	Long-Short (EW)	Long-Short (VW)	Long-Short (EW)
CAPM	0.001**	0.001**	0.000	-0.000
	(2.331)	(2.359)	(0.370)	(-1.405)
FF3F	0.001**	0.001**	0.000	-0.001
	(2.446)	(2.387)	(0.229)	(-1.503)
FF5F	0.001**	0.001**	0.000	-0.001
	(2.505)	(2.335)	(0.285)	(-1.539)
+ BAB	0.001**	0.001**	0.000	-0.001
	(2.490)	(2.326)	(0.246)	(-1.557)
+ SLR	0.001***	0.001**	0.000	-0.001
	(2.846)	(2.322)	(0.067)	(-1.571)
+ UMD	0.001**	0.001**	0.000	-0.001
	(2.545)	(2.353)	(0.206)	(-1.580)
Q5	0.001*	0.001*	0.000	-0.000
	(1.765)	(1.846)	(0.732)	(-1.187)

Table A.5. Other asset classes

Risk price estimates for MFID and the excess return on the market. Risk prices are the mean slopes of period-by-period cross-sectional regression of portfolio excess return on risk exposures (betas), reported in percentage terms. Betas are estimated in a first-stage time-series regression. The sample is from 1998 to 2012. T-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Risk prices

	CDS	Bonds	Sov. Bonds	Currency	Options
MFID	0.313***	0.168***	0.235**	0.216***	-0.339**
	(4.231)	(2.846)	(2.417)	(4.308)	(-2.498)
MKT	-0.006	-0.005	0.019	0.019	0.105***
	(-0.392)	(-0.404)	(1.029)	(1.206)	(3.317)
Intercept	0.004***	0.005***	0.003	-0.001	0.003
	(6.155)	(11.362)	(1.309)	(-0.588)	(0.822)
RMSE	0.006	0.007	0.004	0.001	0.002
R2 (in %)	86.62	81.19	98.07	84.29	87.12
RMSE without	0.001	0.002	0.003	0.007	0.002
R2 (in %)	42.11	52.20	43.28	9.99	87.40
Assets	20	20	6	12	18

Panel B: State-dependent risk prices

	CDS	Bonds	Sov. Bonds	Currency	Options
MFID · d_H	0.229***	0.203**	0.149*	0.241***	0.283***
	(3.814)	(2.303)	(1.736)	(3.704)	(2.726)
MFID · d_L	0.001	-0.050	0.061	-0.039	-0.486***
	(0.015)	(-0.594)	(0.645)	(-0.591)	(-4.693)
MKT	-0.015	-0.018	0.016	0.011	0.029
	(-1.007)	(-1.436)	(0.989)	(1.003)	(0.932)
Intercept	0.003***	0.004***	0.003	-0.002	0.003
	(5.116)	(11.278)	(1.342)	(-1.386)	(0.747)
RMSE	0.006	0.007	0.004	0.001	0.003
R2 (in %)	90.93	84.20	99.79	85.53	99.55
Assets	20	20	6	12	18

Table A.6. MFID variation

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily stock market variance. The average returns in the high- and low-variance periods are estimates of α^{H}_{i,t_H} and $\alpha^{L}_{i,t}$ in the regression:

$$R_{i,t} = \alpha^{H}_{i,t} \cdot d^{H}_{t} + \alpha^{L}_{i,t} \cdot d^{L}_{t} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d^{H}_{t} and d^{L}_{t} are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month *t* on the long leg, or short leg, and the difference of MFID-sorted value-weighted portfolios, X_t refers to Fama and French's 5 Factors (2015) including momentum. In each row, we change the filters used to estimate MFID. In variations (1) and (2), we use ITM and OTM options, remove options with zero volume, open interest, or bids, and respectively upfloat weighting or replace missing option prices observations with the relevant stock price; in variation (3), we use ITM and OTM options, remove options with a volume less than two, zero open interest or bids, and upfloat weighting or replace missing option prices observations with the stock price; in variations (4) and (5), we use OTM options, remove options with zero open interest or bids, and upfloat weighting. Upfloat weighting refers to the recalculation of index weight to construct the comononotic index. *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta during the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Variance > Median			Variance < Median		
Variation	Long	Short	Long-Short	Long	Short	Long-Short
1.	0.011***	0.001	0.011*	0.004	0.011***	-0.008
	(3.168)	(0.192)	(1.736)	(0.833)	(3.215)	(-1.085)
2.	0.016***	0.003	0.014**	0.004	0.010***	-0.007
	(3.506)	(0.906)	(1.976)	(1.048)	(3.380)	(-1.155)
3.	0.016***	0.003	0.013**	0.003	0.011***	-0.008
	(3.474)	(0.894)	(2.052)	(0.766)	(4.515)	(-1.433)
4.	0.016***	0.003	0.013**	0.005	0.011***	-0.006
	(3.727)	(0.971)	(2.118)	(1.328)	(4.291)	(-1.093)
5.	0.016***	0.004	0.012*	0.004	0.012***	-0.008
	(3.730)	(1.595)	(1.906)	(1.405)	(4.538)	(-1.621)

Table A.7. Option-implied risk factors

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily stock market variance. The average returns in the high- and low-variance periods are estimates of α^{H}_{i,t_H} and $\alpha^{L}_{i,t}$ in the regression:

$$R_{i,t} = \alpha^{H}_{i,t} \cdot d^{H}_{t} + \alpha^{L}_{i,t} \cdot d^{L}_{t} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d^{H}_{t} and d^{L}_{t} are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month *t* on the long leg, or short leg, and the difference of MFID-sorted value-weighted portfolios, X_t refers to risk factors used in the asset-pricing model, where *Aggregate Tail Risk* is the aggregate tail risk (Kelly et al, 2016), *CIX* is the corridor model-free implied variance (MFIV) as in Andersen and Bondarenko (2007), *Disaster* is the option-implied disaster probability of Barro and Liu (2020), *Implied Correlation* is the implied correlation metric of Driessen et al. (2006), *MFIK*, *MFIS*, and *MFIV* are model-free implied kurtosis, skewness or variance, respectively (Rehman and Vilkov, 2012), *RC* is realized correlation metric of Driessen et al. (2006), *Risk Aversion* is the risk-aversion index of Bekaert et al. (2020), *SVIX* follows Martin (2012) (without interpolation), and *VIX* refers to the CBOE volatility index. *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta, over 60 months, in the previous month. Factor portfolios are constructed similarly. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Variance > Median			Variance < Median		
FF5F + UMD	Long	Short	Long-Short	Long	Short	Long-Short
+ Aggregate Tail Risk	0.018***	0.005	0.013**	0.004*	0.009***	-0.005
	(6.018)	(1.537)	(2.423)	(1.736)	(4.548)	(-1.418)
+ CIX	0.015***	0.007***	0.008**	0.005**	0.009***	-0.003
	(7.217)	(2.869)	(2.280)	(2.099)	(3.889)	(-0.858)
+ Disaster	0.016***	0.008***	0.009*	0.005	0.008***	-0.003
	(4.921)	(3.122)	(1.744)	(1.342)	(3.691)	(-0.498)
+ Implied correlation	0.017***	0.006**	0.007***	0.005*	0.009***	-0.004
	(6.557)	(2.575)	(2.809)	(1.748)	(3.834)	(-1.035)
+ MFIK	0.018***	0.004	0.014**	0.003	0.010***	-0.007
	(5.253)	(1.362)	(2.368)	(0.862)	(4.148)	(-1.267)
+ MFIS	0.018***	0.005	0.013**	0.003	0.010***	-0.007
	(5.452)	(1.473)	(2.330)	(0.913)	(4.294)	(-1.371)
+ MFIV	0.014***	0.007***	0.007**	0.005**	0.008***	-0.003
	(6.978)	(3.118)	(2.124)	(2.027)	(3.958)	(-0.841)
+ Realized correlation	0.016***	0.005*	0.011**	0.003	0.010***	-0.007
	(5.899)	(1.920)	(2.270)	(1.061)	(4.384)	(-1.509)
+ Risk aversion	0.016***	0.007***	0.009*	0.005	0.007***	-0.002
	(4.759)	(2.692)	(1.746)	(1.436)	(3.549)	(-0.344)
+ SVIX	0.014***	0.007***	0.007**	0.005**	0.008***	-0.003
	(6.984)	(3.157)	(1.975)	(2.260)	(3.921)	(-0.898)
+ VIX	0.014***	0.007***	0.007**	0.006**	0.008***	-0.002
	(6.900)	(3.116)	(1.960)	(2.262)	(3.814)	(-0.696)

Table A.8. Bivariate risk factors

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily stock market variance. The average returns in the high- and low-variance periods are estimates of α_{i,t_H}^{H} and $\alpha_{i,t}^{L}$ in the regression:

$$R_{i,t} = \alpha_{i,t}^{H} \cdot d_t^H + \alpha_{i,t}^{L} \cdot d_t^L + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d_t^H and d_t^L are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month *t* on long-short difference MFID-sorted value-weighted portfolios while matching disaster probability, risk aversion, and VIX, X_t refers to risk factors used in the asset-pricing model, which is the Fama and French five-factor model including betting-against-beta. *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta and bivariate sort over 60 months, in the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Bivariate sort	Disaster	Risk aversion	VIX
Alpha $\cdot\, d^H$	0.011**	0.015***	0.013***
	(2.261)	(4.301)	(3.604)
Alpha $\cdot\, d^L$	0.008	0.002	0.003
	(1.343)	(0.445)	(0.701)
MKT	-0.007	-0.091	-0.046
	(-0.063)	(-0.913)	(-0.570)
SMB	0.244	0.356***	0.292***
	(1.271)	(2.824)	(2.423)
HML	-0.322*	-0.079	0.012
	(-1.706)	(-0.581)	(0.125)
CMA	0.125	0.057	-0.114
	(0.522)	(0.305)	(-0.648)
RMW	0.212	-0.409**	-0.618***
	(0.747)	(-2.019)	(-3.171)
BAB	-0.261***	-0.280***	-0.269***
	(2.672)	(-3.142)	(-3.413)
R^2 (%)	1.68	13.04	14.93

Table A.9. Benchmark-adjusted returns during high and low variance: classic risk factors

The table reports average benchmark-adjusted returns following high stock market variance, based on the median level of daily stock market variance. The average returns in the high- and low-variance periods are estimates of α^{H}_{i,t_H} and $\alpha^{L}_{i,t}$ in the regression:

$$R_{i,t} = \alpha^{H}_{i,t} \cdot d^{H}_{t} + \alpha^{L}_{i,t} \cdot d^{L}_{t} + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d^{H}_{t} and d^{L}_{t} are dummy variables indicating high-variance periods (and 0 otherwise), $R_{i,t}$ is the excess return in month *t* on the long and short leg, and the difference between long and short of MFID-sorted value-weighted (Panel A and C) and equally-weighted (Panel B) portfolios. X_t refers to all risk factors used in the asset-pricing model; Fama & French 5 Factors (FF5F), *Betting-against beta* (BAB), *Short and long-term reversal* (SLR), *Momentum* (UMD), *Short and long-term behavioral* factors of Daniel et al. (2018) (DHS), and *Q-5 factor* model (Q5). *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta over 60 months during the previous month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Variance > Median			Variance > Median		
Risk factor model	Long	Short	Long-Short	Long	Short	Long-Short
			Panel A: Value-weighted returns			
FF5F	0.014***	-0.006	0.020***	0.003	0.010***	-0.007
	(3.079)	(-1.635)	(2.779)	(0.728)	(3.804)	(-1.114)
+ BAB	0.014***	-0.006	0.020***	0.005	0.009***	-0.004
	(3.329)	(-1.429)	(2.733)	(1.451)	(3.509)	(-0.731)
+ SLR	0.014***	-0.006	0.020***	0.004	0.010***	-0.005
	(3.040)	(-1.555)	(2.718)	(1.008)	(3.665)	(-0.931)
+ UMD	0.014***	-0.006*	0.020***	0.003	0.010***	-0.007
	(3.606)	(-1.655)	(3.091)	(0.966)	(4.080)	(-1.333)
DHS	0.020***	-0.007*	0.020***	0.007	0.011***	-0.004
	(2.868)	(-1.880)	(2.868)	(1.391)	(4.840)	(-0.642)
Q5	0.019***	-0.006*	0.019***	0.003	0.011***	-0.008
	(2.987)	(-1.662)	(2.987)	(0.944)	(4.405)	(-1.508)
			Panel B: Equally-weighted returns			
FF5F	0.008**	-0.012***	0.020***	0.002	0.011***	-0.009
	(1.994)	(-3.581)	(2.840)	(0.471)	(4.316)	(-1.557)
+ BAB	0.010**	-0.013***	0.022***	0.003	0.011***	-0.008
	(2.319)	(-3.682)	(3.087)	(0.847)	(4.042)	(-1.312)
+ SLR	0.007*	-0.012***	0.019***	0.003	0.011***	-0.008
	(1.705)	(-3.570)	(2.636)	(0.756)	(4.144)	(-1.325)
+ UMD	0.009**	-0.012***	0.020***	0.002	0.011***	-0.009*
	(2.221)	(-3.639)	(3.043)	(0.596)	(4.729)	(-1.783)
DHS	0.005	-0.015***	0.020***	0.005	0.012***	-0.007
	(0.948)	(-4.256)	(2.829)	(1.259)	(5.008)	(-1.200)
Q5	0.008**	-0.011***	0.019***	0.003	0.012***	-0.009*
	(2.154)	(-3.584)	(3.055)	(0.776)	(5.261)	(-1.865)

Table A.10. Benchmark-adjusted returns during high and low variance: excluding financials

The table reports average benchmark-adjusted returns following high and low levels of stock market variance, based on the median level of daily in-month stock market variance. The average returns in the high- and low-variance periods are estimates of α^H_{i,t_H} and $\alpha^L_{i,t}$ in the regression:

$$R_{i,t} = \alpha^H_{i,t} \cdot d^H_t + \alpha^L_{i,t} \cdot d^L_t + \gamma_{i,t} \cdot X_t + \epsilon_{i,t}$$

where d^H_t and d^L_t are dummy variables indicating high- and low-variance periods, $R_{i,t}$ is the excess return in month *t* on the long and short leg, and the difference between long and short of MFID-sorted value-weighted portfolios. X_t refers to all risk factors used in the asset-pricing model; Fama & French 5 Factors (FF5F), *Betting-against beta* (BAB), *Short and long-term reversal* (SLR), *Momentum* (UMD), *Short and long-term behavioral* factors of Daniel et al. (2018) (DHS), and *Q-5 factor* model (Q5). *T*-statistics in parentheses are based on Newey and West's (1987) standard errors with the appropriate lags. MFID-sorted portfolios are constructed by sorting individual stocks, each month, based on their MFID beta over 60 months during the previous month. We excluded all financial companies. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Variance > Median			Variance < Median		
	Long	Short	Long-Short	Long	Short	Long-Short
FF5F	0.065***	-0.003	0.067***	0.011***	0.004	-0.007
	(8.002)	(-0.448)	(5.335)	(4.255)	(1.533)	(-1.619)
+ BAB	0.060***	-0.003	0.063***	0.011***	0.005**	-0.006
	(6.604)	(-0.441)	(4.643)	(4.204)	(2.291)	(-1.248)
+ SLR	0.064***	-0.003	0.068***	0.011***	0.003	-0.008*
	(7.675)	(-0.490)	(5.076)	(4.743)	(1.473)	(-1.832)
+ UMD	0.060***	-0.002	0.061***	0.011***	0.004*	-0.006
	(8.286)	(-0.246)	(5.363)	(4.124)	(1.952)	(-1.421)
DHS	0.065***	0.002	0.063***	0.012***	0.005*	-0.007
	(8.183)	(0.275)	(4.864)	(4.603)	(1.940)	(-1.600)
Q5	0.065***	0.000	0.064***	0.012***	0.005*	-0.007
	(9.146)	(0.056)	(5.299)	(4.389)	(1.945)	(-1.546)