# Disagreement on Tail*

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**Abstract**

We propose a novel measure, DOT, to capture belief divergence on extreme tail events in stock returns. Defined as the standard deviation of expected probability forecasts generated by distinct information processing functions and neural network models, DOT exhibits significant predictive power for future stock returns. A value-weighted (equal-weighted) long-short portfolio based on DOT yields an average return of -1.07% (-0.98%) per month. Furthermore, we document novel evidence supporting a risk-sharing channel underlying the negative relation between DOT and the equity premium following extreme negative shocks. Finally, our findings are also in line with a mispricing channel in normal periods.

**JEL Classifications**: C45, G12, G17
**Keywords**: Disagreement, tail risk, machine learning, neural network model, return prediction

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# 1 Introduction

Tail events, characterized by their low probability (intensity) and extreme negative outcomes (severity), play an essential role in shaping risk premia in financial markets (Rietz, 1988; Barro, 2006; Gabaix, 2012). By nature, assessing the intensity and severity of these events is ambiguous, leading to disagreements in beliefs about tail events (Chen et al., 2012). While a body of literature has sought to measure tail risk, a method to accurately capture the dispersion of beliefs about tail events remains elusive.[1] In this paper, we propose a novel measure of disagreement on tail events and then examine how it is related to expected stock returns in the cross-section.

The primary challenge of measuring disagreement on tail stems from measurement difficulties. Starting from Diether et al. (2002), the common approach in the literature is to rely on the variance of analyst forecasts to quantify belief dispersion. However, while analyst forecasts cover the average of their beliefs about an economic variable (e.g., earnings per share or GDP), they do not specifically capture beliefs regarding tail events. Therefore, a precise measure of disagreements about tail risk is still lacking.[2]

We overcome this difficulty by proposing a new empirical framework to measure firm-level disagreement on tail events (termed DOT) based on machine learning techniques. Next, using a large sample from the U.S. stock market, our empirical analysis uncovers a strong cross-sectional predictability of DOT for subsequent individual stock returns. Finally, leveraging the DOT measure, we examine the economic mechanisms underlying the DOT's predictive power. We find evidence that DOT's predictive power originates from the risk-sharing channel of Chen et al. (2012) in after-tail-event periods and from the short-sale constraint channel of Miller (1977) in normal periods.

First, when developing a firm-level measure for disagreement on tail events, our

[1] For examples of tail risk measures, see, e.g., Backus et al. (2011a) using option data, Kelly and Jiang (2014) using cross-sectional equity data, and Manela and Moreira (2017a) relying on news texts.

[2] While a few exceptions exist, such as the survey of professional forecasters that includes analyst forecasts of economic variable distributions and recession probabilities, these measures are usually not at the individual firm level.

method involves two key steps: 1) simulating diverse investors who independently make predictions, and 2) capturing disagreement specifically related to tail events among these investors. In the first step, we follow Bali et al. (2023) to measure the dispersion of investor beliefs using predictions of future stock returns derived from various machine learning model specifications, referred to as machine forecast disagreement (MFD). However, this step alone is insufficient for our purpose, as it captures disagreement over average returns rather than specifically focusing on tail events.

To complete the second step, we employ the *classification method* in machine learning. In general, machine learning tasks can be categorized into two types. The first is estimation, as exemplified by Gu et al. (2020) and Bali et al. (2023), along with numerous asset pricing studies. These machine-learning methods in these studies address the question: *How much* will the return be? The second type is classification, which asks: *What type* of return will it be? Classification methods have been widely applied in finance, such as in default detection and anti-money laundering (Kelly et al., 2023), as well as in natural sciences, including tumor detection and astronomical data analysis (Jordan and Mitchell, 2015). Specifically, we translate the measurement of tail-event beliefs into a classification task. We categorize all returns into four event types: Tail (T), Down (D), Up (U), and Surge (S), corresponding to monthly excess returns falling within $(-\infty, -u_t)$, $[-u_t, 0)$, $[0, u_t)$, and $[u_t, +\infty)$, respectively. In our baseline analysis, we set $u_t = 25\%$, where a tail event is defined as a monthly excess return below –25%. We show that our inference is robust to alternative fixed and dynamic thresholds for tail events.[3]

After defining tail events, we employ the neural network model (NNM) as our machine learning method to predict return classifications. NNM excels at handling complex expectations by integrating large datasets into financial forecasting. In our application, NNM predicts the probabilities of the four event types based on historical information using a 10-year rolling window at the firm-month level. In each classification task, NNM

[3]For example, we test both fixed thresholds (ranging from 20% to 50%) and dynamic thresholds based on the fifth percentile of cross-sectional returns. Our results remain robust across all specifications.

answers the question: How likely is a tail event to occur in the next month, given the historical data?

We consider a large set of firm characteristics from Gu et al. (2020) as the input information for the neural network models. Disagreement among investors may arise from differences in prior beliefs, access to information, or rationality. In our baseline analysis, we assume that all investors observe the same information and are fully rational, with variation only in their prior beliefs. This assumption is relaxed in our robustness analysis. Under these conditions, dispersed tail event beliefs are generated using 100 random model specification.

Using the distinct NNM classification probabilities for tail events from 100 different model specifications, we overcome measurement difficulties and observe varying machine tail event forecast probabilities. The lowest probability represents the most optimistic forecast, while the highest represents the most pessimistic forecast. To quantify the degree of disagreement among investors regarding tail events, we calculate the standard deviation (STD) of these probability predictions. This measure, termed DOT, captures the dispersion of investor beliefs, with a larger STD indicating greater disagreement on the tail event forecasts.

Next, we empirically examine the relation between DOT and expected stock returns in the cross-section. We find that stocks with higher DOT exhibit lower subsequent returns, evern after controlling for firm characteristics and adjusted for conventional risk exposures. In the univariate portfolio analysis, a long-short portfolio that goes long stocks in the top DOT decile and short those in the bottom DOT decile earns a value-weighted (equal-weighted) average return of -1.07% (-0.98%) per month with a $t$ statistics of -2.98 (-2.95), indicting an economic sizable -12.84% (-11.76%) annual return. Interestingly, these values are comparable to those of Bali et al. (2022) who focus on average return disagreement. After controlling for risk factors (such as the CAPM, the Fama-Frech three-factor and five-factor models), the DOT long-short portfolio continues to generate economically

and statistically significant alphas. Furthermore, Fama-MacBeth regressions deliver a same negative relationship, showing a statistically and economically significant coefficient of -0.35 for DOT on excess returns, with a $t$-statistic of -4.36. A series of further robustness checks consistently support the strong negative relations between DOT and future stock returns.

We conduct comparative analyses to demonstrate that DOT do capture disagreement on tail by analyzing its relationship with tail risk and total disagreement. We first compare DOT with tail risk, including Kelly and Jiang (2014) Tail Risk (TR), the CBOE Volatility Index (VIX), and the St. Louis Fed Financial Stress Index (FSI). For comparability, we calculate the value-weighted average of DOT to generate a time series. We observe that DOT exhibits sharp, periodic spikes during times of market stress, such as the 1973-1974 oil crisis, the early 1980s recession, the 1987 Black Monday, the early 2000s dot-com bubble, the 2008 financial crisis, and the 2020 COVID-19 pandemic. The time-series curve of DOT shows great similarity with VIX and FSI. Interestingly, TR does not follow the same pattern as DOT, VIX, and FSI. TR follows a more gradual upward trend, with increases that are more sustained during and after major crises, reflecting prolonged concerns about extreme risks. This pattern suggests that DOT may contain distinct information compared to TR. In further analysis, we examine the predictability of DOT conditional on TR using bivariate portfolio analysis. We document that the negative relationship between DOT and future stock returns remains large and significant in all TR quintiles. We interpret the interaction between realized tail risk and perceived tail disagreement as the reason why TR cannot subsume DOT. When tail risk is high, the likelihood of extreme negative events becomes more certain, leading to greater consensus among investors. As a result, DOT should be lower, as most investors agree on the heightened risk. Conversely, when tail risk is low, there is less clarity about the likelihood of extreme events, leading to more diverse investor opinions. This increased uncertainty fosters greater disagreement, resulting in a higher DOT. We observe a negative correlation

between DOT and TR, which partially confirms this interpretation.

We then examine the relationship between disagreement on tail and total disagreement. Traditional measures of disagreement primarily capture the divergence in analysts' subjective average forecasts. In such cases, an analyst considers probabilities across all scenarios to derive a weighted average prediction, which we refer to as total disagreement. In contrast, DOT offers a novel perspective by concentrating on the left tail of the return distribution—events that are rare but carry significantly bad impact. To compare total disagreement with DOT, we employ two well-established measures: the AFD from Diether et al. (2002) and the MFD from Bali et al. (2022). As expected, given that these measures address the same concept from different agents, we find that DOT is positively correlated with both AFD and MFD, with Pearson correlation coefficients of 0.22 and 0.63, respectively. In a bivariate portfolio analysis that conditions DOT on AFD (MFD), we find that the negative relationship between DOT and future stock returns is most pronounced in the highest AFD (MFD) quintile, where the FF5 alpha is -1.11% (-1.57%), with a $t$-statistic of -2.64 (-4.71). The results indicate that when total disagreement is high, the source of disagreement—specifically from tail events—significantly influences asset pricing. DOT may provide additional information beyond that captured by total disagreement.

Finally, we conduct additional analyses to understand the economic mechanisms behind the negative predictability of DOT for stock returns. When examining the underlying mechanisms, we find that the return predictability of DOT arises from two channels in different market conditions. First, we find supportive evidence for the mispricing channel from Miller (1977). In normal periods, when a stock's DOT is high, optimists could buy the stock to express their bullish view, while pessimists could only step aside from the market due to short-sale constraints. In this case, high DOT indicates greater overpricing and lower subsequent returns. We employ the mispricing score from Stambaugh and Yuan (2017) to test this hypothesis. In bivariate portfolio analysis, the long-short port-

folio is negatively significant, with a -1.69% monthly excess return and a -3.81 $t$-statistic, but only in the highest mispricing quintile. Fama-MacBeth regression also generates similar evidence, with the interaction term between mispricing score and DOT yielding a coefficient of -0.12 and a $t$-statistic of -5.64. [4]

Second, we also find novel evidence for the risk-sharing channel proposed by Chen et al. (2012). In their theoretical framework, after tail events, the risk-sharing capacity of optimists is largely diminished. Investors would uniformly bid at a heavily discounted price and demand a high tail event premium. In such scenarios, even a small increase in disagreement on tail events, driven by a few optimists, could lead to a higher current price and a significant reduction in the tail event premium. Due to the lack of a specific measure for tail event belief dispersion, the risk-sharing channel has not been seriously examined. To the best of our knowledge, our work is the first to document supportive evidence for the risk-sharing channel in Chen et al. (2012). In the sample following tail events, we find that the mispricing channel no longer holds. However, we observe a positive subsequent premium in the lowest DOT decile. By combining from decile 2, which contains slightly more optimists, to decile 10, we create a "rest" decile relative to the lowest decile. The long-short portfolio between the rest decile and the lowest decile generates a -1.49% excess return with a -2.29 $t$-statistic after tail events. Fama-MacBeth analysis also shows that the subsequent returns of deciles 2–10 are significantly lower than those of the lowest decile. The evidences support the hypothesis in Chen et al. (2012) that after tail events, a small increase in disagreement on tail event would significantly reduce the tail event premium.

This paper connects two strands of literature: tail events and belief dispersion. Various measures have been developed to capture tail event risk. For instance, Kelly and Jiang (2014) propose a tail risk measure based on cross-sectional equity returns, while

[4] In robustness analysis, we also capture short-sale constraints using institutional ownership from Nagel (2005) and illiquidity as a measure of limits to arbitrage from Amihud (2002). The results are consistent with the baseline analysis.

Backus et al. (2011b) infer disaster risk from options data, and Manela and Moreira (2017b) construct a tail event measure using news text data. However, as noted in Chen et al. (2012), a systematic method to capture how beliefs disperse around tail events remains lacking. There also exist a bunch of measures to capture the belief dispersion, such as analyst forecast dispersion (Diether et al., 2002), option volume (Ge et al., 2016), and abnormal trading volume (Garfinkel, 2009). Our work introduces a novel approach to capture event-specific belief dispersion, bridging the gap between these two strands of research.

The remainder of this paper is organized as follows: Section 2 details the data and variables. Section 3 outlines the methodology. Section 4 presents the empirical results. Section 5 presents a number of robustness tests. Section 6 explores why DOT captures disagreement on tail. Section 7 examines mispricing channel and risk-sharing channel. Section 8 concludes the study.

# 2 Data and variables

## 2.1 Data description

We obtained a publicly available dataset from Gu et al. (2020), which includes 94 firm characteristics. The return and industry data are from the Center for Research in Security Prices (CRSP). The analysts' earnings forecasts data are sourced from the Institutional Brokers' Estimate System (I/B/E/S) and the institutional holdings data are sourced from the Thomson Reuters Institutional Holdings (13F) database. Our sample begins in January 1957 (a little earlier than the start date of the S&P 500), and ends in December 2021, covering a total of 65 years. We restrict the sample to common stocks listed in the NYSE, AMEX, and NASDAQ. Additionally, we cross-sectionally remove the bottom decile of stocks by market capitalization period-by-period. We regard this processed dataset as the information set $\mathbf{Z}$ accessible to investors.

### 2.2 Control variables

In our FM regression analysis, we control for various firm characteristics known to predict future stock returns. These control variables are sourced from Green et al. (2017). In particular, BETA is estimated market beta from weekly returns and equal weighted market returns for 3 years ending month $t-1$ with at least 52 weeks of returns following Fama and MacBeth (1973). SIZE is natural log of market capitalization at end of month $t-1$ following Banz (1981). BM is book value of equity divided by end of fiscal year-end market capitalization following Rosenberg et al. (1985). GP is revenues minus cost of goods sold divided by lagged total assets following Novy-Marx (2013). AG is the percent growth rate of total assets between two consecutive fiscal years following Cooper et al. (2008). ILL is Average of daily (absolute return / dollar volume) following Amihud (2002). TURN is average monthly trading volume for most recent 3 months scaled by number of shares outstanding in current month following Datar et al. (1998). MOM is 11-month cumulative returns ending one month before month end following Jegadeesh (1990).

## 3 Methodology

### 3.1 Differentiated investors

Disagreement among investors can result from differences in prior beliefs, access to information, or rationality. In our research, we assume that investors observe the same information and are fully rational, with the only variation being their prior beliefs. To quantify forecast disagreement, we begin by defining a set of differentiated investors, each denoted by $n$, where $n = 1, 2, \ldots, \mathrm{N}$. Suppose these investors face a public, complete and identical information set $\mathbf{Z} = (\mathbf{z}_{i,t})$ where $\mathbf{z}_{i,t} = (z^1_{i,t}, z^2_{i,t}, \cdots, z^{\mathrm{K}}_{i,t})'$ is a K-dimensional

vector representing K firm characteristics of stock $i$ in month $t$. [5] Due to their differing prior beliefs, these investors will interpret the same information set in distinct ways, particularly by assigning different weights to the K firm characteristics. Therefore, after processing the original information, the actual information set $\mathbf{X}_n = (\mathbf{x}_{n,i,t})$ obtained by investor $n$ based on their individual beliefs can be represented as:

$$\mathbf{x}_{n,i,t} = g_n(\mathbf{z}_{i,t}), \tag{1}$$

and $g_n(\cdot)$ denotes the unique function applied by investor $n$ to the information set $\mathbf{z}_{i,t}$ as follow:

$$g_n(\mathbf{z}_{i,t}) = \mathbf{D}_n \mathbf{z}_{i,t}, \tag{2}$$

where $\mathbf{D}_n$ is a K-order diagonal matrix, and the elements on the diagonal $d_{jj}$ $(j = 1, 2, \ldots, \mathrm{K})$ satisfy $d_{jj} \sim iid\mathrm{N}(0, 1)$. Each $d_{jj}$ scales the $j$-th element of the vector $\mathbf{z}_{i,t}$ by a different factor, reflecting the unique importance that investor $n$ assigns to specific characteristic based on their personal belief. This scaling process individualizes the influence of each characteristic, thereby introducing sufficient differentiation across $\mathbf{X}_n$.

## 3.2 Four return-based events

We define four events—Tail (T), Down (D), Up (U), and Surge (S)—corresponding to monthly expected excess returns falling within the intervals $(-\infty, -u_t)$, $[-u_t, 0)$, $[0, u_t)$, and $[u_t, +\infty)$, respectively. By categorizing the monthly expected excess returns into these distinct events, we utilize the neural network model described in Section 3.3 to estimate the probabilities of each event occurring. The threshold $u_t$ is set at 25%, and under this setting, the proportion of Tail and Surge events among all events is approxi-

[5] To reduce differences in firm characteristics and improve model training, we normalize the training data to Z-scores using the formula $z^k_{i,t} = \frac{z^k_{i,t} - \mu_k}{\sigma_k}$, where $\mu_k$ is the mean and $\sigma_k$ is the standard deviation. The normalization parameters from the training set are then applied to transform the test set data to avoid look-ahead bias.

mately 5%. The threshold is set by the researchers and it is not necessarily innocuous. An inappropriately mild threshold does not meet the definition of rare events, while an extreme threshold would introduce excessive noise from too few data points. In Section 5.4, we adjust the threshold to 20%, 30%, 40%, and 50%, and observe that the empirical results remain consistent across these settings.

## 3.3 Machine learning method

A neural network model (NNM) is a computational model inspired by the structure and function of biological neural networks in the human brain. It comprises layers of interconnected nodes, or neurons, where each node performs a mathematical operation by calculating a weighted sum of its inputs, adding a bias, and applying a non-linear activation function. NNMs, widely regarded as the most powerful tools in machine learning, are theoretically established as "universal approximators" for any smooth predictive relationship (Hornik et al. (1989); Cybenko (1989)). Their versatility in learning complex data patterns has led to extensive applications across domains, including image recognition, natural language processing, and financial forecasting.

Our NNM is a four-class classification feedforward neural network designed to classify input data into one of four classes and estimate the probabilities associated with each class. It consists of an input layer, multiple hidden layers, and an output layer, with the network learning through the adjustment of weights and biases via backpropagation. It utilizes activation functions and optimization algorithms during training. Once trained, it can predict class labels and associated probabilities for new data.

Consider a NNM with one input layer, L hidden layer, and one output layer. The formulation of it can be expressed as follows:

$$\mathbf{y} = softmax\left(\mathbf{W}^{(\mathrm{L}+1)}\mathbf{a}^{(\mathrm{L})} + \mathbf{b}^{(\mathrm{L}+1)}\right) \tag{3}$$

where:

$$\mathbf{a}^{(l)} = \mathrm{ReLU}(\mathbf{u}^{(l)}), \quad \mathbf{u}^{(l)} = \mathbf{W}^{(l)}\mathbf{a}^{(l-1)} + \mathbf{b}^{(l)}, \quad \mathbf{a}^{(0)} = \mathbf{x}, \quad l = 1, 2, \ldots, \mathrm{L}$$

In this structure, $\mathbf{x}$ represents the input vector, which has a shape of $\mathrm{K} \times 1$ where K is the number of firm characteristics. $\mathbf{W}^{(l)}$ is the weight matrix for layer $l$, which has a shape of $m_l \times m_{l-1}$, where $m_l$ is the number of neurons in layer $l$ and $m_{l-1}$ is the number of neurons in the previous layer $l-1$. For clarity, $m_0 = \mathrm{K}$ refers to the input dimension, and $m_{l+1} = \mathrm{M}$ is the number of output classes. The bias vector $\mathbf{b}^{(l)}$, with a shape of $m_l \times 1$, allows for more flexible transformations by shifting the output. The unactivated input vector $\mathbf{u}^{(l)}$, with a shape of $m_l \times 1$, is the result of the linear transformation using $\mathbf{W}^{(l)}$ and $\mathbf{b}^{(l)}$. The activations $\mathbf{a}^{(l)}$ are the outputs of layer $l$ after applying the ReLU activation function, [6] which introduces non-linearity. Finally, the output $\mathbf{y}$ is obtained by applying the softmax activation function to the final layer, [7] converting them into a probability distribution over M classes, where $y$ has a shape of $\mathrm{M} \times 1$.

We introduce this NNM as our belief-generation model, which serves as the foundation for constructing an empirical measure of disagreement on tail. Specifically, we simulate the variance in beliefs among investors by equipping them with distinct models for predicting event probabilities based on their own information set $\mathbf{X}_n$. We postulate that investor $n$ forecasts event probabilities according to the following formulation:

$$\mathbf{P}_n = \mathrm{NN}_n\left(\mathbf{x}_{n,i,t}\right) \tag{4}$$

[6] The ReLU activation function is defined as: $\mathrm{ReLU}(u_i^{(l)}) = \max(0, u_i^{(l)})$, where $u_i^{(l)}$ is the $i$-th element of the unactivated input vector $\mathbf{u}^{(l)}$, $l = 1, 2, \ldots, \mathrm{L}$. It introduces non-linearity into neural networks, enabling them to learn complex patterns.

[7] The softmax activation function is defined as: $softmax(u_i^{(\mathrm{L}+1)}) = \frac{e^{u_i^{(\mathrm{L}+1)}}}{\sum_{j=1}^{\mathrm{M}} e^{u_j^{(\mathrm{L}+1)}}}$, where $u_i^{(\mathrm{L}+1)}$ is the $i$-th element of the unactivated input $\mathbf{u}^{(\mathrm{L}+1)}$, and M is the total number of classes. The softmax function converts the input values into a probability distribution over M classes.

Where $\mathrm{NN}_n(\cdot)$ refers to the neural network model defined in equation 3 and $\mathbf{P}_n = (p_{n,1}, p_{n,2}, p_{n,3}, p_{n,4})'$ are the probabilities forecasted by investor $n$ for the events Tail, Down, Up, and Surge, respectively.

### 3.4 DOT measure

The process for constructing the Disagreement on Tail (DOT) involves several key steps, each designed to accurately reflect the variation in investor beliefs regarding tail events. The detailed procedure is outlined as follows:

We begin by simulating 100 distinct investors, denoted by N = 100. Each investor is represented by a unique neural network model (NNM) trained to forecast event probabilities based on their own information set $\mathbf{X}_n$. The configuration of these neural networks is critical; thus, we adhere to best practices in neural network design. Specifically, our NNM consists of three hidden layers containing 32, 16, and 8 neurons, respectively, following the geometric pyramid rule as suggested by Masters (1993). This structure allows for an efficient reduction in complexity while retaining sufficient capacity to model intricate patterns in the data. Our NNM configuration is also inspired by the work of Gu et al. (2020), who demonstrated its efficacy in predicting future stock returns.

For each period under study, we utilize the most recent 10 years of historical data to train the 100 individual NNMs, with each model representing a different investor. Given the computational demands of training neural networks, we do not update these models on a monthly basis. Instead, to balance computational feasibility with model efficiency, we opt to refit the models annually. This annual refitting aligns with the typical frequency at which firm characteristics are updated and ensures that our models remain responsive to long-term trends without being overly sensitive to short-term fluctuations.

Once the NNMs are trained, they are used to generate monthly predictions for the upcoming year based on the latest available information. For stock $i$ in month $t$, we collect the event probability predictions from all 100 NNMs. To quantify the degree of

disagreement among investors regarding tail events, we calculate the standard deviation (STD) of these probability predictions. This statistical measure captures the dispersion of investor beliefs, with a larger STD indicating greater disagreement. Specifically, the disagreement on tail events, referred to as DOT, is derived from this process.

Through these steps, we construct a sophisticated and computationally efficient framework for measuring disagreement on tail events. This framework not only enhances our understanding of investor behavior but also offers a powerful tool for future research in asset pricing and market analysis.

# 4 Empirical results

In this section, we first present summary statistics to give an overview of the data. Next, we conduct both parametric and nonparametric tests to assess the predictive power of DOT over future stock returns. We begin with univariate portfolio analysis and then proceed to bivariate portfolio analysis, where we control for market capitalization. Finally, we present the results of Fama-MacBeth regressions.

## 4.1 Summary statistics

Table 1 provides summary statistics for the primary variables in our analysis. Our focal variable, DOT, exhibits a time-series average of 0.01 for the monthly cross-sectional mean, median, and standard deviation. The distribution of DOT is notably skewed and leptokurtic, with an average skewness of 1.47 and excess kurtosis of 2.71, suggesting a distribution with a long right tail and more extreme values than a normal distribution.

Table 2 displays the time-series averages of the monthly cross-sectional Pearson product–moment and Spearman rank correlations between different variables. It indicates a negative relationship between DOT and future stock returns. Furthermore, the table highlights several interesting relations between DOT and other firm characteristics.

Stocks with smaller market capitalization, higher analyst forecast dispersion, and higher machine forecast disagreement are associated with higher levels of DOT. This suggests that disagreement on tail is more pronounced in firms that are potentially less stable or more difficult to value. Additionally, stocks with lower institutional ownership ratio, lower liquidity and higher mispricing score also exhibit higher DOT, implying that investors' disagreement on tail is more significant in firms that are perceived to be mispriced.

## 4.2 Univariate portfolio analysis

We begin our investigation of the cross-sectional relationship between DOT and expected returns with univariate portfolio analysis. Each month, we sort all stocks in our sample into decile portfolios based on an ascending sort of DOT. The results of the portfolio analysis are shown in Table 3.

In table 3, we present the average monthly excess returns of each decile portfolio, and the long-short portfolio. Additionally, We calculate abnormal returns (alphas) using various factor models. These include the capital asset pricing model (CAPM) with the market (MKT) factor, the three-factor model (FF3) by Fama and French (1993) which includes market (MKT), size (SMB), and value (HML) factors, the five-factor model (FF5) by Fama and French (2015) which includes market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors.

The results demonstrate a clear pattern: both excess returns and alphas decrease as we move from the first to the tenth decile, indicating an negative relationship between DOT and future returns. The excess return declines from 0.68% per month for the first decile portfolio to -0.38% per month for the tenth decile portfolio. The long-short portfolio that short-sells stocks in the bottom decile of DOT (decile 1) and buys stocks in the top decile of DOT (decile 10) earns a value-weighted (equal-weighted) average return of -1.07% (-0.98%) per month, with a $t$-statistic of -2.98 (-2.59). This translates into an annualized return of -12.84% (-11.76%). Notably, controlling for common risk factors does

not significantly change the magnitude and statistical significance of the return spreads on the DOT-sorted portfolios.

A striking feature of the analysis is the pronounced underperformance of the tenth decile portfolio compared to the other deciles. In fact, the difference in excess return between the tenth decile and the ninth decile portfolios is larger than the difference between the ninth and first decile portfolios. This finding suggests that the negative relationship between DOT and future returns is predominantly driven by stocks in the highest DOT decile, where disagreement on tail among investors is most pronounced. The pattern indicates that there exist a small fraction of firms in top decile that are most debatable for tail events and these firms contribute greatly on the empirical regularities. The small fraction also is also in line with the intuition that there is only a small fraction of firm that are expected to experience tail event.

Further analysis of the alphas reveals that the value-weighted portfolios in the tenth decile exhibit statistically significant negative alphas across all factor models. In contrast, the alphas for the first decile portfolios are not statistically different from zero when using the five-factor model, indicating that low-DOT stocks are fairly priced relative to their risk profiles. This contrast suggests that high-DOT stocks are overvalued relative to stocks with lower DOT, implying that the observed return predictability is likely driven by mispricing rather than compensation for risk.

## 4.3 Bivariate portfolio analysis

Next, we continue our examination of the negative relationship between DOT and future stock returns by controlling for firm's market capitalization (MC). We conduct a 5x10 bivariate dependent-sort portfolio analysis based on MC and DOT. Specifically, each month, we first sort stocks into quintile portfolios based on MC, and then further sort them by DOT into decile portfolios within each MC quintile. This approach results in 50 conditionally double-sorted portfolios. The results of the portfolio analysis are shown in

Table 4.

In table 4, we present the excess returns and FF5 alphas of the bivariate portfolios. Panel A (Panel B) reports results for the equal-weighted (value-weighted) portfolio sorts. Examining the returns and alphas of the DOT long-short portfolio within each of the MC quintile, we see that the negative relationship between DOT and future returns is statistically significant across all MC quintiles except for the highest (quintile five) and is strongest in MC quintile one. The strength of this relationship decreases as the market capitalization of the stocks in the portfolio gets larger. These results indicate that even after controlling market capitalization in bivariate portfolios, there is a strong negative relationship between DOT and future stock returns. DOT matters mainly among small and medium firms.

## 4.4 Fama-MacBeth regression analysis

In this section, we conduct Fama-MacBeth regression analysis to examine whether DOT predicts the cross-section of excess stock returns while simultaneously controlling for other established predictors. Each month, we conduct a cross-sectional regression of excess stock returns on the previous month's DOT and several control variables, including the market beta (BETA), natural log of market capitalization (SIZE), book-to-market ratio (BM), gross profitability (GP), asset growth (AG), illiquidity (ILL), turnover ratio (TURN), and momentum (MOM). These stock-level cross-sectional regressions are conducted monthly, and the standard errors of the average slope coefficients are adjusted for heteroskedasticity and autocorrelation, following Newey and West (1987).

Table 5 presents the results of Fama-MacBeth regression analysis. In column (1), we include DOT as well as BETA, SIZE, BM, GP, and AG as control variables. The regression results reveal a coefficient on DOT of -0.35, which is both statistically and economically significant, with a $t$-statistic of -4.36. This finding is consistent with our portfolio analysis, confirming the negative relationship between DOT and future returns.

In column (2), we extend the model by adding ILL, TURN, and MOM as additional return predictors. Despite the inclusion of these influential return predictors, the negative relationship between DOT and future stock returns remains significant. The coefficient on DOT is slightly reduced to -0.29 but remains statistically robust, with a $t$-statistic of -3.92. DOT is also highly economically significant. The spread in the average standardized DOT between deciles 10 and 1 is approximately 3.16, and multiplying this spread by the average slope coefficient of -0.29 yields a return difference of -0.82% per month, controlling for all else.

In columns (3) and (4), we adjust the regression model to account for industry effects by replacing the dependent variable with the industry-adjusted return. Specifically, we subtract the value-weighted industry return, based on the Fama-French 48-industry classification, from each stock's own return. This adjustment allows us to isolate the predictive power of DOT from the one-month industry momentum effect identified by Moskowitz and Grinblatt (1999). The results continue to demonstrate the significance of DOT, with the coefficient on DOT remaining large and statistically significant. This robustness suggests that DOT's predictive power is not merely an artifact of industry-level effects but rather reflects a deeper, cross-sectional relationship between disagreement on tail and future stock returns.

Overall, these regression results highlight the persistent and economically meaningful impact of DOT on future stock returns. The negative coefficient across various regression specifications underscores the importance of considering investor disagreement on tail, when analyzing stock performance. The evidence suggests that DOT captures unique information about future stock returns that is not fully accounted for by traditional risk factors or industry effects, making it a valuable measure for understanding cross-sectional return variations.

# 5 Robustness checks

In this section, we perform a number of robustness checks to further validate the negative cross-sectional relationship between DOT and future stock returns based on the methodology used to construct DOT in Section 3. Firstly, we adjust the settings of the model representing investors in Section 5.1. Secondly, we modify the method for calculating DOT from "random weights" to "random selection" in Section 5.2. Finally, we change the threshold of tail events in Section 5.4.

## 5.1 Model settings

In this section, we adjust the hyper-parameters of the neural network model, specifically the number of hidden layers and the number of neurons in each hidden layer, to test whether the negative relationship between DOT and future stock returns is sufficiently robust. The number of hidden layers ranges from 1 to 5, with neurons per hidden layer ranging from 8 to 128, following the geometric pyramid rule suggested by Masters (1993).

In table IA 1, we report the results of univariate portfolio analysis based on different neural network architectures. Across all models, the returns and FF5 alphas of the long-short portfolio are consistently and significantly negative, confirming that portfolios with higher DOT values have lower future returns. The negative relationship between DOT and future stock returns is robust across different neural network architectures. Whether using equal-weighted or value-weighted portfolios, varying the model complexity (number of layers and neurons) does not affect the overall conclusion. The consistent significance in both the returns and FF5 alphas of the long-short portfolio further reinforces the strength and robustness of this finding.

## 5.2 Random selection

In Section 3.1, we define different types of investors based on how they interpret the information set $\mathbf{Z}$, achieved by assigning varying weights to the K firm characteristics as specified in equation 2. This approach, termed "random weights," effectively captures the diversity in investor beliefs, reflecting the fact that different investors may prioritize certain firm characteristics over others when making investment decisions.

However, alternative methods exist for defining investors. One such approach considers investors' information acquisition and processing capabilities, similar to the framework proposed by Bali et al. (2023). This model assumes that investors can only access and process a subset of the K firm characteristics. Specifically, each investor $n$ accesses their own information set $\mathbf{X}_n$, which is a subset of the complete information set $\mathbf{Z}$. In this setting, the function $g_n(\cdot)$ is redefined as:

$$g_n(\mathbf{z}_{i,t}) = (z_{i,t}^{k_{n,1}}, \ldots, z_{i,t}^{k_{n,\mathrm{K}/2}}), \tag{5}$$

where $k_n = \{k_{n,i} \in \{1, \ldots, \mathrm{K}\} \mid \forall i \neq j : k_{n,i} \neq k_{n,j}\}$ and $\mid k_n \mid = \mathrm{K}/2$. This formulation acknowledges that each investor processes only a portion of the available information, highlighting the differences in their beliefs. In comparison with random weights approach, we term the approach as "random selection".

In table IA 2, we present the results of univariate portfolio analysis. Similar to Section 4.2, we can find that both excess returns and alphas of the DOT-sorted portfolios show a decreasing trend from decile 1 to decile 10. The excess return decreases, although not monotonically, from 0.67% per month for the first decile portfolio to -0.47% per month for the 10th decile portfolio. The long-short portfolio that short-sells stocks in the bottom decile of DOT (decile 1) and buys stocks in the top decile of DOT (decile 10) earns a value-weighted (equal-weighted) average return of -1.13% (-1.03%) per month with a $t$-statistic of -3.17 (-2.86), translating into an annualized return of -13.56% (-12.36%).

Importantly, controlling for common risk factors does not diminish the magnitude and statistical significance of the return spreads in the DOT-sorted portfolios. Table IA 3 presents the results of Fama-MacBeth regression analysis, which further reinforces these findings. The coefficient of DOT remains both substantial and statistically significant across all regression specifications, underscoring the robustness of the negative relationship between DOT and future stock returns.

## 5.3 Different thresholds

In Section 3.2, we defined different events using a 25% threshold. Next, we change the threshold to 20%, 30%, 40%, and 50%, respectively, to test whether the negative relationship between DOT and future stock returns still holds.

Table IA 4 presents the results of univariate portfolio analysis of the relationship between DOT and future stock returns across these different thresholds. The findings consistently show that regardless of the threshold—whether set at 20%, 30%, 40%, or 50%—the returns and FF5 alphas of the long-short portfolio are significantly negative. This consistency indicates that the negative cross-sectional association between DOT and future stock returns is remarkably robust to the choice of threshold.

Additionally, Table IA 5 presents the results of Fama-MacBeth regression analysis further validating our conclusions. Even when the threshold is adjusted, the average slope coefficient of DOT remains significantly negative across all specifications. This persistent relationship suggests that the observed negative impact of DOT on future stock returns is not only robust but also resilient to variations in the definition of events.

## 5.4 Dynamic threshold

In this section, we refine our analysis by dynamically setting the threshold of tail events as the fifth percentile of the cross-sectional returns each period, aligning with the methodology proposed by Kelly and Jiang (2014). This approach tests the robustness of the

negative relationship between DOT and future stock returns under varying market conditions.

Table IA 6 presents the results of univariate portfolio analysis. Similar to Section 4.2, both excess returns and alphas of portfolios sorted by DOT exhibit a declining trend from decile 1 to decile 10. Notably, excess returns decrease from 0.57% per month in the first decile to -0.52% in the tenth, although the decline is not strictly monotonically. The long-short portfolio that short-sells stocks in the bottom decile of DOT (decile 1) and buys stocks in the top decile of DOT (decile 10) yields a value-weighted (equal-weighted) average return of -1.09% (-1.13%) per month with a $t$-statistic of -2.95 (-3.06), translating into an annualized return of -13.08% (-13.56%). Importantly, even after adjusting for common risk factors, the magnitude and statistical significance of the return spreads across the DOT-sorted portfolios remain pronounced. Table IA 7 presents the results of Fama-MacBeth regression analysis, which further reinforces these findings. The coefficient of DOT remains both substantial and statistically significant across all regression specifications, affirming the robustness of the negative relationship between DOT and future stock returns.

# 6 Why DOT captures disagreement on tail?

In this section, we demonstrate that DOT captures disagreement on tail. We first compare DOT with tail risk in Section 6.1 and then compare DOT with total disagreement in Section 6.2.

## 6.1 DOT and tail risk

DOT measures the divergence of beliefs among investors regarding extreme outcomes in the distribution of a stock's future returns. Tail events here refer to outcomes that returns fall in $(-\infty, -25\%)$. These events are generally less predictable and more subject

to disagreement among investors. Different investors may have varying beliefs about the likelihood of these extreme outcomes, which can arise from differences in prior beliefs, access to information, or rationality, etc. DOT quantifies the extent of this disagreement.

To compare DOT with tail risk, we follow the methodology outlined by Kelly and Jiang (2014) to construct a measure of time-varying tail risk that is directly estimable from the cross-section of returns. We then estimate stocks' tail risk sensitivity from monthly returns and tail risk for 10 years ending month $t-1$ with at least 36 months of returns. Tail risk refers to the actual risk associated with extreme events in the tail of the return distribution, focusing on the potential magnitude of very low returns. Unlike DOT, which reflects investor disagreement about these extreme outcomes, tail risk represents the objective risk posed by such events.

Figure 1 shows the monthly time-series plot of the value-weighted average DOT, alongside Kelly and Jiang (2014) Tail Risk (TR), CBOE Volatility Index (VIX) and St. Louis Fed Financial Stress Index (FSI). We observe that DOT rises significantly during recessions, while remaining much more stable during expansions. This pattern is intuitive: in economic expansions, the probability of tail events is lower, resulting in less attention and disagreement among investors, keeping DOT at subdued levels. During recessions, however, the likelihood of tail events increases, attracting greater focus and leading to heightened disagreement, causing sharp spikes in DOT. While both DOT and TR respond to economic conditions, they do so in distinct ways. DOT exhibits sharp, periodic spikes during times of market stress, such as the 1973-1974 oil crisis, the early 1980s recession, the 1987 Black Monday, the early 2000s dot-com bubble, the 2008 financial crisis, and the 2020 COVID-19 pandemic. These movements are abrupt, with DOT rising during crises and declining rapidly as conditions stabilize. In contrast, TR follows a more gradual upward trend, with increases that are more sustained during and after major crises, reflecting prolonged concerns about extreme risks. Compared to DOT, VIX and FSI display similar patterns with spikes during periods of market stress, but

their movements are smoother and less abrupt. The similar behavior of DOT, VIX, and FSI further supports the idea that DOT captures information related to tail risk.

The connection between DOT and tail risk lies in their interaction: when tail risk is high, the likelihood of extreme negative events becomes more certain, leading to greater consensus among investors. As a result, DOT should be lower, since most investors agree on the heightened risk. Conversely, when tail risk is low, there is less clarity about the likelihood of extreme events, leading to more diverse investor opinions. This increased uncertainty fosters greater disagreement, resulting in a higher DOT. Thus, if DOT indeed captures disagreement on tail events, we should observe a negative relationship between TR and DOT.

Panel A of Table 6 indicates this negative relationship between TR and DOT through the univariate portfolio analysis. The average value of TR decreases in DOT deciles and the spread in TR between DOT deciles 10 and 1 is -23.59 with a $t$-statistic of -5.01. We then conduct bivariate portfolio analysis in Panel B of Table 6. Examining the returns and alphas of the DOT long-short portfolio within each of the TR quintile, we see that the negative relationship between DOT and future stock returns remain large and significant in all TR quintiles. These results indicate that DOT is not subsumed by TR.

In summary, DOT effectively captures disagreement among investors about tail events, and this disagreement is closely linked to, but not explained by, tail risk. The persistence of the negative relationship between DOT and future stock returns, even after controlling for TR, underscores that DOT contains unique information beyond what is captured by tail risk alone.

## 6.2 DOT and total disagreement

Traditional measures of disagreement typically center on the divergence of analysts' average subjective belief, capturing how much they differ in their forecasts. However, DOT offers a more nuanced perspective by focusing on the tail of the return distribution, specif-

ically measuring the extent of divergence between the most optimistic and pessimistic investors regarding extreme outcomes. This characteristic makes DOT particularly relevant for understanding the dispersion of expectations related to rare but impactful events.

To assess total disagreement, we construct two key measures: Analyst Forecast Dispersion (AFD) and Machine Forecast Disagreement (MFD). AFD is defined as the standard deviation of analyst earnings forecasts divided by the firm's stock price, following the methodology outlined in Garfinkel (2009). This measure captures the level of human-based disagreement among analysts. On the other hand, MFD represents the divergence in forecasts generated by machine learning models, following the specification provided in Bali et al. (2023). MFD serves as a measure of machine-based disagreement, reflecting the variability in model forecasts.

From a structural and distributional perspective, DOT reflects heightened uncertainty about extreme outcomes within the return distribution. This elevated uncertainty can manifest in a broader range of predictions, influencing both AFD and MFD. Specifically, when DOT is high, it indicates a wider spread of opinions regarding tail risk, which can lead to greater dispersion in both analyst forecasts and machine-generated predictions.

Panel A of Table 7 demonstrates a positive relationship between AFD and DOT. The analysis reveals that the average value of AFD increases monotonically across DOT deciles. The spread of 0.04 is statistically significant, with a $t$-statistic of 14.85, indicating a robust association. To further investigate this relation, we conduct a bivariate portfolio analysis in Panel B of Table 7. The results show that the negative relationship between DOT and future returns is most pronounced in the highest AFD quintile (quintile five), where the FF5 alpha is -1.11%, accompanied by a $t$-statistic of -2.64. This suggests that DOT's influence on future returns is particularly strong among stocks with high analyst forecast dispersion, highlighting its relevance in high total disagreement contexts.

Similarly, Panel A of Table 8 indicates a positive relationship between MFD and DOT. The average MFD value also increases monotonically across DOT deciles, with

a spread of 1.59 ($t$-statistic=4.40) between the highest and lowest DOT deciles. The subsequent bivariate portfolio analysis presented in Panel B of Table 8 further elucidates the relationship between DOT and future returns. The analysis reveals that the negative relationship between DOT and future returns intensifies as MFD increases, with the strongest effect observed in the highest MFD quintile (quintile five). In this MFD quintile, the FF5 alpha is -1.57%, with a $t$-statistic of -4.71. Notably, the negative relationship between DOT and future returns is statistically significant across all MFD quintiles except for the lowest (quintile one). These findings underscore that while both DOT and MFD capture elements of disagreement, DOT's influence on returns persists independently of MFD, demonstrating that it captures unique aspects of total disagreement.

Due to the similarity between MFD and DOT in their construction, we include MFD in the Fama-MacBeth regression analysis. As shown in table 9, in columns (2) and (5), where MFD is the primary variable of interest (without DOT), the significant negative coefficient suggests that higher MFD is associated with lower one-month-ahead excess returns. This finding aligns with Bali et al. (2023). However, in columns (3) and (6), when both MFD and DOT are included as independent variables, MFD's coefficient becomes small and statistically insignificant. This suggests that DOT captures a more critical aspect of disagreement that MFD alone does not, particularly in the context of predicting extreme outcomes. The insignificance of MFD in the presence of DOT indicates that DOT may be capturing a broader or more relevant spectrum of investor disagreement, particularly concerning tail risk, which machine forecasts disagreement alone may not fully encompass.

In summary, the analyses highlight the importance of DOT in understanding how disagreement about tail events impacts future stock returns, particularly in contexts of high analyst and machine forecast dispersion. The results suggest that DOT is a crucial factor in explaining return predictability, with its effects being most pronounced when total disagreement, as measured by AFD and MFD, is high. Moreover, what sets DOT

apart is its unique ability to capture the disagreement about extreme outcomes—those events that reside in the tail of the return distribution. It captures a critical aspect of total disagreement that other measures may miss.

# 7 Economic mechanisms

In this section, we investigate the economic mechanisms through which DOT may influence future stock returns. We find evidence supporting two well-established theoretical channels: the mispricing channel, as proposed by Miller (1977), and the risk-sharing channel, as outlined by Chen et al. (2012). Both channels suggest a negative relationship between DOT and subsequent returns, but our findings indicate that they operate under different market conditions. Specifically, during normal periods, DOT predicts future returns through the mispricing channel, while in the aftermath of tail events, the risk-sharing channel predominates. We first present evidence supporting the mispricing channel, followed by evidence for the risk-sharing channel.

## 7.1 Mispricing Channel

Miller (1977) argues that when there is significant divergence of opinion among investors regarding the value of a security, and short sale constraints limit the actions of pessimistic investors, security prices tend to be upwardly biased. In his theoretical model, overvaluation arises because pessimistic investors, who would typically short-sell the security, are unable to act on their beliefs. As a result, prices are driven primarily by the views of optimistic investors. Therefore, securities with higher levels of investor disagreement are likely to be overvalued, leading to lower subsequent returns.

If the relationship between DOT and future stock returns is indeed driven by mispricing, we would expect DOT to work in conjunction with well-established mispricing phenomena documented in the literature. To test this hypothesis, we compare DOT with

the mispricing measure (MISP) developed by Stambaugh et al. (2015), which captures mispricing by aggregating information across 11 prominent anomalies through averaging rankings. Panel A of Table 10 provides evidence of a strong positive relationship between MISP and DOT. The analysis indicates that the average value of MISP increases across DOT deciles, with a substantial spread of 14.04 between the highest (10th) and lowest (1st) DOT deciles. This significant spread, with a $t$-statistic of 22.58, indicates a strong association between MISP and DOT. It suggests that as investors' disagreement on tail grows, so too does the degree of mispricing.

To delve deeper into how mispricing influences the relationship between DOT and future stock returns, we conduct a bivariate portfolio analysis, as shown in Panel B of Table 10. The results demonstrate that the relationship between DOT and future stock returns is highly sensitive to the level of mispricing, as measured by MISP. In the quintile of stocks with the highest MISP (quintile five), the long-short portfolio of DOT exhibits a monthly excess return of -1.69% with a $t$-statistic -3.81, and a FF5 alpha of -1.31% with a $t$-statistic of -4.62. Interestingly, the significantly negative relationship between DOT and subsequent return only exist in the highest mispricing quintile, which indicates that DOT actually work via mispcing channel on equity returns.

Table 11 presents the results of the Fama-MacBeth regression analysis, controlling for MISP. We conduct the analysis on two sample settings: the full sample and the "after tail events" sample. The "after tail events" sample comprises only stocks which experienced a tail event in month $t-1$, where a tail event is defined as a stock's excess return falling below -25%. This definition is inspired by Chen et al. (2012), who conjecture that their risk-sharing channel may primarily take effect after tail events. Our results confirm this conjecture, as we do observe distinct patterns in the two sample sets.

The full sample analysis is presented in the left panel of Table 11. The leftmost column shows that DOT itself negatively predicts the subsequent return, with a coefficient of -0.26% and a $t$-statistic of -4.62. We highlight the third column, which includes the

interaction term between MISP and DOT. After controlling for this interaction, the negative relationship of DOT alone weakens to -0.12 and becomes less significant. The interaction term absorbs a large share of the negative effect, with a coefficient of -0.12 and a $t$-statistic of -5.64. This result supports the idea that a significant portion of DOT's negative effect originates from overpricing. However, in the right panel, we conduct the same test in after-tail-event periods, which yields very distinct evidence. We find that the coefficient of the interaction term is insignificant, while DOT's negative effect still holds. This pattern suggests that the negative relationship between DOT and returns may arise from a different channel in the after-tail-event sample. We will explore this further in the next subsection, where we discuss the risk-sharing channel.

In addition to the mispricing score in Stambaugh and Yuan (2017), Nagel (2005) argue that short sale constraints are most likely to bind among stocks with low levels of institutional ownership, and Amihud (2002) shows that illiquidity (ILL) captures the limits to arbitrage. Therefore, we employ their measures of Institutional Ownership (IOR) and Illiquidity (ILL) to examine the mispricing channel, and we also find supportive evidence. For conciseness, the results are presented in the appendix.

## 7.2 Risk-sharing Channel

In this subsection, we test the risk-sharing explanation in Chen et al. (2012). In their theoretical framework, a tail event shock significantly erodes the risk-sharing capacity of market participants. In such cases, if investors uniformly adopt a pessimistic view, they would likely bid only at a heavily discounted price, which would imply a low DOT and a high subsequent return. However, if a small group of optimists believes the tail risk has resolved, some may accept a lightly discounted price, leading to a slightly higher DOT and a relatively lower subsequent return. Thus, our prediction is as follows: after a tail event, high DOT stocks would be expected to have lower future returns than low DOT stocks, and even a slight increase in DOT would substantially reduce the tail risk

premium. To test this hypothesis, we investigate the relationship between DOT and future stock returns following a tail event. A tail event, as defined in Section 3.2, refers to a stock's excess return in month $t-1$ falling below –25%. Only stocks that experienced a tail event are included in the analysis.

Table 12 presents the results of the univariate portfolio analysis. Panel A shows the full sample analysis, and Panel B presents the after-tail-event sample. A notable finding is that in Panel A, the excess return of decile 2 (0.65%) is very similar to decile 1 (0.68%) in both magnitude and significance. However, in Panel B, we observe a sharp decline in excess return from decile 1 (1.67%) to decile 2 (0.80%) in both magnitude and significance. For the factor loading test, we observe the same pattern: in Panel A, decile 1's CAPM, FF3, and FF5 alphas are similar to those of decile 2 in magnitude, but in Panel B, decile 1's alphas are much higher. These findings indicate that in the after-tail-event sample, even a slight increase in DOT leads to a significant difference in excess return.

We next define a portfolio as the "Rest" portfolio, which contains the stocks in deciles 2-10, to highlight the difference between the lowest decile and the rest of the deciles. It's important to note that the average return of the R-L portfolio is insignificant in the full sample period, but it becomes highly significant in after-tail-event periods. Specifically, in the after-tail-event periods, we observe a notable decrease in the monthly average return from 1.67% to 0.18% as we transition from decile 1 (Low) to decile 2-10 (Rest), accompanied by a drop in the $t$-statistic from 2.43 to 0.25. However, we do not observe a similar pattern in normal periods. R-L portfolio's alphas are also much larger in after-tail-event sample than full sample. These empirical facts suggest that a small group of optimists among pessimists may slightly increase the DOT, but optimists' risk-sharing behavior leads to a significant reduction in the tail risk premium.

Table 13 presents the results of the Fama-MacBeth regression. The analysis is conducted on the full sample, with a subsample analysis following tail events. I(DOT) is an indicator that takes the value of 1 when DOT is greater than the 10th percentile, and

0 otherwise. Compared to normal periods, the coefficient of the intercept in after-tail-event periods is much larger, confirming the existence of the tail event premium. This suggests that investors generally require a higher return to compensate for the risk of a tail event, establishing a baseline expectation for risk compensation in the absence of heightened DOT. In both normal and after-tail-event periods, the coefficient of DOT is significantly negative, demonstrating the robustness of DOT's predictive power for future stock returns. The coefficient of I(DOT) is insignificant in normal periods but becomes significantly negative (-0.89 with a $t$-statistic = -2.14) in after-tail-event periods. This further reinforces the idea that even a small increase in optimistic investors can substantially decrease expected returns for sharing tail risk. These results support our hypothesis that increased investor optimism, reflected through higher levels of DOT, effectively reduces the tail risk premium. These analyses highlight the importance of the risk-sharing channel in explaining the negative relationship between DOT and future stock returns.

# 8 Conclusions

This paper introduces a novel measure, termed Disagreement on Tail (DOT), designed to capture divergence in investor beliefs specifically regarding extreme tail events in stock returns. By simulating variations in prior beliefs using distinct information-processing functions and neural network models, we quantify DOT as the standard deviation of expected probability forecasts generated by different machine agents. We provide strong evidence that DOT effectively reflects investors' disagreement on tail events by comparing it with both tail risk and total disagreement measures.

Our analysis reveals a robust and significant negative cross-sectional relationship between DOT and future stock returns. A value-weighted (equal-weighted) long-short portfolio that shorts stocks in the bottom DOT decile and goes long in the top yields an average monthly return of -1.07% (-0.98%), underscoring DOT's predictive power. Fama-

MacBeth regressions further confirm this relationship, demonstrating that DOT contains unique information about future stock returns that is not fully captured by traditional risk factors or industry effects. This highlights its value in explaining cross-sectional return variations. Additional tests reinforce the robustness of the negative relationship between DOT and future stock returns. Finally, we explore the economic mechanisms underlying DOT's predictive power. As suggested by Chen et al. (2012), we present novel evidence supporting the risk-sharing channel, which predominates in the periods following tail events. Our findings also provide evidence for the mispricing channel (Miller (1977)) during normal periods.

# References


Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Backus, D., Chernov, M., Martin, I., 2011a. Disasters implied by equity index options. The Journal of Finance 66, 1969–2012.

Backus, D., Chernov, M., Martin, I., 2011b. Disasters implied by equity index options. The Journal of finance 66, 1969–2012.

Bali, T. G., Brown, S. J., Tang, Y., 2022. Disagreement in economic forecasts and equity returns: risk or mispricing? .

Bali, T. G., Kelly, B. T., Mörke, M., Rahman, J., 2023. Machine forecast disagreement .

Banz, R. W., 1981. The relationship between return and market value of common stocks. Journal of Financial Economics 9, 3–18.

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

Chen, H., Joslin, S., Tran, N.-K., 2012. Rare Disasters and Risk Sharing with Heterogeneous Beliefs. The Review of Financial Studies 25, 2189–2224.

Cooper, M. J., Gulen, H., Schill, M. J., 2008. Asset Growth and the Cross-Section of Stock Returns. The Journal of Finance 63, 1609–1651.

Cybenko, G., 1989. Approximation by superpositions of a sigmoidal function. Mathematics of Control, Signals and Systems 2, 303–314.

Datar, V. T., Y. Naik, N., Radcliffe, R., 1998. Liquidity and stock returns: An alternative test. Journal of Financial Markets 1, 203–219.

Diether, K. B., Malloy, C. J., Scherbina, A., 2002. Differences of Opinion and the Cross Section of Stock Returns. The Journal of Finance 57, 2113–2141.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

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

Fama, E. F., MacBeth, J. D., 1973. Risk, Return, and Equilibrium: Empirical Tests. Journal of Political Economy 81, 607–636.

Gabaix, X., 2012. Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance *. The Quarterly Journal of Economics 127, 645–700.

Garfinkel, J. A., 2009. Measuring Investors' Opinion Divergence. Journal of Accounting Research 47, 1317–1348.

Ge, L., Lin, T.-C., Pearson, N. D., 2016. Why does the option to stock volume ratio predict stock returns? Journal of Financial Economics 120, 601–622.

Green, J., Hand, J. R. M., Zhang, X. F., 2017. The Characteristics that Provide Independent Information about Average U.S. Monthly Stock Returns. The Review of Financial Studies 30, 4389–4436.

Gu, S., Kelly, B., Xiu, D., 2020. Empirical Asset Pricing via Machine Learning. The Review of Financial Studies 33, 2223–2273.

Hornik, K., Stinchcombe, M., White, H., 1989. Multilayer feedforward networks are universal approximators. Neural Networks 2, 359–366.

Jegadeesh, N., 1990. Evidence of Predictable Behavior of Security Returns. The Journal of Finance 45, 881–898.

Jordan, M. I., Mitchell, T. M., 2015. Machine learning: Trends, perspectives, and prospects. Science 349, 255–260.

Kelly, B., Jiang, H., 2014. Tail Risk and Asset Prices. The Review of Financial Studies 27, 2841–2871.

Kelly, B., Xiu, D., et al., 2023. Financial machine learning. Foundations and Trends® in Finance 13, 205–363.

Manela, A., Moreira, A., 2017a. News implied volatility and disaster concerns. Journal of Financial Economics 123, 137–162.

Manela, A., Moreira, A., 2017b. News implied volatility and disaster concerns. Journal of Financial Economics 123, 137–162.

Masters, T., 1993. Practical Neural Network Recipes in C++. Morgan Kaufmann.

Miller, E. M., 1977. Risk, Uncertainty, and Divergence of Opinion. The Journal of Finance 32, 1151–1168.

Moskowitz, T. J., Grinblatt, M., 1999. Do Industries Explain Momentum? The Journal of Finance 54, 1249–1290.

Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. Journal of Financial Economics 78, 277–309.

Newey, W., West, K., 1987. A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703–08.

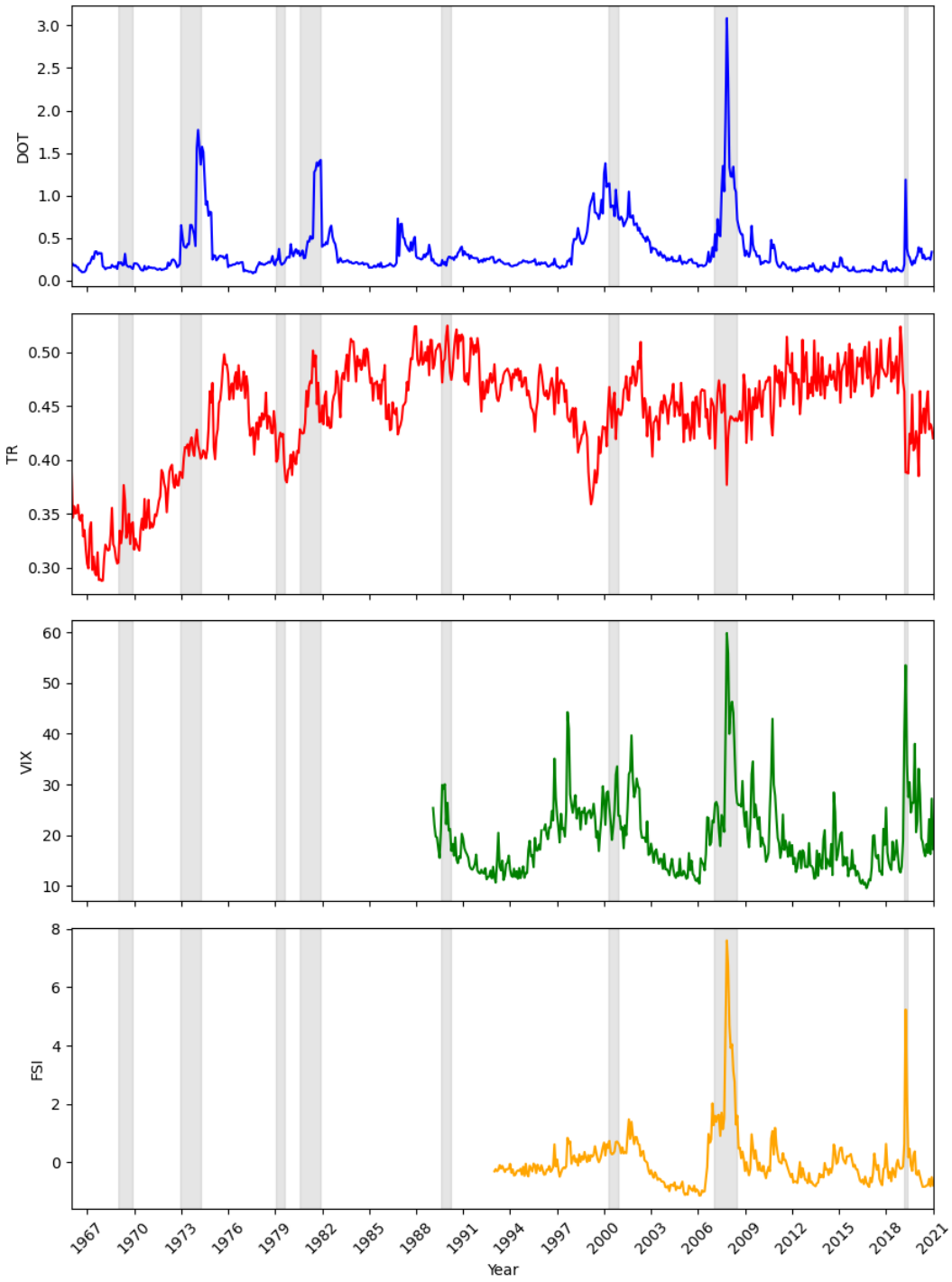
Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of Financial Economics 108, 1–28.

Rietz, T. A., 1988. The equity risk premium a solution. Journal of Monetary Economics 22, 117–131.

Rosenberg, B., Reid, K., Lanstein, R., 1985. Persuasive evidence of market inefficiency. The Journal of Portfolio Management 11, 9–16.

Stambaugh, R. F., Yu, J., Yuan, Y., 2015. Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle. The Journal of Finance 70, 1903–1948.

Stambaugh, R. F., Yuan, Y., 2017. Mispricing Factors. The Review of Financial Studies 30, 1270–1315.




The figure shows the monthly time-series plot of the value-weighted average DOT, alongside Kelly and Jiang (2014) Tail Risk (TR), CBOE Volatility Index (VIX) and St. Louis Fed Financial Stress Index (FSL). Shading denotes NBER-dated recessions. The sample period is from January 1967 to December 2021.

**Figure 1** Disagreement on Tail, Tail Risk, VIX and FSL

**Table 1** Summary Statistics

This table presents summary statistics for different variables. The sample includes all common stocks listed in the NYSE, AMEX, and NASDAQ. The bottom decile of stocks are removed by market capitalization period-by-period. RET is the one-month-ahead return in excess of the risk-free rate of individual stocks. DOT is the disagreement on tail variable. BETA is estimated market beta from weekly returns and equal weighted market returns for 3 years ending month $t-1$ with at least 52 weeks of returns following Fama and MacBeth (1973). MC is the market capitalization at end of month $t-1$ and recorded in $billions following Banz (1981). BM is book value of equity divided by end of fiscal year-end market capitalization following Rosenberg et al. (1985). GP is revenues minus cost of goods sold divided by lagged total assets following Novy-Marx (2013). AG is is the percent growth rate of total assets between two consecutive fiscal years following Cooper et al. (2008). AFD is standard deviation of analyst earnings forecasts divided by the firm's stock price following Garfinkel (2009). MFD is the machine forecast disagreement variable following Bali et al. (2023). TR is estimated tail risk sensitivity from monthly returns and tail risk for 10 years ending month $t-1$ with at least 36 months of returns following Kelly and Jiang (2014). MISP is a mispricing measure determined by combining 11 return anomalies following Stambaugh et al. (2015). IOR is the fraction of shares outstanding held by institutional investors following Nagel (2005). ILL is average of daily (absolute return / dollar volume) following Amihud (2002). TURN is average monthly trading volume for most recent 3 months scaled by number of shares outstanding in current month following Datar et al. (1998). MOM is 11-month cumulative returns ending one month before month end following Jegadeesh (1990). The sample period is from January 1967 to December 2021.

| | Mean | Std | Skew | Kurt | Min | Median | Max | Count |
|---|---|---|---|---|---|---|---|---|
| RET | 0.70 | 14.01 | 1.87 | 28.33 | -68.27 | -0.13 | 183.27 | 4265 |
| DOT | 0.01 | 0.01 | 1.47 | 2.71 | 0.00 | 0.01 | 0.06 | 4265 |
| BETA | 1.09 | 0.60 | 0.52 | 0.06 | -0.12 | 1.01 | 2.81 | 3861 |
| MC | 2.40 | 11.26 | 16.18 | 389.46 | 0.02 | 0.27 | 303.11 | 4265 |
| BM | 0.77 | 0.69 | 3.48 | 60.07 | -0.88 | 0.66 | 10.27 | 3573 |
| GP | 0.37 | 0.32 | 0.81 | 1.45 | -0.36 | 0.32 | 1.48 | 3341 |
| AG | 0.16 | 0.36 | 2.87 | 11.84 | -0.45 | 0.08 | 2.17 | 3350 |
| AFD | 0.19 | 0.48 | 5.20 | 30.25 | 0.00 | 0.05 | 3.56 | 1993 |
| MFD | 1.29 | 0.82 | 3.25 | 61.25 | 0.44 | 1.10 | 9.02 | 4265 |
| TR | 0.09 | 0.71 | -0.01 | 0.17 | -7.39 | 0.12 | 5.59 | 3281 |
| MISP | 50.34 | 13.55 | 0.19 | -0.24 | 11.70 | 49.73 | 93.84 | 2838 |
| IOR | 0.41 | 0.26 | 1.13 | 23.36 | 0.00 | 0.41 | 2.48 | 4096 |
| ILL | 2.43 | 8.62 | 8.72 | 101.61 | 0.00 | 0.26 | 117.91 | 3901 |
| TURN | 1.04 | 1.28 | 2.85 | 11.91 | 0.00 | 0.69 | 9.87 | 3860 |
| MOM | 0.16 | 0.49 | 1.32 | 3.32 | -0.72 | 0.08 | 2.14 | 3924 |

**Table 2** Cross-Sectional Correlations

This table presents the time-series averages of the monthly cross-sectional Pearson product–moment and Spearman rank correlations between different variables. Below-diagonal entries present the average Pearson product–moment correlations. Above-diagonal entries present the average Spearman rank correlations.

| | RET | DOT | BETA | MC | BM | GP | AG | AFD | MFD | TR | MISP | IOR | ILL | TURN | MOM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RET | | -0.08 | -0.04 | 0.05 | 0.03 | 0.01 | -0.00 | -0.03 | -0.06 | 0.02 | -0.05 | 0.05 | -0.04 | -0.02 | 0.05 |
| DOT | -0.04 | | 0.51 | -0.48 | -0.17 | 0.08 | 0.04 | 0.40 | 0.64 | -0.09 | 0.30 | -0.26 | 0.37 | 0.32 | -0.17 |
| BETA | -0.02 | 0.45 | | -0.00 | -0.16 | 0.11 | 0.05 | 0.29 | 0.43 | -0.04 | 0.16 | 0.14 | -0.05 | 0.46 | -0.09 |
| MC | 0.00 | -0.14 | -0.07 | | -0.20 | 0.01 | 0.13 | -0.26 | -0.27 | 0.08 | -0.11 | 0.59 | -0.89 | 0.23 | 0.19 |
| BM | 0.02 | -0.10 | -0.11 | -0.06 | | -0.27 | -0.23 | 0.10 | -0.16 | 0.01 | -0.06 | -0.04 | 0.24 | -0.20 | 0.04 |
| GP | 0.01 | -0.03 | 0.06 | 0.01 | -0.19 | | 0.26 | -0.11 | 0.06 | -0.01 | -0.21 | 0.18 | -0.05 | 0.14 | 0.03 |
| AG | -0.02 | 0.17 | 0.10 | -0.01 | -0.15 | 0.24 | | -0.09 | 0.05 | 0.02 | 0.50 | 0.08 | -0.15 | 0.12 | -0.03 |
| AFD | -0.02 | 0.22 | 0.15 | -0.07 | 0.07 | -0.05 | -0.00 | | 0.30 | -0.07 | 0.22 | -0.09 | 0.21 | 0.17 | -0.21 |
| MFD | -0.03 | 0.62 | 0.38 | -0.05 | -0.05 | 0.01 | 0.15 | 0.14 | | -0.07 | 0.20 | -0.16 | 0.22 | 0.24 | -0.15 |
| TR | 0.01 | -0.11 | -0.06 | 0.02 | 0.02 | 0.01 | -0.01 | -0.03 | -0.08 | | -0.02 | 0.06 | -0.08 | 0.00 | 0.05 |
| MISP | -0.04 | 0.32 | 0.18 | -0.10 | -0.06 | -0.18 | 0.48 | 0.17 | 0.19 | -0.04 | | -0.12 | 0.08 | 0.09 | -0.33 |
| IOR | 0.02 | -0.27 | 0.11 | 0.14 | -0.04 | 0.13 | 0.01 | -0.07 | -0.15 | 0.06 | -0.12 | | -0.59 | 0.39 | 0.05 |
| ILL | -0.01 | 0.18 | -0.07 | -0.06 | 0.10 | -0.03 | -0.06 | 0.06 | 0.11 | -0.05 | 0.01 | -0.19 | | -0.46 | -0.19 |
| TURN | -0.02 | 0.33 | 0.38 | -0.03 | -0.11 | 0.10 | 0.14 | 0.08 | 0.26 | -0.02 | 0.10 | 0.23 | -0.16 | | 0.07 |
| MOM | 0.03 | -0.09 | -0.05 | 0.02 | 0.03 | 0.04 | -0.04 | -0.12 | -0.04 | 0.04 | -0.29 | 0.01 | -0.10 | 0.15 | |

**Table 3** Univariate Portfolio Analysis on DOT

This table presents the results of univariate portfolio analysis of the relation between DOT and future stock returns. Each month $t$, stocks are sorted into decile portfolios based on DOT which is constructed using data available up to month $t-1$. Panel A shows the results for equal-weighted portfolios, while Panel B shows the results for value-weighted portfolios. RET is the return in excess of the risk-free rate. Alphas represent the intercept from a time-series regression of monthly excess returns on the factors of common asset pricing models: the CAPM, Fama and French (1993) three-factor model and Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| Panel A: Equal-Weighted Portfolios | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L |
| RET | 0.81*** | 0.84*** | 0.91*** | 0.93*** | 0.94*** | 0.90*** | 0.80*** | 0.61* | 0.42 | -0.17 | -0.98*** |
| t-stat | (5.38) | (4.54) | (4.54) | (4.26) | (3.90) | (3.34) | (2.66) | (1.75) | (1.11) | (-0.39) | (-2.59) |
| CAPM | 0.41*** | 0.34*** | 0.37*** | 0.35*** | 0.29** | 0.19 | 0.01 | -0.25 | -0.50** | -1.15*** | -1.55*** |
| t-stat | (4.03) | (3.09) | (3.34) | (2.83) | (2.31) | (1.44) | (0.06) | (-1.37) | (-2.25) | (-4.02) | (-4.93) |
| FF3 | 0.28*** | 0.18** | 0.21*** | 0.18*** | 0.12** | 0.05 | -0.10 | -0.35*** | -0.59*** | -1.27*** | -1.56*** |
| t-stat | (3.71) | (2.55) | (3.27) | (2.80) | (2.02) | (0.89) | (-1.56) | (-3.70) | (-4.65) | (-6.50) | (-6.57) |
| FF5 | 0.14** | 0.04 | 0.08 | 0.08 | 0.07 | 0.10* | 0.07 | -0.09 | -0.24* | -0.74*** | -0.89*** |
| t-stat | (2.23) | (0.59) | (1.38) | (1.43) | (1.21) | (1.73) | (0.88) | (-1.02) | (-1.86) | (-3.77) | (-4.19) |
| Sharpe | 0.80 | 0.69 | 0.69 | 0.65 | 0.59 | 0.51 | 0.40 | 0.27 | 0.17 | -0.06 | -0.39 |
| Panel B: Value-Weighted Portfolios | | | | | | | | | | | |
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L |
| RET | 0.68*** | 0.68*** | 0.62*** | 0.80*** | 0.62** | 0.66** | 0.48* | 0.60* | 0.16 | -0.38 | -1.07*** |
| t-stat | (4.81) | (3.72) | (3.24) | (3.73) | (2.54) | (2.43) | (1.66) | (1.82) | (0.42) | (-0.92) | (-2.98) |
| CAPM | 0.24*** | 0.11* | 0.01 | 0.12 | -0.12 | -0.14 | -0.39*** | -0.32* | -0.83*** | -1.44*** | -1.68*** |
| t-stat | (3.07) | (1.76) | (0.18) | (1.64) | (-1.62) | (-1.31) | (-2.96) | (-1.90) | (-4.04) | (-6.05) | (-5.75) |
| FF3 | 0.20*** | 0.07 | -0.02 | 0.11* | -0.13* | -0.13 | -0.33*** | -0.24** | -0.78*** | -1.43*** | -1.62*** |
| t-stat | (3.19) | (1.27) | (-0.44) | (1.71) | (-1.89) | (-1.45) | (-3.71) | (-2.00) | (-4.57) | (-7.23) | (-7.01) |
| FF5 | -0.01 | -0.08 | -0.15** | 0.09 | -0.06 | -0.04 | -0.12 | 0.08 | -0.38*** | -0.87*** | -0.86*** |
| t-stat | (-0.30) | (-1.43) | (-2.51) | (1.51) | (-0.82) | (-0.47) | (-1.21) | (0.72) | (-2.58) | (-4.68) | (-4.45) |
| Sharpe | 0.64 | 0.52 | 0.44 | 0.51 | 0.36 | 0.35 | 0.23 | 0.26 | 0.06 | -0.13 | -0.44 |

**Table 4** Bivariate Portfolio Analysis - Controlling for MC

This table presents the results of bivariate dependent-sort portfolio analysis of the relation between DOT and future stock returns after controlling for the effect of market capitalization (MC). Each month $t$, stocks are sorted into quintile portfolios based on MC. Within each MC portfolio, stocks are sorted into decile portfolios based on DOT. Panel A shows the results for equal-weighted portfolios, while Panel B shows the results for value-weighted portfolios. Alphas represent the intercept from a time-series regression of Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| Panel A: Equal-Weighted Portfolios | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | FF5 | t-stat |
| MC Low | 0.96 | 1.07 | 1.00 | 0.98 | 0.86 | 0.85 | 0.69 | 0.48 | 0.30 | -0.32 | -1.28*** | (-3.06) | -1.27*** | (-3.89) |
| MC 2 | 1.01 | 1.03 | 1.08 | 1.01 | 1.09 | 0.83 | 0.62 | 0.36 | 0.19 | -0.28 | -1.28*** | (-3.20) | -1.32*** | (-5.03) |
| MC 3 | 0.88 | 1.01 | 1.05 | 0.95 | 0.83 | 0.90 | 0.75 | 0.60 | 0.35 | -0.22 | -1.09*** | (-2.89) | -1.01*** | (-4.82) |
| MC 4 | 0.80 | 0.86 | 0.94 | 0.97 | 1.03 | 0.88 | 0.80 | 0.73 | 0.54 | -0.06 | -0.85*** | (-2.59) | -0.69*** | (-4.30) |
| MC High | 0.65 | 0.71 | 0.74 | 0.74 | 0.72 | 0.76 | 0.62 | 0.61 | 0.65 | 0.42 | -0.23 | (-0.71) | -0.05 | (-0.31) |
| Panel B: Value-Weighted Portfolios | | | | | | | | | | | | | | |
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | FF5 | t-stat |
| MC Low | 0.95 | 1.06 | 1.00 | 0.95 | 0.86 | 0.83 | 0.63 | 0.44 | 0.26 | -0.37 | -1.32*** | (-3.08) | -1.30*** | (-3.84) |
| MC 2 | 1.01 | 1.04 | 1.08 | 1.02 | 1.10 | 0.81 | 0.58 | 0.31 | 0.20 | -0.28 | -1.29*** | (-3.22) | -1.32*** | (-5.08) |
| MC 3 | 0.86 | 1.00 | 1.04 | 0.96 | 0.86 | 0.90 | 0.75 | 0.61 | 0.37 | -0.18 | -1.04*** | (-2.72) | -0.95*** | (-4.65) |
| MC 4 | 0.79 | 0.86 | 0.93 | 0.95 | 1.02 | 0.87 | 0.78 | 0.72 | 0.55 | -0.07 | -0.86*** | (-2.61) | -0.68*** | (-4.32) |
| MC High | 0.62 | 0.66 | 0.68 | 0.66 | 0.64 | 0.64 | 0.51 | 0.69 | 0.51 | 0.45 | -0.17 | (-0.55) | 0.12 | (0.72) |

**Table 5** Fama-MacBeth Regressions

This table presents the results of Fama and MacBeth (1973) regression analysis of the relation between DOT and future stock returns. Each column in the table presents results for a different cross-sectional regression specification. The dependent variable in columns (1) and (2) is the future stock return (RET), while in columns (3) and (4), the dependent variable is the future stock return over its value-weighted industry peers' return (Industry-adj. RET). The independent variables are winsorized at the 1% level and standardized on a monthly basis. DOT and the control variables in month $t$ are matched to future stock returns in month $t+1$. The control variables are described in Section 2.2. The table presents average slope and intercept coefficients along with $t$-statistics (in parentheses), adjusted following Newey and West (1987) using six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| | RET | RET | Industry-adj. RET | Industry-adj. RET |
|---|---|---|---|---|
| DOT | -0.35*** | -0.29*** | -0.35*** | -0.29*** |
| | (-4.36) | (-3.92) | (-4.53) | (-3.94) |
| BETA | 0.14* | 0.14** | 0.15*** | 0.15*** |
| | (1.89) | (2.04) | (2.77) | (3.19) |
| SIZE | -0.18*** | -0.25*** | -0.16*** | -0.21*** |
| | (-3.57) | (-4.75) | (-3.50) | (-4.73) |
| BM | 0.07* | 0.06* | 0.07** | 0.07** |
| | (1.86) | (1.74) | (2.48) | (2.39) |
| GP | 0.13*** | 0.10*** | 0.10*** | 0.08*** |
| | (3.76) | (3.05) | (3.41) | (2.61) |
| AG | -0.22*** | -0.21*** | -0.20*** | -0.19*** |
| | (-6.72) | (-6.73) | (-7.48) | (-7.42) |
| ILL | | -0.12*** | | -0.11*** |
| | | (-4.03) | | (-3.82) |
| TURN | | -0.15*** | | -0.15*** |
| | | (-4.13) | | (-4.23) |
| MOM | | 0.35*** | | 0.31*** |
| | | (6.27) | | (6.60) |
| Const | 0.76*** | 0.76*** | 0.10 | 0.10 |
| | (3.07) | (3.06) | (1.01) | (1.01) |
| No. Obs. | 3315 | 3142 | 3315 | 3142 |
| Adj. $R^2$ | 5.37% | 6.61% | 3.79% | 4.72% |

**Table 6** Tail Risk (TR) and DOT

Panel A shows the equal-weighted average values of TR for stocks in each DOT decile portfolio, where TR is estimated tail risk sensitivity from monthly returns and tail risk for 10 years ending month $t-1$ with at least 36 months of returns following Kelly and Jiang (2014). Panel B presents the results of bivariate dependent-sort value-weighted portfolio analysis. Each month $t$, stocks are sorted into quintile portfolios based on TR. Within each TR portfolio, stocks are sorted into decile portfolios based on DOT. Alphas represent the intercept from a time-series regression of Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| Panel A: Average TR in DOT Decile Portfolio | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | | |
| TR | 0.14 | 0.13 | 0.13 | 0.13 | 0.13 | 0.12 | 0.11 | 0.08 | 0.04 | -0.09 | -0.24*** | (-5.01) | | |
| Panel B: Bivariate Portfolio Sort on TR | | | | | | | | | | | | | | |
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | FF5 | t-stat |
| TR Low | 0.62 | 0.54 | 0.66 | 0.81 | 0.45 | 0.41 | 0.77 | 0.72 | 0.08 | -0.52 | -1.06** | (-2.23) | -1.04*** | (-3.24) |
| TR 2 | 0.66 | 0.55 | 0.70 | 0.49 | 0.46 | 0.61 | 0.55 | 0.64 | 0.82 | -0.03 | -0.72** | (-2.06) | -0.72*** | (-3.03) |
| TR 3 | 0.71 | 0.70 | 0.68 | 0.83 | 0.80 | 0.62 | 0.69 | 0.80 | 0.50 | 0.07 | -0.71** | (-1.98) | -0.57** | (-2.44) |
| TR 4 | 0.84 | 0.75 | 0.92 | 0.83 | 0.91 | 1.00 | 0.72 | 0.98 | 0.40 | 0.05 | -0.77** | (-2.30) | -0.93*** | (-3.85) |
| TR High | 0.92 | 1.01 | 1.05 | 1.01 | 0.83 | 0.83 | 0.47 | 0.32 | 0.07 | -0.66 | -0.97** | (-2.21) | -0.87*** | (-2.84) |

**Table 7** Analyst Forecast Dispersion (AFD) and DOT

Panel A shows the equal-weighted average values of AFD for stocks in each DOT decile portfolio, where AFD is standard deviation of analyst earnings forecasts divided by the firm's stock price following Garfinkel (2009). Panel B presents the results of bivariate dependent-sort value-weighted portfolio analysis. Each month $t$, stocks are sorted into quintile portfolios based on AFD. Within each AFD portfolio, stocks are sorted into decile portfolios based on DOT. Alphas represent the intercept from a time-series regression of Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from July 1982 to December 2021.

| Panel A: Average AFD in DOT Decile Portfolio | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | | |
| AFD | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.04 | 0.04*** | (14.85) | | |
| Panel B: Bivariate Portfolio Sort on AFD | | | | | | | | | | | | | | |
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | FF5 | t-stat |
| AFD Low | 0.87 | 0.86 | 0.99 | 1.01 | 0.72 | 0.80 | 0.61 | 0.74 | 0.76 | 0.77 | -0.10 | (-0.23) | 0.46 | (1.36) |
| AFD 2 | 0.80 | 0.87 | 0.83 | 0.83 | 1.22 | 0.97 | 1.00 | 1.00 | 1.34 | 0.78 | -0.02 | (-0.05) | 0.25 | (0.96) |
| AFD 3 | 0.79 | 0.94 | 0.63 | 1.01 | 0.75 | 0.83 | 0.88 | 0.50 | 0.79 | 0.73 | -0.06 | (-0.13) | 0.14 | (0.47) |
| AFD 4 | 0.90 | 0.90 | 0.82 | 0.82 | 0.93 | 0.94 | 0.60 | 0.89 | 0.52 | -0.03 | -0.93** | (-2.12) | -0.59** | (-2.17) |
| AFD High | 0.64 | 0.70 | 1.02 | 0.95 | 0.53 | 0.86 | 0.80 | 0.56 | 0.11 | -0.37 | -1.01 | (-1.62) | -1.11*** | (-2.64) |

**Table 8** Machine Forecast Disagreement (MFD) and DOT

Panel A shows the equal-weighted average values of MFD for stocks in each DOT decile portfolio, where MFD is the machine forecast disagreement variable following Bali et al. (2023). Panel B presents the results of bivariate dependent-sort value-weighted portfolio analysis. Each month $t$, stocks are sorted into quintile portfolios based on MFD. Within each MFD portfolio, stocks are sorted into decile portfolios based on DOT. Alphas represent the intercept from a time-series regression of Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| Panel A: Average MFD in DOT Decile Portfolio | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | | |
| MFD | 0.84 | 0.92 | 0.99 | 1.07 | 1.13 | 1.20 | 1.29 | 1.41 | 1.64 | 2.43 | 1.59*** | (4.40) | | |
| Panel B: Bivariate Portfolio Sort on MFD | | | | | | | | | | | | | | |
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | FF5 | t-stat |
| MFD Low | 0.67 | 0.66 | 0.64 | 0.66 | 0.71 | 0.72 | 0.59 | 0.88 | 0.76 | 0.74 | 0.08 | (0.29) | -0.05 | (-0.26) |
| MFD 2 | 0.80 | 0.73 | 0.71 | 0.65 | 0.77 | 0.75 | 0.75 | 0.87 | 0.69 | 0.36 | -0.44 | (-1.51) | -0.38* | (-1.90) |
| MFD 3 | 0.61 | 0.72 | 0.78 | 0.84 | 0.77 | 0.95 | 0.38 | 0.62 | 0.46 | -0.13 | -0.74** | (-2.18) | -0.63*** | (-2.73) |
| MFD 4 | 0.60 | 0.62 | 0.62 | 0.85 | 0.58 | 0.51 | 0.71 | 0.31 | 0.16 | -0.32 | -0.92** | (-2.50) | -0.85*** | (-3.09) |
| MFD High | 0.79 | 0.40 | 0.51 | 0.60 | 0.07 | 0.13 | 0.15 | -0.22 | -0.29 | -0.89 | -1.68*** | (-4.19) | -1.57*** | (-4.71) |

**Table 9** Fama-MacBeth Regressions - Controlling for MFD

This table presents the results of Fama and MacBeth (1973) regression analysis of the relation between DOT and future stock returns, as well as MFD and future stock returns. MFD is the machine forecast disagreement variable following Bali et al. (2023). Each column in the table presents results for a different cross-sectional regression specification. The dependent variable in all specifications is the future stock return (RET). The independent variables are winsorized at the 1% level and standardized on a monthly basis. DOT and the control variables in month $t$ are matched to future stock returns in month $t+1$. The control variables are described in Section 2.2. The table presents average slope and intercept coefficients along with $t$-statistics (in parentheses), adjusted following Newey and West (1987) using six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| | RET | RET | RET | RET | RET | RET |
|---|---|---|---|---|---|---|
| DOT | -0.35*** | | -0.38*** | -0.29*** | | -0.32*** |
| | (-4.36) | | (-4.70) | (-3.92) | | (-4.33) |
| MFD | | -0.13** | 0.04 | | -0.10* | 0.04 |
| | | (-2.28) | (0.97) | | (-1.82) | (0.89) |
| BETA | 0.14* | 0.06 | 0.14* | 0.14** | 0.09 | 0.14** |
| | (1.89) | (0.65) | (1.87) | (2.04) | (1.14) | (2.06) |
| SIZE | -0.18*** | -0.07 | -0.18*** | -0.25*** | -0.16*** | -0.24*** |
| | (-3.57) | (-1.20) | (-3.52) | (-4.75) | (-2.67) | (-4.67) |
| BM | 0.07* | 0.12*** | 0.07* | 0.06* | 0.10*** | 0.06* |
| | (1.86) | (2.99) | (1.94) | (1.74) | (2.59) | (1.74) |
| GP | 0.13*** | 0.17*** | 0.13*** | 0.10*** | 0.14*** | 0.10*** |
| | (3.76) | (4.74) | (3.61) | (3.05) | (3.95) | (2.88) |
| AG | -0.22*** | -0.26*** | -0.22*** | -0.21*** | -0.24*** | -0.20*** |
| | (-6.72) | (-8.24) | (-6.54) | (-6.73) | (-8.15) | (-6.55) |
| ILL | | | | -0.12*** | -0.15*** | -0.12*** |
| | | | | (-4.03) | (-4.87) | (-3.95) |
| TURN | | | | -0.15*** | -0.20*** | -0.14*** |
| | | | | (-4.13) | (-4.67) | (-3.72) |
| MOM | | | | 0.35*** | 0.36*** | 0.35*** |
| | | | | (6.27) | (6.27) | (6.27) |
| Const | 0.76*** | 0.76*** | 0.76*** | 0.76*** | 0.76*** | 0.76*** |
| | (3.07) | (3.07) | (3.07) | (3.06) | (3.06) | (3.06) |
| No. Obs. | 3315 | 3315 | 3315 | 3142 | 3142 | 3142 |
| Adj. $R^2$ | 5.37% | 5.09% | 5.53% | 6.61% | 6.43% | 6.74% |

**Table 10** Mispricing (MISP) and DOT

Panel A shows the equal-weighted average values of MISP for stocks in each DOT decile portfolio, where MISP is a mispricing measure determined by combining 11 return anomalies following Stambaugh et al. (2015). Panel B presents the results of bivariate dependent-sort value-weighted portfolio analysis. Each month $t$, stocks are sorted into quintile portfolios based on MISP. Within each MISP portfolio, stocks are sorted into decile portfolios based on DOT. Alphas represent the intercept from a time-series regression of Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to January 2014.

Panel A: Average MISP in DOT Decile Portfolio

| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MISP | 46.16 | 45.70 | 46.45 | 47.36 | 48.48 | 49.60 | 51.13 | 52.89 | 55.43 | 60.20 | 14.04*** | (22.58) |

Panel B: Bivariate Portfolio Sort on MISP

| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | FF5 | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MISP Low | 0.65 | 0.61 | 0.81 | 0.81 | 0.89 | 1.02 | 0.98 | 1.05 | 1.35 | 1.12 | 0.47 | (1.48) | 0.71*** | (3.20) |
| MISP 2 | 0.60 | 0.72 | 0.65 | 0.59 | 0.80 | 0.83 | 1.01 | 0.63 | 0.60 | 0.74 | 0.13 | (0.40) | 0.49* | (1.66) |
| MISP 3 | 0.55 | 0.64 | 0.51 | 0.58 | 0.85 | 0.49 | 0.59 | 0.52 | 0.74 | 0.60 | 0.05 | (0.15) | 0.27 | (0.98) |
| MISP 4 | 0.51 | 0.42 | 0.37 | 0.47 | 0.49 | 0.37 | 0.50 | 0.46 | 0.41 | 0.22 | -0.29 | (-0.65) | -0.08 | (-0.28) |
| MISP High | 0.30 | 0.16 | 0.22 | 0.15 | 0.06 | -0.08 | 0.08 | -0.69 | -0.61 | -1.39 | -1.69*** | (-3.81) | -1.31*** | (-4.62) |

**Table 11** Fama-MacBeth Regressions - Mispricing Channel

This table presents the results of Fama and MacBeth (1973) regression analysis of the relation between DOT and future stock returns, after controlling for MISP. MISP is a mispricing measure determined by combining 11 return anomalies following Stambaugh et al. (2015). The analysis is conducted on the full sample, with a subsample analysis following tail events. The tail event, as defined in Section 3.2, refers to a stock's excess return in month $t-1$ falling within $(-\infty, -25\%)$. Only stocks that experienced a tail event are included in the subsample analysis. Each column in the table presents results for a different cross-sectional regression specification. The dependent variable in all specifications is the future stock return (RET). The independent variables are winsorized at the 1% level and standardized on a monthly basis. DOT and the control variables in month $t$ are matched to future stock returns in month $t+1$. The control variables are described in Section 2.2. The table presents average slope and intercept coefficients along with $t$-statistics (in parentheses), adjusted following Newey and West (1987) using six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to January 2014.

| | Full Sample | | | After Tail Events | | |
|---|---|---|---|---|---|---|
| | RET | RET | RET | RET | RET | RET |
| DOT | -0.26*** | | -0.12** | -1.29*** | | -1.15*** |
| | (-4.62) | | (-2.30) | (-3.44) | | (-3.23) |
| MISP | | -0.27*** | -0.27*** | | -1.54*** | -1.23*** |
| | | (-8.60) | (-8.53) | | (-4.53) | (-3.42) |
| DOT*MISP | | | -0.12*** | | | 0.14 |
| | | | (-5.64) | | | (0.50) |
| BETA | 0.11 | 0.05 | 0.10 | 0.07 | -0.10 | 0.10 |
| | (1.55) | (0.62) | (1.38) | (0.21) | (-0.30) | (0.32) |
| SIZE | -0.24*** | -0.21*** | -0.25*** | -0.53* | -0.47 | -0.66** |
| | (-4.99) | (-3.91) | (-5.12) | (-1.76) | (-1.47) | (-2.16) |
| BM | 0.10*** | 0.13*** | 0.10** | -0.39* | -0.26 | -0.38* |
| | (2.75) | (3.14) | (2.56) | (-1.75) | (-1.25) | (-1.82) |
| GP | 0.11*** | 0.04 | 0.02 | -0.31 | -0.55** | -0.64** |
| | (3.11) | (1.01) | (0.39) | (-1.26) | (-2.22) | (-2.37) |
| AG | -0.19*** | -0.09*** | -0.03 | -0.38 | -0.03 | 0.12 |
| | (-6.78) | (-3.15) | (-0.88) | (-1.40) | (-0.09) | (0.33) |
| ILL | -0.20*** | -0.24*** | -0.22*** | -1.13 | -1.06 | -1.00 |
| | (-5.78) | (-6.94) | (-6.26) | (-1.14) | (-1.14) | (-1.08) |
| TURN | -0.17*** | -0.22*** | -0.18*** | 0.28 | -0.12 | 0.32 |
| | (-4.85) | (-5.41) | (-5.20) | (0.88) | (-0.43) | (1.01) |
| MOM | 0.39*** | 0.29*** | 0.29*** | 1.14*** | 0.49* | 0.71* |
| | (6.68) | (4.96) | (5.03) | (3.34) | (1.67) | (1.92) |
| Const | 0.71*** | 0.71*** | 0.75*** | -0.10 | -0.09 | -0.14 |
| | (2.89) | (2.90) | (3.06) | (-0.10) | (-0.09) | (-0.13) |
| No. Obs. | 2554 | 2554 | 2554 | 270 | 270 | 270 |
| Adj. $R^2$ | 7.17% | 6.99% | 7.36% | 6.87% | 7.15% | 7.75% |

**Table 12** Univariate Portfolio Analysis on DOT - Risk Sharing Channel

This table presents the results of univariate portfolio analysis of the relation between DOT and future stock returns. The analysis is conducted on the full sample, with a subsample analysis following tail events. Panel A presents the results of the former, while Panel B presents those of the latter. The tail event, as defined in Section 3.2, refers to a stock's excess return in month $t-1$ falling within $(-\infty, -25\%)$. Only stocks that experienced a tail event are included in subsample analysis. Each month $t$, stocks are sorted into decile portfolios based on DOT which is constructed using data available up to month $t-1$. The Low (High) portfolio contains stocks in the bottom (top) decile. The H-L portfolio takes a long position in the top decile and a short position in the bottom decile, whereas the R-L portfolio goes long in deciles 2-10 and shorts the bottom decile. RET is the return in excess of the risk-free rate. Alphas represent the intercept from a time-series regression of monthly excess returns on the factors of common asset pricing models: the CAPM, Fama and French (1993) three-factor model and Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| Panel A: Full Sample | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 5 | 9 | High | Rest | H-L | R-L |
| RET | 0.68*** | 0.65*** | 0.74*** | 0.11 | -0.38 | 0.60*** | -1.06*** | -0.08 |
| t-stat | (4.77) | (3.61) | (3.09) | (0.30) | (-0.91) | (2.76) | (-2.92) | (-0.64) |
| CAPM | 0.24*** | 0.10 | 0.02 | -0.85*** | -1.42*** | -0.09** | -1.66*** | -0.33*** |
| t-stat | (3.21) | (1.54) | (0.27) | (-4.34) | (-5.76) | (-2.47) | (-5.54) | (-3.41) |
| FF3 | 0.20*** | 0.06 | 0.01 | -0.79*** | -1.40*** | -0.09*** | -1.60*** | -0.29*** |
| t-stat | (3.25) | (1.03) | (0.11) | (-5.36) | (-6.56) | (-3.11) | (-6.42) | (-3.70) |
| FF5 | -0.01 | -0.11** | 0.06 | -0.38*** | -0.87*** | -0.05* | -0.86*** | -0.04 |
| t-stat | (-0.20) | (-2.06) | (0.74) | (-2.94) | (-4.34) | (-1.66) | (-4.15) | (-0.65) |
| Sharpe | 0.63 | 0.50 | 0.44 | 0.04 | -0.13 | 0.39 | -0.44 | -0.09 |
| Panel B: After Tail Events | | | | | | | | |
| | Low | 2 | 5 | 9 | High | Rest | H-L | R-L |
| RET | 1.67** | 0.80 | 0.78 | 0.32 | -0.79 | 0.18 | -2.46*** | -1.49** |
| t-stat | (2.43) | (1.08) | (0.90) | (0.30) | (-0.87) | (0.25) | (-2.93) | (-2.29) |
| CAPM | 0.95* | -0.14 | -0.25 | -0.83 | -1.62** | -0.84* | -2.57*** | -1.80*** |
| t-stat | (1.65) | (-0.25) | (-0.35) | (-0.98) | (-2.14) | (-1.67) | (-3.16) | (-2.87) |
| FF3 | 0.93* | 0.03 | 0.20 | -0.44 | -1.17 | -0.51 | -2.10** | -1.44** |
| t-stat | (1.75) | (0.06) | (0.28) | (-0.51) | (-1.63) | (-1.12) | (-2.48) | (-2.36) |
| FF5 | 0.93* | 0.04 | 0.50 | 0.00 | -0.66 | -0.10 | -1.59* | -1.03 |
| t-stat | (1.84) | (0.09) | (0.70) | (0.00) | (-0.84) | (-0.22) | (-1.65) | (-1.63) |
| Sharpe | 0.50 | 0.20 | 0.19 | 0.07 | -0.16 | 0.05 | -0.56 | -0.50 |

**Table 13** Fama-MacBeth Regressions - Risk Sharing Channel

This table presents the results of Fama and MacBeth (1973) regression analysis of the relation between DOT and future stock returns. The analysis is conducted on the full sample, with a subsample analysis following tail events. The tail event, as defined in Section 3.2, refers to a stock's excess return in month $t-1$ falling within $(-\infty, -25\%)$. Only stocks that experienced a tail event are included in the subsample analysis. I(DOT) is an indicator that takes the value of 1 when DOT is greater than the 10th percentile, and 0 otherwise. Each column in the table presents results for a different cross-sectional regression specification. The independent variables are winsorized at the 1% level and standardized on a monthly basis. DOT and the control variables in month $t$ are matched to future stock returns in month $t+1$. The control variables are described in Section 2.2. The table presents average slope and intercept coefficients along with $t$-statistics (in parentheses), adjusted following Newey and West (1987) using six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| | Full Sample | | After Tail Events | |
|---|---|---|---|---|
| | RET | RET | RET | RET |
| DOT | -0.30*** | | -0.78*** | |
| | (-3.89) | | (-2.97) | |
| I(DOT) | | 0.10 | | -0.89** |
| | | (1.38) | | (-2.14) |
| BETA | 0.15** | 0.05 | 0.71** | 0.57* |
| | (2.11) | (0.57) | (2.29) | (1.85) |
| SIZE | -0.22*** | -0.09 | -0.53* | -0.29 |
| | (-4.49) | (-1.43) | (-1.92) | (-1.04) |
| BM | 0.05 | 0.10*** | -0.24 | -0.19 |
| | (1.57) | (2.73) | (-0.91) | (-0.67) |
| GP | 0.11*** | 0.15*** | -0.05 | 0.09 |
| | (3.20) | (4.20) | (-0.22) | (0.48) |
| AG | -0.21*** | -0.26*** | -0.35* | -0.52*** |
| | (-6.76) | (-9.74) | (-1.65) | (-2.74) |
| ILL | -0.07*** | -0.11*** | 0.60* | 0.58* |
| | (-2.59) | (-3.92) | (1.95) | (1.90) |
| TURN | -0.16*** | -0.24*** | -0.47* | -0.69*** |
| | (-4.85) | (-5.54) | (-1.92) | (-3.07) |
| MOM | 0.36*** | 0.37*** | 0.59** | 0.63** |
| | (6.56) | (6.45) | (2.03) | (2.31) |
| Const | 0.74*** | 0.65*** | 2.43** | 3.23*** |
| | (3.02) | (2.94) | (2.56) | (3.84) |
| No. Obs. | 3137 | 3137 | 281 | 281 |
| Adj. $R^2$ | 6.53% | 6.11% | 5.63% | 5.10% |

## Internet Appendix

# Disagreement on Tail

*This Internet Appendix reports the results for robustness tests:*

- **Table IA 1:** Univariate Portfolio Analysis on DOT - Different Model Settings
- **Table IA 2:** Univariate Portfolio Analysis on DOT - Random Selection
- **Table IA 3:** Fama-MacBeth Regressions - Random Selection
- **Table IA 4:** Univariate Portfolio Analysis on DOT - Different Thresholds of Tail Events
- **Table IA 5:** Fama-MacBeth Regressions - Different Thresholds of Tail Events
- **Table IA 6:** Univariate Portfolio Analysis on DOT - Dynamic Threshold of Tail Events
- **Table IA 7:** Fama-MacBeth Regressions - Dynamic Threshold of Tail Events
- **Table IA 8:** Institutional Ownership (IOR) and DOT
- **Table IA 9:** ILLiquidity (ILL) and DOT

**Table IA 1** Univariate Portfolio Analysis on DOT - Different Model Settings

This table presents the results of univariate portfolio analysis of the relation between DOT and future stock returns across different model settings. The hyper-parameters that vary here include the number of hidden layers and the number of neurons in each hidden layer. The number of hidden layers ranges from 1 to 5, with neurons per hidden layer ranging from 8 to 128, following the geometric pyramid rule suggested by Masters (1993). "Neurons First" refers to the number of neurons in the first hidden layer, while "Neurons Last" refers to the number of neurons in the last hidden layer. Each month $t$, stocks are sorted into decile portfolios based on DOT which is constructed using data available up to month $t-1$. Panel A shows the results for equal-weighted portfolios, while Panel B shows the results for value-weighted portfolios. Alphas represent the intercept from a time-series regression of monthly excess returns on Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| Panel A: Equal-Weighted Portfolios | | | | | | | |
|---|---|---|---|---|---|---|---|
| Model | Hidden Layers | Neurons First | Neurons Last | H-L | t-stat | FF5 | t-stat |
| NN | 1 | 32 | 32 | -1.07*** | (-2.84) | -0.96*** | (-4.61) |
| NN | 1 | 64 | 64 | -1.07*** | (-2.79) | -0.94*** | (-4.43) |
| NN | 1 | 128 | 128 | -1.05*** | (-2.69) | -0.92*** | (-4.44) |
| NN | 2 | 32 | 16 | -1.04*** | (-2.75) | -0.93*** | (-4.40) |
| NN | 2 | 64 | 32 | -1.10*** | (-2.91) | -0.99*** | (-4.80) |
| NN | 2 | 128 | 64 | -1.11*** | (-2.90) | -0.99*** | (-4.84) |
| NN | 3 | 64 | 16 | -1.03*** | (-2.72) | -0.95*** | (-4.66) |
| NN | 3 | 128 | 32 | -1.02*** | (-2.66) | -0.88*** | (-4.22) |
| NN | 4 | 64 | 8 | -1.01*** | (-2.71) | -0.85*** | (-3.86) |
| NN | 4 | 128 | 16 | -1.00*** | (-2.64) | -0.86*** | (-3.97) |
| NN | 5 | 128 | 8 | -0.81** | (-2.22) | -0.65*** | (-2.81) |
| Panel B: Value-Weighted Portfolios | | | | | | | |
| Model | Hidden Layers | Neurons First | Neurons Last | H-L | t-stat | FF5 | t-stat |
| NN | 1 | 32 | 32 | -1.14*** | (-3.16) | -0.94*** | (-4.74) |
| NN | 1 | 64 | 64 | -1.09*** | (-2.89) | -0.88*** | (-4.33) |
| NN | 1 | 128 | 128 | -1.07*** | (-2.79) | -0.95*** | (-4.37) |
| NN | 2 | 32 | 16 | -1.04*** | (-2.88) | -0.87*** | (-3.94) |
| NN | 2 | 64 | 32 | -1.05*** | (-2.88) | -0.91*** | (-4.21) |
| NN | 2 | 128 | 64 | -1.20*** | (-3.30) | -1.04*** | (-5.57) |
| NN | 3 | 64 | 16 | -0.99*** | (-2.80) | -0.86*** | (-4.46) |
| NN | 3 | 128 | 32 | -1.03*** | (-2.83) | -0.83*** | (-4.39) |
| NN | 4 | 64 | 8 | -1.04*** | (-3.03) | -0.78*** | (-3.76) |
| NN | 4 | 128 | 16 | -1.09*** | (-2.97) | -0.86*** | (-4.38) |
| NN | 5 | 128 | 8 | -0.86** | (-2.53) | -0.65*** | (-2.89) |

**Table IA 2** Univariate Portfolio Analysis on DOT - Random Selection

This table presents the results of univariate portfolio analysis of the relation between DOT and future stock returns. It is important to note that the method for calculating DOT has been changed from "random weights" to "random selection". Specifically, 47 out of 94 firm characteristics are randomly selected for each investor as her own information set $X_n$, with all other settings remaining unchanged. Each month $t$, stocks are sorted into decile portfolios based on DOT which is constructed using data available up to month $t-1$. Panel A shows the results for equal-weighted portfolios, while Panel B shows the results for value-weighted portfolios. RET is the return in excess of the risk-free rate. Alphas represent the intercept from a time-series regression of monthly excess returns on the factors of common asset pricing models: the CAPM, Fama and French (1993) three-factor model and Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| Panel A: Equal-Weighted Portfolios | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L |
| RET | 0.82*** | 0.91*** | 0.94*** | 0.97*** | 1.00*** | 0.87*** | 0.84*** | 0.59* | 0.27 | -0.21 | -1.03*** |
| t-stat | (5.28) | (4.96) | (4.73) | (4.44) | (4.13) | (3.23) | (2.74) | (1.71) | (0.70) | (-0.49) | (-2.86) |
| CAPM | 0.40*** | 0.41*** | 0.40*** | 0.38*** | 0.34*** | 0.15 | 0.05 | -0.26 | -0.65*** | -1.16*** | -1.56*** |
| t-stat | (3.87) | (3.75) | (3.50) | (3.17) | (2.77) | (1.15) | (0.34) | (-1.39) | (-3.01) | (-4.44) | (-5.31) |
| FF3 | 0.27*** | 0.25*** | 0.23*** | 0.21*** | 0.18*** | 0.03 | -0.06 | -0.37*** | -0.75*** | -1.29*** | -1.57*** |
| t-stat | (3.54) | (3.62) | (3.65) | (3.36) | (3.26) | (0.54) | (-0.86) | (-4.18) | (-6.06) | (-7.34) | (-7.16) |
| FF5 | 0.13** | 0.11* | 0.10* | 0.12* | 0.14** | 0.08 | 0.10 | -0.11 | -0.39*** | -0.78*** | -0.92*** |
| t-stat | (2.06) | (1.83) | (1.77) | (1.95) | (2.57) | (1.41) | (1.41) | (-1.12) | (-2.88) | (-4.39) | (-4.80) |
| Sharpe | 0.78 | 0.74 | 0.71 | 0.67 | 0.62 | 0.49 | 0.42 | 0.26 | 0.11 | -0.07 | -0.43 |
| Panel B: Value-Weighted Portfolios | | | | | | | | | | | |
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L |
| RET | 0.67*** | 0.68*** | 0.69*** | 0.67*** | 0.70*** | 0.68** | 0.60* | 0.36 | 0.10 | -0.47 | -1.13*** |
| t-stat | (4.53) | (3.82) | (3.46) | (2.97) | (2.92) | (2.53) | (1.92) | (1.09) | (0.28) | (-1.10) | (-3.17) |
| CAPM | 0.22*** | 0.11* | 0.06 | -0.03 | -0.05 | -0.13 | -0.29** | -0.55*** | -0.88*** | -1.49*** | -1.71*** |
| t-stat | (3.13) | (1.79) | (0.87) | (-0.49) | (-0.60) | (-1.29) | (-2.16) | (-3.42) | (-4.54) | (-6.24) | (-5.89) |
| FF3 | 0.18*** | 0.08 | 0.04 | -0.06 | -0.07 | -0.10 | -0.26*** | -0.52*** | -0.86*** | -1.50*** | -1.68*** |
| t-stat | (3.22) | (1.42) | (0.60) | (-0.90) | (-0.89) | (-1.32) | (-2.61) | (-4.81) | (-5.66) | (-7.47) | (-7.14) |
| FF5 | -0.01 | -0.06 | -0.05 | -0.05 | -0.00 | 0.05 | -0.05 | -0.24** | -0.45*** | -0.97*** | -0.96*** |
| t-stat | (-0.18) | (-1.22) | (-0.69) | (-0.80) | (-0.04) | (0.74) | (-0.57) | (-2.38) | (-3.65) | (-5.03) | (-4.71) |
| Sharpe | 0.62 | 0.52 | 0.48 | 0.42 | 0.40 | 0.36 | 0.28 | 0.16 | 0.04 | -0.17 | -0.49 |

**Table IA 3** Fama-MacBeth Regressions - Random Selection

This table presents the results of Fama and MacBeth (1973) regression analysis of the relation between DOT and future stock returns. It is important to note that the method for calculating DOT has been changed from "random weights" to "random selection". Specifically, 47 out of 94 firm characteristics are randomly selected for each investor as her own information set $X_n$, with all other settings remaining unchanged. Each column in the table presents results for a different cross-sectional regression specification. The dependent variable in columns (1) and (2) is the future stock return (RET), while in columns (3) and (4), the dependent variable is the future stock return over its value-weighted industry peers' return (Industry-adj. RET). The independent variables are winsorized at the 1% level and standardized on a monthly basis. DOT and the control variables in month $t$ are matched to future stock returns in month $t+1$. The control variables are described in Section 2.2. The table presents average slope and intercept coefficients along with $t$-statistics (in parentheses), adjusted following Newey and West (1987) using six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| | RET | RET | Industry-adj. RET | Industry-adj. RET |
|---|---|---|---|---|
| DOT | -0.41*** | -0.34*** | -0.40*** | -0.34*** |
| | (-5.70) | (-5.30) | (-5.85) | (-5.29) |
| BETA | 0.17** | 0.17** | 0.18*** | 0.17*** |
| | (2.24) | (2.30) | (3.14) | (3.46) |
| SIZE | -0.22*** | -0.27*** | -0.20*** | -0.24*** |
| | (-4.26) | (-5.10) | (-4.22) | (-5.07) |
| BM | 0.07* | 0.06* | 0.07** | 0.07** |
| | (1.79) | (1.76) | (2.40) | (2.42) |
| GP | 0.13*** | 0.11*** | 0.10*** | 0.08*** |
| | (3.83) | (3.12) | (3.43) | (2.65) |
| AG | -0.22*** | -0.21*** | -0.20*** | -0.19*** |
| | (-7.01) | (-7.12) | (-7.83) | (-7.91) |
| ILL | | -0.11*** | | -0.10*** |
| | | (-3.63) | | (-3.41) |
| TURN | | -0.14*** | | -0.14*** |
| | | (-3.65) | | (-3.86) |
| MOM | | 0.34*** | | 0.30*** |
| | | (6.01) | | (6.27) |
| Const | 0.76*** | 0.76*** | 0.10 | 0.10 |
| | (3.07) | (3.06) | (1.01) | (1.01) |
| No. Obs. | 3315 | 3142 | 3315 | 3142 |
| Adj. $R^2$ | 5.31% | 6.56% | 3.71% | 4.65% |

**Table IA 4** Univariate Portfolio Analysis on DOT - Different Thresholds of Tail Events

This table presents the results of univariate portfolio analysis of the relation between DOT and future stock returns. It is important to note that the threshold of the tail events has changed from the original 25% to 20%, 30%, 40%, and 50%, respectively. Consequently, the definition of DOT has also changed. Each month $t$, stocks are sorted into decile portfolios based on DOT which is constructed using data available up to month $t-1$. Panel A shows the results for equal-weighted portfolios, while Panel B shows the results for value-weighted portfolios. Alphas represent the intercept from a time-series regression of monthly excess returns on Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| Panel A: Equal-Weighted Portfolios | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | FF5 | t-stat |
| 20% | 0.79 | 0.86 | 0.92 | 0.95 | 0.94 | 0.91 | 0.79 | 0.61 | 0.34 | -0.12 | -0.91** | (-2.52) | -0.84*** | (-4.08) |
| 30% | 0.83 | 0.84 | 0.90 | 0.92 | 0.92 | 0.88 | 0.81 | 0.58 | 0.40 | -0.09 | -0.92** | (-2.40) | -0.80*** | (-3.83) |
| 40% | 0.83 | 0.85 | 0.88 | 0.91 | 0.90 | 0.89 | 0.80 | 0.57 | 0.35 | 0.01 | -0.82** | (-2.17) | -0.65*** | (-3.06) |
| 50% | 0.84 | 0.87 | 0.87 | 0.91 | 0.91 | 0.85 | 0.75 | 0.56 | 0.37 | 0.08 | -0.76** | (-2.07) | -0.53** | (-2.44) |
| Panel B: Value-Weighted Portfolios | | | | | | | | | | | | | | |
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | FF5 | t-stat |
| 20% | 0.68 | 0.73 | 0.65 | 0.70 | 0.67 | 0.71 | 0.51 | 0.43 | 0.16 | -0.18 | -0.86*** | (-2.65) | -0.69*** | (-3.65) |
| 30% | 0.65 | 0.64 | 0.71 | 0.71 | 0.72 | 0.67 | 0.54 | 0.50 | 0.08 | -0.28 | -0.93** | (-2.47) | -0.73*** | (-3.18) |
| 40% | 0.64 | 0.61 | 0.71 | 0.74 | 0.72 | 0.68 | 0.67 | 0.32 | 0.23 | -0.19 | -0.83** | (-2.29) | -0.61*** | (-2.73) |
| 50% | 0.67 | 0.56 | 0.62 | 0.77 | 0.72 | 0.67 | 0.59 | 0.43 | 0.24 | -0.04 | -0.72** | (-2.12) | -0.46** | (-2.11) |

**Table IA 5** Fama-MacBeth Regressions - Different Thresholds of Tail Events

This table presents the results of Fama and MacBeth (1973) regression analysis of the relation between DOT and future stock returns. It is important to note that the threshold of the tail events has changed from the original 25% to 20%, 30%, 40%, and 50%, respectively. Consequently, the definition of DOT has also changed. Each column in the table presents results for a different cross-sectional regression specification. The dependent variable in all specifications is the future stock return (RET). The independent variables are winsorized at the 1% level and standardized on a monthly basis. DOT and the control variables in month $t$ are matched to future stock returns in month $t+1$. The control variables are described in Section 2.2. The table presents average slope and intercept coefficients along with $t$-statistics (in parentheses), adjusted following Newey and West (1987) using six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| | 20% RET | 30% RET | 40% RET | 50% RET |
|---|---|---|---|---|
| DOT | -0.31*** | -0.26*** | -0.21*** | -0.16** |
| | (-4.47) | (-3.45) | (-2.84) | (-2.28) |
| BETA | 0.15** | 0.13* | 0.11 | 0.09 |
| | (2.12) | (1.91) | (1.55) | (1.22) |
| SIZE | -0.25*** | -0.23*** | -0.21*** | -0.18*** |
| | (-4.71) | (-4.59) | (-4.03) | (-3.42) |
| BM | 0.06* | 0.06* | 0.07** | 0.08** |
| | (1.75) | (1.81) | (2.05) | (2.26) |
| GP | 0.11*** | 0.11*** | 0.11*** | 0.12*** |
| | (3.19) | (3.11) | (3.21) | (3.42) |
| AG | -0.20*** | -0.21*** | -0.23*** | -0.24*** |
| | (-6.46) | (-7.07) | (-7.81) | (-8.55) |
| ILL | -0.12*** | -0.12*** | -0.13*** | -0.14*** |
| | (-4.06) | (-4.16) | (-4.42) | (-4.71) |
| TURN | -0.14*** | -0.16*** | -0.18*** | -0.20*** |
| | (-3.71) | (-4.59) | (-5.22) | (-5.66) |
| MOM | 0.35*** | 0.35*** | 0.34*** | 0.34*** |
| | (6.28) | (6.26) | (6.19) | (6.11) |
| Const | 0.76*** | 0.76*** | 0.76*** | 0.76*** |
| | (3.06) | (3.06) | (3.06) | (3.06) |
| No. Obs. | 3142 | 3142 | 3142 | 3142 |
| Adj. $R^2$ | 6.58% | 6.61% | 6.60% | 6.56% |

**Table IA 6** Univariate Portfolio Analysis on DOT - Dynamic Threshold of Tail Events

This table presents the results of univariate portfolio analysis of the relation between DOT and future stock returns. In this alternative approach, rather than using fixed thresholds, the threshold for defining tail events is dynamically set as the fifth percentile of the cross-sectional returns each period. Consequently, the definition of DOT has also changed. Each month $t$, stocks are sorted into decile portfolios based on DOT which is constructed using data available up to month $t-1$. Panel A shows the results for equal-weighted portfolios, while Panel B shows the results for value-weighted portfolios. RET is the return in excess of the risk-free rate. Alphas represent the intercept from a time-series regression of monthly excess returns on the factors of common asset pricing models: the CAPM, Fama and French (1993) three-factor model and Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| Panel A: Equal-Weighted Portfolios | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L |
| RET | 0.79*** | 0.87*** | 0.92*** | 0.96*** | 0.97*** | 0.97*** | 0.79*** | 0.65* | 0.29 | -0.34 | -1.13*** |
| t-stat | (4.93) | (4.70) | (4.64) | (4.52) | (4.07) | (3.61) | (2.59) | (1.90) | (0.76) | (-0.79) | (-3.06) |
| CAPM | 0.36*** | 0.36*** | 0.39*** | 0.38*** | 0.32** | 0.25* | -0.00 | -0.21 | -0.61*** | -1.29*** | -1.66*** |
| t-stat | (3.36) | (3.36) | (3.54) | (3.28) | (2.57) | (1.87) | (-0.03) | (-1.13) | (-2.76) | (-4.74) | (-5.38) |
| FF3 | 0.22*** | 0.20*** | 0.22*** | 0.22*** | 0.16*** | 0.13** | -0.10 | -0.30*** | -0.72*** | -1.43*** | -1.65*** |
| t-stat | (2.81) | (2.88) | (3.56) | (3.59) | (2.74) | (2.29) | (-1.59) | (-3.40) | (-5.64) | (-7.73) | (-7.16) |
| FF5 | 0.08 | 0.05 | 0.09 | 0.13** | 0.10* | 0.18*** | 0.08 | -0.02 | -0.36*** | -0.93*** | -1.01*** |
| t-stat | (1.14) | (0.84) | (1.52) | (2.27) | (1.79) | (2.92) | (1.04) | (-0.24) | (-2.73) | (-5.18) | (-5.09) |
| Sharpe | 0.74 | 0.70 | 0.71 | 0.68 | 0.61 | 0.54 | 0.39 | 0.29 | 0.12 | -0.12 | -0.48 |
| Panel B: Value-Weighted Portfolios | | | | | | | | | | | |
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L |
| RET | 0.57*** | 0.67*** | 0.73*** | 0.80*** | 0.72*** | 0.71** | 0.59* | 0.55 | 0.09 | -0.52 | -1.09*** |
| t-stat | (3.75) | (3.63) | (3.69) | (3.65) | (2.93) | (2.53) | (1.87) | (1.62) | (0.24) | (-1.17) | (-2.95) |
| CAPM | 0.10* | 0.09* | 0.11** | 0.09 | -0.04 | -0.12 | -0.30** | -0.40** | -0.89*** | -1.59*** | -1.69*** |
| t-stat | (1.70) | (1.65) | (2.06) | (1.20) | (-0.53) | (-1.09) | (-2.18) | (-2.48) | (-4.64) | (-6.30) | (-5.82) |
| FF3 | 0.06 | 0.06 | 0.10* | 0.10 | -0.04 | -0.09 | -0.25** | -0.31*** | -0.85*** | -1.56*** | -1.62*** |
| t-stat | (1.06) | (1.14) | (1.91) | (1.39) | (-0.65) | (-1.07) | (-2.42) | (-2.60) | (-5.81) | (-7.04) | (-6.45) |
| FF5 | -0.09 | -0.03 | 0.04 | 0.11 | 0.02 | 0.04 | 0.04 | 0.07 | -0.46*** | -0.96*** | -0.88*** |
| t-stat | (-1.58) | (-0.56) | (0.74) | (1.45) | (0.31) | (0.45) | (0.44) | (0.70) | (-3.86) | (-4.80) | (-4.06) |
| Sharpe | 0.52 | 0.51 | 0.51 | 0.49 | 0.41 | 0.37 | 0.27 | 0.23 | 0.03 | -0.18 | -0.45 |

**Table IA 7** Fama-MacBeth Regressions - Dynamic Threshold of Tail Events

This table presents the results of Fama and MacBeth (1973) regression analysis of the relation between DOT and future stock returns. In this alternative approach, rather than using fixed thresholds, the threshold for defining tail events is dynamically set as the fifth percentile of the cross-sectional returns each period. Consequently, the definition of DOT has also changed. Each column in the table presents results for a different cross-sectional regression specification. The dependent variable in columns (1) and (2) is the future stock return (RET), while in columns (3) and (4), the dependent variable is the future stock return over its value-weighted industry peers' return (Industry-adj. RET). The independent variables are winsorized at the 1% level and standardized on a monthly basis. DOT and the control variables in month $t$ are matched to future stock returns in month $t+1$. The control variables are described in Section 2.2. The table presents average slope and intercept coefficients along with $t$-statistics (in parentheses), adjusted following Newey and West (1987) using six lags. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| | RET | RET | Industry-adj. RET | Industry-adj. RET |
|---|---|---|---|---|
| DOT | -0.47*** | -0.42*** | -0.48*** | -0.43*** |
| | (-5.76) | (-5.46) | (-6.18) | (-5.67) |
| BETA | 0.17** | 0.17** | 0.19*** | 0.18*** |
| | -2.25 | -2.45 | -3.38 | -3.9 |
| SIZE | -0.24*** | -0.29*** | -0.22*** | -0.26*** |
| | (-4.54) | (-5.59) | (-4.85) | (-5.91) |
| BM | 0.05 | 0.05 | 0.05* | 0.05* |
| | -1.4 | -1.28 | -1.79 | -1.74 |
| GP | 0.13*** | 0.10*** | 0.10*** | 0.07** |
| | -3.61 | -2.9 | -3.22 | -2.32 |
| AG | -0.20*** | -0.19*** | -0.18*** | -0.17*** |
| | (-6.30) | (-6.31) | (-7.00) | (-6.91) |
| ILL | | -0.09*** | | -0.08*** |
| | | (-3.04) | | (-2.72) |
| TURN | | -0.14*** | | -0.13*** |
| | | (-3.49) | | (-3.38) |
| MOM | | 0.36*** | | 0.31*** |
| | | -6.41 | | -6.7 |
| Const | 0.75*** | 0.75*** | 0.1 | 0.1 |
| | -3.04 | -3.03 | -1.05 | -1.05 |
| No. Obs. | 3330 | 3157 | 3330 | 3157 |
| Adj. $R^2$ | 5.33% | 6.59% | 3.68% | 4.64% |

**Table IA 8** Institutional Ownership (IOR) and DOT

Panel A shows the equal-weighted average values of IOR for stocks in each DOT decile portfolio, where IOR is the fraction of shares outstanding held by institutional investors following Nagel (2005). Panel B presents the results of bivariate dependent-sort value-weighted portfolio analysis. Each month $t$, stocks are sorted into quintile portfolios based on IOR. Within each IOR portfolio, stocks are sorted into decile portfolios based on DOT. Alphas represent the intercept from a time-series regression of Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from August 1979 to December 2021.

Panel A: Average IOR in DOT Decile Portfolio

| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| IOR | 0.45 | 0.47 | 0.47 | 0.47 | 0.46 | 0.44 | 0.41 | 0.37 | 0.31 | 0.25 | -0.20*** | (-14.72) |

Panel B: Bivariate Portfolio Sort on IOR

| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | FF5 | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| IOR Low | 0.76 | 0.85 | 0.95 | 0.38 | 0.34 | 0.30 | -0.31 | -0.37 | -0.59 | -1.50 | -2.26*** | (-4.42) | -1.99*** | (-5.68) |
| IOR 2 | 0.74 | 0.99 | 0.98 | 1.00 | 1.13 | 0.85 | 0.62 | 0.57 | -0.23 | 0.29 | -0.45 | (-0.78) | -0.23 | (-0.64) |
| IOR 3 | 0.80 | 0.92 | 0.94 | 0.88 | 0.68 | 0.86 | 0.56 | 0.87 | 0.36 | 0.16 | -0.64 | (-1.27) | -0.39 | (-1.15) |
| IOR 4 | 0.91 | 0.90 | 0.78 | 0.97 | 0.91 | 0.76 | 0.86 | 0.64 | 0.94 | 0.15 | -0.76* | (-1.79) | -0.59** | (-2.26) |
| IOR High | 0.82 | 0.70 | 0.73 | 0.93 | 0.82 | 0.73 | 0.94 | 0.87 | 0.79 | 0.46 | -0.36 | (-0.86) | -0.18 | (-0.69) |

**Table IA 9** ILLiquidity (ILL) and DOT

Panel A shows the equal-weighted average values of ILL for stocks in each DOT decile portfolio, where ILL is average of daily (absolute return / dollar volume) following Amihud (2002). Panel B presents the results of bivariate dependent-sort value-weighted portfolio analysis. Each month $t$, stocks are sorted into quintile portfolios based on ILL. Within each ILL portfolio, stocks are sorted into decile portfolios based on DOT. Alphas represent the intercept from a time-series regression of Fama and French (2015) five-factor model. $t$-stat are Newey and West (1987) adjusted $t$-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1967 to December 2021.

| Panel A: Average ILL in DOT Decile Portfolio | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | | |
| ILL | 0.31 | 0.56 | 0.84 | 1.18 | 1.46 | 1.79 | 2.24 | 3.03 | 4.28 | 8.59 | 8.28*** | (6.69) | | |
| Panel B: Bivariate Portfolio Sort on ILL | | | | | | | | | | | | | | |
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | H-L | t-stat | FF5 | t-stat |
| ILL Low | 0.63 | 0.61 | 0.66 | 0.67 | 0.70 | 0.58 | 0.61 | 0.71 | 0.60 | 0.24 | -0.39 | (-1.15) | -0.08 | (-0.41) |
| ILL 2 | 0.74 | 0.78 | 0.73 | 0.88 | 0.92 | 0.69 | 0.78 | 0.61 | 0.48 | 0.04 | -0.70** | (-2.03) | -0.60*** | (-3.56) |
| ILL 3 | 0.68 | 0.81 | 0.86 | 0.96 | 0.79 | 0.67 | 0.65 | 0.29 | 0.14 | -0.34 | -1.03*** | (-2.65) | -0.89*** | (-4.09) |
| ILL 4 | 0.85 | 1.01 | 0.94 | 0.85 | 0.81 | 0.58 | 0.44 | 0.44 | -0.04 | -0.31 | -1.16*** | (-2.91) | -1.16*** | (-4.61) |
| ILL High | 0.77 | 0.91 | 0.79 | 0.73 | 0.35 | 0.27 | 0.18 | -0.14 | -0.51 | -0.83 | -1.61*** | (-4.32) | -1.62*** | (-6.93) |