Dislocation

By

Huben Liu

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Authored by: Huben Liu
MIT Sloan School of Management
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Certified by: Leonid Kogan
Nippon Telegraph and Telephone Professor of Management, Thesis Supervisor

Accepted by: Urmi Samadar
Assistant Dean, MIT Sloan Master of Finance Program

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ABSTRACT

Price dislocations are common in fixed-income markets. I propose a dislocation factor (DIS), the first principle of three fixed-income market dislocations, including covered interest parity, on/off the run spread, and treasury noise measure. DIS surges when the market is under stress and indicates broad market conditions such as liquidity, volatility, and credit. DIS has insights for understanding asset prices both in time series and cross-section. In the time series, DIS has both explanatory and predictive power for the performance of equity long-short strategies: high DIS is usually followed by lower return and higher co-movement. In the cross-section, DIS is a priced risk factor and helps explain the return variation: more negative exposure to DIS results in a higher average return, compensating correlated risks.

Thesis Supervisor: Leonid Kogan
Title: Nippon Telegraph and Telephone Professor of Management

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1 Introduction

According to the law of one price, prices of assets should line with the fundamental value. However, there are many dislocations of prices in the fixed-income market. Dislocation is often high when the market is in distress. Intermediary asset pricing theory believes that when the market is in distress, financial institutes such as hedge funds lack arbitrage liquidity, thus making the price deviates from the fundamental value. Also, studies show that asset prices ask for compensation for the risk regarding that liquidity issue. In other words, dislocation is a valid risk factor.

I propose a new measure of dislocation, called DIS, by taking the first principle component of several price dislocations and near-dislocations in the fixed-income market. The new DIS factor is a good proxy for the overall market condition, not only in the fixed-income market. As is expected, DIS is correlated with the overall market liquidity conditions. It also contains other information, such as market credit and volatility conditions. 67% of the daily DIS can also be predicted by many market variables.

So why does dislocation matter? I tested the effect of the dislocation factor on prices of 169 equity long-short strategy portfolios and found strong time series and cross-sectional predictability. In the time series, on the one hand, I found that DIS has explanatory and predictive power for the performance of those equity long-short strategies. When the dislocation factor is high the day before, strategies tend to lose money the following day. On the other hand, on average, when the dislocation is high in the previous month, the co-movement of many long-short strategies is also high in the month following. This monthly effect is especially distinct for liquidity, momentum, valuation, and profitability factor long-short portfolios. These time series predictability gives insights for asset managers in the following three aspects. First, when the dislocation factor is high, it is evidence of a lack of arbitrage profitability. Second, the dislocation also signals that strategies perform worse than usual. Third, those strategies co-moves - it is harder to diversify risks.

Cross-sectionally, by conducting the Fama Macbeth regression, I found that the dislocation factor of the previous day is priced among those long-short strategies. Specifically, long-short strategies having higher negative exposure on DIS have a higher expected return. Those portfolios with lower beta on DIS are more exposed to risks correlated with market stress, such as liquidity. One correlated observation is that the return for those portfolios drops quickly after DIS spikes. However, in the more extended period, their return reverses and bounces back more as the market condition improves.

Furthermore, Fama Macbeth estimation shows that the DIS-correlated risk is also priced in the overall market. The risk premium within Fama French 25 size value portfolios and 10 industry portfolios exist after we take out the component of variables mostly correlated with DIS, including VIX, default spread, and LIBOR spread. However, compared to portfolios, DIS could be better at explaining the cross-sectional variations of individual stocks with the component of those variables.

Much literature has studied that price dislocations in many aspects indicate market stress, and the dislocation is correlated with many market conditions. For example, Fleckenstein, Longstaff, and Lustig (2014)[1] shows that the arbitrage relationship between TIPS, inflation swap, and treasury strip spikes when the market is under stress. The correlated mispricing is correlated with additional capital flows into the market. Hu, Pan, and Wang (2013)[2] shows that the deviation between the fitted yield curve and the actual yield curve, usually treated as noise, spikes when the market is under liquidity stress. Furthermore, the noise measures market liquidity conditions. Correlated literature also includes corporate bond/CDS arbitrage by Duffie (2010)[3], on-the-run/off-the-run spread by Krishnamurthy (2002)[4], and

Refcorp-Treasury spread by Longstaff (2004)[5]. There are various economic reasons for different mispricings spike, which also drive asset prices. However, not much literature has aggregated different mispricing measures in the market to pick up the general information across different mispricing factors, nor did it estimate the explanatory and predictive power of those mispricing measures, in time series, for the performance (including the average return and co-movement) of equity strategies.

Regarding the interpretability of the mispricing measures of asset returns, some literature proposes that dislocation measures are valid risk factors. In other words, the economic condition correlated with mispricing is priced and can explain cross-sectional asset returns on average. Hu, Pan, and Wang (2013) show that their noise measure can be used to explain hedge fund cross-sectional returns. Pasquariello (2014)[6] shows that investors demand statistically and economically significant risk premiums to hold financial assets performing poorly during market dislocations. Du, Hebert, and Huber (2022)[7] shows that the first principle component of many price dislocations and near-dislocations can be used to explain cross-sectional asset returns of many traditional asset classes. My study differs from these papers in the following aspects: First, I used different price dislocation measures to aggregate to get the dislocation factor; second, I used different testing assets: a group of equity long-short factor portfolios, to get more insights about returns of equity strategies; Finally, I used the dislocation in the previous day as the factor instead of the contemporaneous one, to show that the lagged variable has more predictive power.

2 Dislocation factor

2.1 Construct the dislocation factor

I used three daily series of mispricing in the fixed-income market to construct my dislocation measure.

- CIP (Covered interest rate parity)

$$f^*_{\frac{A}{B},t} = S_{\frac{A}{B}} \frac{1 + r_{A,t}}{1 + r_{B,t}}$$

$$\text{CIP} = |\log(f^*) - \log(f)| * 10000$$

  CIP is a well-known no-arbitrage pricing relationship in the foreign exchange market. My estimated CIP series is calculated using the simple average of 5 forward periods (1w, 1m, 3m, 6m, 1y) on 5 currency exchange rates (CHFUSD, GBPUSD, USDEUR, USDJPY, EURCHF) from May 1990 to Feb 2022, daily. I used LIBOR rates as short-term interest rates. LIBORs, exchange rates, and forward rates are all from DataStream.

- On-the-run/off-the-run spread

  On-the-run/off-the-run spread is not a strict "mispricing" measure since it is usually treated as compensation for taking liquidity risk. On the other hand, some empirical exercises, such as Fleckenstein, Longstaff, and Lustig (2014) and Du, Hebert, and Huber (2022), treated the on-the-run/off-the-run spread as near-arbitrage. Adding on-the-run/off-the-run spread would capture more liquidity information, which is believed to be a primary reason for many dislocations in the market.

  I took the difference between the newly issued 10-year treasury (no more than 6 months after its issuance) monthly yield and the already issued (at least 6 months) 10-year treasury monthly yield. I used the simple average to aggregate yields between different bonds. The data is from Jan 1991 to Jun 2021 from the WRDS CRSP treasury database.

- Treasury noise measure

  According to Hu, Pan, and Wang (2013), the deviation between the fitted and actual yield curves is a good proxy for market distress. Also, it is a risk factor primarily correlated with liquidity. Treasury noise daily data from Jan 1987 to Dec 2021, the data source is Jun Pan's website[1].

Table I: **Selected Price Dislocations Data Description**

	Data description								Correlation (%)	
	# days	Mean	SD	Min	Max	Skewness	Kurtosis	Maximum day	Noise	On/off
CIP	7985	5.16	4.26	0.85	57.03	3.22	19.73	Jan 2, 1997	28	29
Noise	7750	2.87	2.05	0.69	20.47	4.06	27.01	Dec 10, 2008	/	64
On/off	7337	0.02	0.01	0.00	0.12	2.61	14.96	Nov 4, 2008	/	/

SD stands for standard deviation, and Maximum day indicates the date when the maximum value occurs. All mean, SD, min, and max numbers are in basis points.

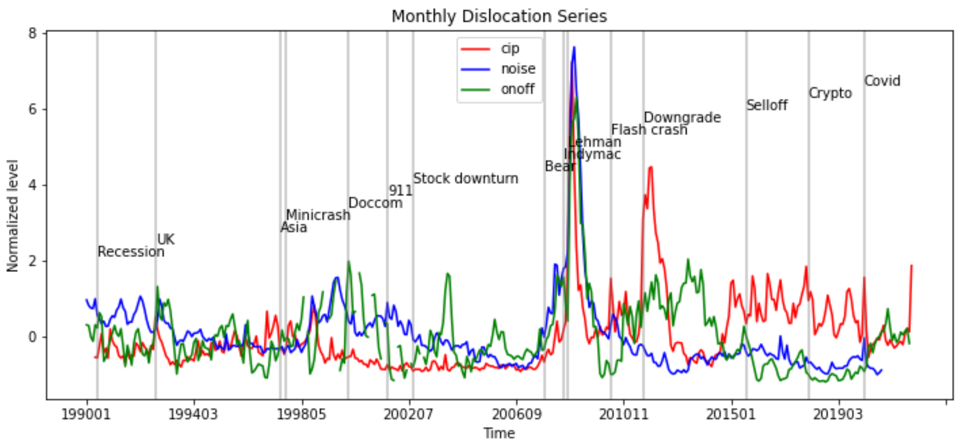

Figure 1: Monthly time series of selected dislocation measures from Jan 1990 to Dec 2020. The market stress events are noted using gray bars. All variables are standardized using the historical mean and standard deviation.

The descriptive statistics are shown in Table I. Within the sample period from June 1990 to Dec 2020, when all three dislocation series have no missing data, CIP and Noise levels are around 5 and 3 bps daily. However, the relatively low level of on/off the run spread compared to the other two dislocation measures does not mean it contains less information. Therefore, I standardized 3 dislocation series using their whole sample mean and standard deviation in the following analysis.

All three dislocation measures are positively skewed, meaning they have significant positive outliers. However, these outliers are instead information than noise since these dislocations shoot up significantly during market crisis dates, which we care about. For example, CIP peaked in 1997 when the FX market largely fluctuated, while two money market dislocations peaked during the 2008 financial crisis. To make the trend easier to observe, Figure 1 shows the monthly series of 3 standardized dislocation measures and the time of market crisis. Detailed

[1]Jun Pan's Website https://en.saif.sjtu.edu.cn/junpan/

market crisis time is reported in the appendix. Almost all financial distress times are picked up by at least one of these dislocation measures.

Spotting from figure 1, we may also notice that not every price dislocation is picking up the same information. For example, during 2000 - 2003, noise and on/off the spread fluctuated more than CIP deviation; and in Aug 2015, when the stock market sold off, only on/off the run spread spiked up. The correlation coefficients reported in Table I show that the biggest pairwise correlation amongst these 3 dislocation measures is 64% between two money market dislocations. The result is in line with Krishnamurthy (2002) and Hu, Pan, and Wang (2014) since both are liquidity measures in some way. CIP's correlations with the other two measures are around 28% and 29%, indicating that CIP is picking up more orthogonal information not shared among all 3 measures.

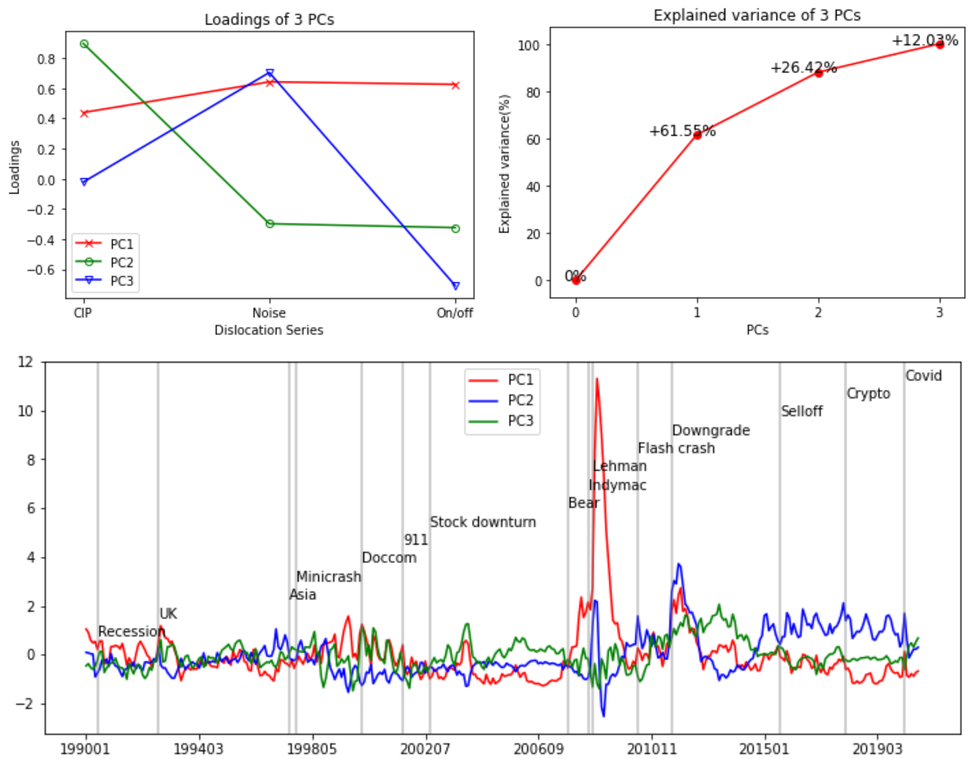

Figure 2: Top left: Loadings of 3 PCs on 3 mispricing measures. Top right: cumulative explained variance (in percentage) of the 3 PCs. The number reported in the graph is the marginal value. Bottom: Time series of 3 PCs. To clarify the trend, the daily series's monthly average is plotted.

The next step is to aggregate the three dislocation series to maximize the information they picked up. A natural method to reduce dimension is taking the first several principal components. The whole sample is from Jan 1990 to Dec 2020 with daily frequency.

The top part of Figure 2 shows the weights and the explained whole sample variance of the 3 PCs. The top left part of Figure 2 shows that the first PC has almost the same loadings on 3 dislocation measures, which can be treated as their average level. It explained almost 62% of the total variance. Another 26% of the cross-sectional variance is explained by the second PC, which is the spread between foreign exchange dislocation, CIP, and equal-weighted dislocations in the treasury market. It shows that the additional dislocation picked up uniquely by the FX market is essential. The third PC is a spread between noise measure and on/off the run spread, which explains 12% of the variance. The third PC has almost no loading on CIP. The bottom part of Figure 2 shows the monthly time series of 3 PCs. We see that the first two PCs picked up at almost all of the market crisis times, and the first PC played an essential role. In the following analysis, I used mainly the first PC for simplicity. I treated it as the dislocation factor (noted as DIS in the following text).

2.2 Time-series characteristics of the dislocation factor

To further investigate the connection between DIS and many important market variables, I report the OLS regression results of the daily DIS on several important market variables in Table II. Variables are divided into 4 groups according to their economic characteristics: treasury rates, liquidity, stock market, and credit market. I first did uni-variate regression on every variable one by one and then did multi-variate regression within each group. Finally, I regressed DIS on variables altogether to compare their relative contribution. Pairwise correlations of DIS and other market variables are also reported. To make the result comparable between different market variables, all market variables are standardized using their whole sample mean and standard deviation. All regression are done first contemporaneously (DIS_t regressed on variables_t) and then predicatively (DIS_t regressed on variables_{t-1}).

2.2.1 Treasury rate

Two of the three main components of DIS are constructed based on variables highly related to treasury yield rates. Thus, I first investigated the relationship of DIS with treasury rates to see how DIS varies with the treasury yield curve and volatility dynamics.

The 3-month T-bill rate can be treated as the level of the yield curve. The regression result of the DIS on the 3-month T-bill rate implies that the dislocation is high when the treasury yield is low at the same time. The explanation is that the dislocation is high when the market is in a downturn. The market liquidity condition is bad, bringing flight-to-quality issues that lower short-term treasury yields. The term spread between the 10-year and the 3-month T-bill rate is also statistically significant in interpreting DIS. The positive correlation indicates that DIS is high when the treasury yield slope is high, consistent with the observation that market conditions worsen contemporaneously with the steepening yield. However, the explaining power of the level and the slope of the yield curve is limited within an R squared of 2% and 6%, respectively, showing that the DIS is not only driven by treasury term structure. This is a good signal that though DIS is constructed from the yield curve, it is flexible and not determined by the yield curve.

Since DIS is related tightly to treasury rates, I also tested how DIS varies with the volatility of prices of treasury bonds. The overall treasury bond volatility is estimated using the volatility of the Bloomberg treasury bond index within a rolling window of 22 business days. The relation is positive and statistically significant, which indicates that the DIS spikes when the volatility is high in the treasury market. Compared to the limited explaining power of term structure variables, the bond volatility explains around 15% of the DIS time-variation, which indicates that DIS contains a significant amount of information about market volatility.

Putting these variables together, I notice that the treasury yield level is not significant anymore. One standard deviation increase of yield slope and bond volatility contributes to 0.20 and 0.35 standard deviation increases of DIS, which supports that DIS is more sensitive to changes in bond volatility. We see from the R squared that around 82% of the variation of DIS is unrelated to the treasury market. The predictive regression result is almost the same as the contemporaneous one, and we can predict around 18% of time t DIS by the variables realized in a business day before. The consistency of the treasury market variables can narrow this difference. However, the slightly higher explaining power of the predictive regression may also be the consequence that DIS reflects the previous day's market condition and does not efficiently

Table II: **DIS Regressed on Other Market Variables, Contemporaneously and Predicatively**

(a) Treasury Rate

	Contemporaneous				Predictive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3M	**-0.15**			0.02	**-0.15**			0.02
	(-12.21)			(0.97)	**(-12.15)**			(0.86)
Term		**0.24**		**0.20**		**0.24**		**0.20**
		(21.07)		**(9.19)**		**(20.96)**		**(9.16)**
BondV			**0.39**	**0.35**			**0.40**	**0.35**
			(21.57)	**(19.89)**			**(21.94)**	**(19.98)**
R2(%)	2.08	5.77	14.92	18.19	2.06	5.71	15.36	18.31
#Observations	6,980	7,237	2,647	2,816	6,980	7,237	2,647	2,815

(b) Liquidity

	Contemporaneous				Predictive			
	(1)	(2)	(3)*	(4)*	(5)	(6)	(7)*	(8)*
Onoff	**0.85**			**0.51**	**0.84**			**0.49**
	(137.51)			**(13.66)**	**(134.26)**			**(12.15)**
RefCorp		**0.09**		**0.15**		**0.09**		**0.14**
		(7.96)		**(4.61)**		**(7.9)**		**(3.99)**
Lev			**0.32**	**-0.11**			**0.30**	**-0.11**
			(6.19)	**(-2.31)**			**(5.86)**	**(-2.13)**
R2(%)	73.21	2.50	9.44	64.14	72.26	2.46	8.52	58.41
#Observations	6,920	2,433	358	117	6,920	2,433	358	117

(c) Stock Market

	Contemporaneous				Predictive			
	(1)	(2)	(3)*	(4)*	(5)	(6)	(7)*	(8)*
Stockexr	**-0.02**			-0.03	**-0.04**			0.05
	(-2.02)			(-0.68)	**(-2.97)**			(1.05)
VIX		**0.60**		**0.63**		**0.60**		**0.61**
		(63.56)		**(13.95)**		**(63.92)**		**(12.76)**
PSLiq			**-0.21**	0.05			**-0.24**	0.07
			(-4.01)	(1.03)			**(-4.55)**	(1.51)
R2(%)	0.04	36.67	4.32	39.39	0.11	36.94	5.48	33.28
#Observations	6,980	6,975	358	358	6,980	6,975	358	357

(d) Credit Market

	Contemporaneous				Predictive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Repo	**-0.22**			**-0.12**	**-0.22**			**-0.12**
	(-13.87)			**(-12.56)**	**(-13.82)**			**(-12.37)**
Libor		**0.58**		**0.35**		**0.58**		**0.34**
		(60.92)		**(37.91)**		**(61.59)**		**(36.57)**
Default			**0.71**	**0.59**			**0.71**	**0.60**
			(88.53)	**(61.01)**			**(88.1)**	**(61.59)**
R2(%)	3.53	33.89	51.99	67.21	3.51	34.39	51.75	66.92
#day	5,222	7,237	7,237	5,222	5,222	7,237	7,237	5,221

(e) All variables in one regression

	Term	Bondexr	BondV	RefCorp	Stockexr	VIX	Repo
Correlation	24.06	-14.51	38.72	16.68	-2.61	60.71	-18.62
Contem Reg	**0.23**	**0.23**	-0.01	**0.05**	0.00	**0.13**	**-0.22**
	(26.12)	**(21.39)**	(-0.61)	**(4.19)**	(0.18)	**(12.88)**	**(-20.38)**
Predic Reg	**0.22**	**0.22**	-0.00	**0.04**	-0.01	**0.14**	**-0.21**
	(25.2)	**(20.42)**	(-0.24)	**(3.0)**	(-1.6)	**(12.88)**	**(-19.87)**

(Panel (e) cont')

	Libor	Default	Lev	PSLiq	R2(%)	# days
Correlation	58.22	72.11	31.15	-20.78		
Contem Reg	**0.29**	**0.48**			67.04	7,237
	(32.52)	**(47.29)**				
Predic Reg	**0.30**	**0.47**			66.94	7,237
	(33.85)	**(46.71)**				

Reported are OLS regression coefficients with t-stat's in brackets, R squared, and sample size. Column 4 in panels (a) - (d) reports the multivariate regression results on all of the variables in the column simultaneously, and all other columns in panels (a) - (d) report uni-variate regression results. The first row of the panel (e) reports the correlation coefficient of contemporaneous PC and variables. The rows "contemp" and "predic" report the contemporaneous and predictive regression result of DIS on all of the variables simultaneously (since lacking daily data, Lev and PSLiq are not included; on/off the run spread is not included since DIS is constructed from it). 3M is the 3-month T-bill rate. Term is the spread of 10-year over 3-month treasury yields. BondV is the volatility of the Bloomberg US treasury index excess return using a rolling window of 21 business days. Onoff is the on-the-run premium constructed in section 2.1. RefCorp is the average spread between the 5-year and 10-year T bill rate and the RefCorp bond of the same term. Lev is 1 - market equity ratio of primary dealers from He, Kelly, and Manela (2017). Stockexr is the CRSP value-weighted excess return. VIX is the volatility index from CBOE. PSLiq is the liquidity factor by Pastor and Stambaugh. Repo is the overnight general collateral repo rate. LIBOR is the spread between the 3-month LIBOR rate and the 3-month T-bill. Default is the spread between Moody's Baa and Aaa bond yields. Monthly regression was conducted in columns with the star since the lack of daily data.

adjust.

2.2.2 Liquidity

Much literature has emphasized the importance of liquidity in explaining price dislocations. The test on liquidity variables supports this argument. Results are shown in Table 2 Panel (b).

One widely used liquidity measure is on/off-the-run premium, which is already a DIS component. Contemporaneous on/off-the-run premium explains 73% of the DIS time-variation. The high explaining power is not surprising since DIS loads almost evenly on three dislocation components, including on/off the run spread.

Another measure of liquidity is from Longstaff (2004), which reflects the flight-to-quality liquidity premium of treasury bonds on the bond issued by RefCorp, a US government agency. Fight-to-quality premium is typically high when the market is illiquid. The RefCorp spread is constructed using the average spread between 5-year and 10-year T-bill rates and Refcorp bond rates. The correlation between Refcorp spread and DIS is positive and statistically significant, showing that DIS is high when the flight-to-quality spread is high. In other words, the DIS meets with a measure of illiquidity. The explaining power of 2.5% shows that DIS contains information differently from the liquidity condition captured by RefCorp premium.

The on/off the run premium and RefCorp premium are liquidity conditions reflected in the treasury prices. Another liquidity measure I used is more from the fundamental aspect. One channel that affects the overall market liquidity condition is broker-dealer leverage. The assumption is that when broker-dealers' leverage is high, they are less willing to extend credit to their customers and thus weakening the market liquidity. One measure of broker-dealer's leverage is from He, Kelly, and Manela (2017)[8]. They used the capital ratio of NY Fed primary dealers' publicly-traded holding companies[2]. I constructed the broker-dealer leverage based on the variable they used as $1 - \frac{\text{Market equity}}{\text{Market equity+Book debt}}$. This regression is conducted monthly since only the monthly data of broker-dealer leverage is available. The coefficient shows that one standard deviation increase of the broker-dealer's leverage in a month will lead to a statistically significant 0.32 standard deviation increase in DIS. One interpretation of the correlation would be that when the broker-dealer is levered up, their customers are likely to have liquidity issues. Then they are less likely to fill arbitrage opportunities, resulting in price dislocations. To compare the coefficient, if we assume gradual change, a 0.32 per month increase implies around 0.01 increase daily. This coefficient is not as strong as the RefCorp spread since the leverage ratio is at company fundamental level and may not affect the market price swiftly as market variable related to price does. However, the explaining power of around 9% is higher than the RefCorp premium.

I did a monthly regression for three liquidity variables together. All three variables are still significant, while the coefficient of broker-dealer leverage changes to be negative. The high explaining power is mostly due to the on/off-the-run premium. The predictive regression on a monthly level yields only a slightly weaker correlation and slightly less explaining power, but it is still strong. We can predict around 58% of DIS using the variables one month before.

2.2.3 Stock market

Though DIS is constructed mainly using money market variables, given the importance of US treasury bonds and currencies, treasury prices are likely to display stock market conditions. First, I tested the co-movement of DIS with the overall stock market performance. I used

[2]Intermediary capital ratio from https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/

CRSP value-weighted stock excess return as an index for stock market performance. The result is shown in Table II Panel (c). The correlation is negative and statistically significant, which means that DIS is high when stock market performs poorly. However, the R squared is only 0.04%.

So what matters in the stock market for DIS? It turns out that the CBOE VIX index, which indicates the stock market volatility, explains almost 37% of the variance. The regression coefficient is also much more significant than other variables. It means that an increase in the overall stock market volatility, also known as the "fear gauge", is likely to indicate an increase in DIS. Reviewing the result of the treasury market, it is clear that DIS is very sensitive to the overall market volatility for both treasury and stock. On average, DIS spikes when the market fluctuates.

Another variable I tested in the stock market is the Pastor and Stambaugh liquidity factor. The liquidity factor is only available in the monthly frequency, so the monthly regression is conducted. Although the liquidity measure they used is very different from the one we tested in 2.2.2, it is still statistically significant. The negative correlation implies that an increase in the DIS would accompany a negative shock to the equity liquidity factor. The R squared is around 4%.

Putting stock market variables together in a monthly regression, the R squared is 39%, and the stock market return and PS liquidity become insignificant. The result means that compared to VIX, the stock market's overall return and liquidity factor provide much less explaining power. The result emphasizes the significant contribution of VIX. The predictive regression still does not change much. However, it is interesting to see that moving from contemporaneous to predictive, the explaining power of uni-variate regression becomes bigger, and the coefficient is also more significant. This shows that the stock variables one day/month before affect the current DIS more than the contemporaneous stock market conditions. The multivariate regression has a lower R squared since it is conducted monthly and may not match the increasing explaining power in the daily frequency.

2.2.4 Credit market

Finally, variables regarding the credit market are tested. I regressed the DIS on the overnight general collateral repo rates, LIBOR spreads, and default spreads (Baa and Aaa-rated bond yield). DIS decreases when the repo rate is high and increases when LIBOR spread is high. The results are in the expected direction. The default spread increases when DIS increases since the default spread contains information about the overall market liquidity. The regression coefficient is high compared to other variables, and the t stat's shows a very strong correlation. The R squared is about 4% for the Repo rate and 34% and 52% for LIBOR and default spread. The result implies that credit condition is a very important indicator of DIS.

Putting three variables together, I find that they explain around 67% of the variance altogether, and the three variables are statistically significant. For the predictive regression, the interpretability of Repo and LIBOR decreases while that for default spread increases. The overall explaining power decreases negligibly around 0.3%.

2.2.5 Put everything together

Panel (e) of Table 2 shows the daily regression result of the DIS on 30-year 3-month term spread, 3-month T-bill rate, bond volatility, RefCorp spread, stock market return, VIX, repo rate, LIBOR spread, and default spread together. Broker-dealer leverage and PS liquidity factor are not included since they are only available monthly. The on/off-the-run spread is not included since it is already the component of the DIS. Also, please note that the missing value is replaced by the cross-sectional average to avoid shrinking the regression period too small. The R squared may be smaller than some of the regression results above since the regressions in Panels (a) - (d) are conducted in the sub-sample that no variables have missing values. Contemporaneous correlations between DIS and variables coefficients are reported in the first row.

The contemporaneous regression result shows that the default spread, LIBOR rate, treasury rate slope, treasury rate level, repo rate, and VIX are the most important 6 variables in interpreting DIS. At the same time, the correlation coefficient picks the default spread, VIX, LIBOR rate, bond volatility, treasury rate slope, and repo rate - credit market variables, treasury rate slope, and market volatility have the highest contribution. Comparing the regression coefficients, DIS is most sensitive to default spread, with a coefficient of 0.48. One characteristic of these variables is that they are all very sensitive to market conditions since they change fast when the market turns into distress. The R squared is around 67.0%, which shows that around 33% of the time variation of DIS is not captured by those well-known market indicators. The predictive regression only reduces the R squared by 0.1% - we can predict around 66.9% of the DIS by variables one day before. The realization of the same-day variable adds little explaining power. This could be evidence of the lagged reaction of DIS to many market variables. However, it is also likely to be the persistence of market variables.

3 Time-Series predictability

In this section I tested the predictability of DIS for asset prices. I used the daily stock long-short portfolio as testing assets. Each long-short portfolio is based on one market factor, that is, for each market factor, the universe market stocks are sorted into deciles and the difference between returns of the top and the bottom decile is taken as the return of the long-short portfolio of this factor. Obviously, the long-short portfolio has the maximum exposure to the corresponding factor. There are a total of 169 factors selected, thus there are 169 portfolios.[3] One reason of selecting these testing assets is that it is a good approximation of different equity strategies of asset management institutions. Since dislocation is related to lack of arbitrages, and those institutions are main arbitrageurs, it is natural to link DIS to performance of these institutions. Studying the correlation of the performance of equity strategies and DIS would be insightful to provide constructive instruction on asset and risk management for those institutions.

The 169 factors the portfolios based on are from different economic aspects. Some of them depend on swift-changing market variables while some of them depend on the slow-changing corporate fundamentals. It is reasonable to divide those portfolios into categories based on their economy status. Categories that contain less than 7 portfolios are excluded to avoid idiosyncratic effect. There are finally 6 categories: external financing, investment, liquidity, momentum, profitability, and valuation. The detailed factor components of those categories are listed in Table 3. The following analysis are tested within portfolios in each category and then on all of the 169 portfolios finally. Details of portfolios not included in the 6 categories are attached in the appendix.

The DIS spikes when the market condition is poor, at that time, the stock strategies also perform badly and volatile a lot. Also, equity strategy prices depend on many market variables which co-move with DIS as analyzed in Section 2. Therefore, it is natural to assume that there are some correlation between DIS and the overall performance of equity strategies in the time-series. The effect of DIS on stock strategies' return and volatility, respectively, is analyzed in the following two sections.

[3]The factors and the portfolio returns are from https://www.openassetpricing.com.

Table III: **Factors Long-short Portfolios in Different Categories**

Factor Categories	Component	# portfolios
External Financing	Net debt, net equity, external financing, composite equity, debt issuance, share issuance 5y, share issuance 1y, Δcurrent operating liabilities, Δfinancial liabilities	9
Investment	Asset growth, growth in book equity, growth in long term operating assets, Δnet operating assets, Δ ppe and inv/assets, Δ equity/assets, Δlong-term inv, investment/revenue, employment growth, brand capital investment, growth in advertising expenses, deferred revenue, Δcurrent operating assets, Δnet financial assets, total accruals, Δnet non-current op assets, Δnet working capital, inventory growth	18
Liquidity	Amihud's illiquidity, bid-ask spread, share turnover volatility, volume variance, probability of informed trading, days with zero trades, Pastor-Stambaugh liquidity beta	7
Momentum	Junk stock momentum, momentum based on FF3 residuals, 52 week high, industry momentum, momentum (12 & 6 month), intermediate momentum, firm age - momentum	8
Profitability	Return on assets (qtrly), cash-based operating profitability, operating profitability R&D adjusted, inventory growth, analyst earnings per share, operating profits/book equity, net income/book equity, gross profits/total assets	8
Valuation	Sales-to-price, earnings-to-price ratio, net payout yield, payout yield, equity duration, operating cash flows to price, earnings forecast to price, total assets to market, book to market using December ME, analyst value, cash flow to market, enterprise multiple, efficient frontier index, enterprise component of BM, book to market using most recent ME	15

The component column shows factors the portfolios are based on in each category. The last column is the number of portfolios each category have. The economic status is according to the openassetpricing website.

3.1 Time-series predictability - returns

To test the predictability of DIS on strategy returns, I regressed the aggregate return of each strategy (equal-weighted return of portfolios within each category) on changes and lagged changes of DIS as is shown in Equation (1) and (2).

$$\text{Contemporaneous:} \quad r_{c,t} - r_{f,t} = \beta_c \Delta \text{DIS}_t + \beta_0 + \epsilon_{c,t} \tag{1}$$

$$\text{Predicative:} \quad r_{c,t} - r_{f,t} = \beta_p \Delta \text{DIS}_{t-1} + \beta_0 + \epsilon_{c,t} \tag{2}$$

c denotes the category, $c = 1, 2, ..., 7$. The whole sample is from Jan 1990 - Dec 2020, daily. To exclude the information contained in the commonly used market factors, I orthogonalized the portfolio return on Fama-french 3 factors. The regression result is presented in Table IV.

Table IV: **Portfolio Returns Regressed on Daily Changes of DIS, Contemporaneously and Predicatively**

	Contemporaneous	Predictive		Predictive Orthogonalized	
	ΔDIS_t β_p	ΔDIS_{t-1} β_p	R2(%)	ΔDIS_{t-1} $\tilde{\beta_p}$	R2(%)
external financing	0.03	**-0.04**	0.06	**-0.04**	0.12
	(1.96)	**(-2.14)**		**(-2.92)**	
investment	-0.01	0.01	0.00	-0.00	0.00
	(-0.67)	(0.38)		(-0.21)	
liquidity	**0.05**	-0.04	0.04	0.02	0.01
	(2.26)	(-1.61)		(0.88)	
momentum	0.09	**-0.18**	0.15	-0.09	0.05
	(1.73)	**(-3.3)**		(-1.84)	
profitability	0.06	**-0.10**	0.12	**-0.07**	0.12
	(1.84)	**(-3.01)**		**(-2.97)**	
valuation	0.02	0.01	0.00	**-0.06**	0.19
	(0.81)	(0.44)		**(-3.74)**	
All	**0.02**	**-0.03**	0.20	**-0.03**	0.23
	(2.65)	**(-3.79)**		**(-4.05)**	

Reported are OLS regression coefficients with t-stat's in brackets, and R squared. The contemporaneous column reports coefficient for ΔDIS_t in regression (1), and the predictive column reports coefficient and R squared for ΔDIS_{t-1} in regression (2). The results of regression (2) using FF 3 factor orthogonalized returns are reported in the predictive orthogonalized column.

First, the contemporaneous result shows that only liquidity portfolio returns significantly change with the concurrent changes of DIS. The positive correlation comes from our construction of liquidity long-short portfolios: longing liquid assets and shorting illiquid assets. Liquid assets perform better than illiquid assets under stress. Also, the correlation for liquidity portfolios turns insignificant as we move from contemporaneous to predictive regression. This result implies that liquidity portfolios react swiftly to DIS.

For the predictive regression, the coefficients show that the return of the profitability, momentum, and external financing portfolios have significant correlation with lagged changes in DIS. In other words, DIS has significant predictive power for the aggregated returns of portfolios in these categories. However, the R squared is very small, even less than 1%. So, although the correlation is significant, it is still very hard to predict the time variation of the stock portfolios. This result is reasonable according to the market efficiency. The significant coefficient is negative, meaning that holding everything unchanged, when the change of DIS is high the day before, the stock strategies constructed on external financing, momentum, and profitability factors are likely to lose money in the day following. Those portfolios are longing assets performing badly and shorting assets performing well when the market is under stress. Also, we notice that the portfolio built on the fundamentals reacts slightly slower to DIS than liquidity since the contemporaneous regression coefficients for them display insignificant.

Momentum portfolios are usually built on quickly changing market variables such as returns. However, the predictive result shows that it is also sensitive to the lagged DIS instead of concurrent DIS. One adjustment would be to orthogonalize the return on Fama Frech three factors since the portfolio returns are significantly driven by Fama French three factors. I tested the effect of DIS on the residuals of returns regressed on Fama French three factors. After the adjustment, the result becomes insignificant for momentum. The result shows that the previous significant predictability for momentum portfolios is more from Fama French risk factors.

After the adjustment, the predictabilities of DIS on profitability, external financing, and valuation portfolios are significant. Those are factors building on slow-changing fundamentals.

Finally, I did the same regression on the average return of all 169 portfolios, and the correlation is still significant. It shows that lagged DIS has predictability for the average performance of the equity long-short strategies. On average, the negative coefficient warns us that the stock portfolios tend to lose money right after DIS spikes.

3.2 Time-series predictability - co-movements

As is shown in the last section, equity long-short strategies tend to lose money when DIS spikes a day before. How about the average volatility or the co-movement of those equity strategies? Co-movement of a bunch of strategies is an important characteristic for asset managers since it is much more difficult to diversify risks when the co-movement between strategies surges up.

The monthly co-movement of equity strategy returns is extracted using the daily returns within each month. One method in practice to extract asset price co-movement is from the explained variance of the first principle component. For example, Longstaff, Pan, Pedersen, and Singleton (2011)[9] used explained variance of the first PC to represent the co-movement of cross-sectional sovereign debt prices. Following the insight, to get the co-movement of each month, I extracted the explained variance of the first PC of the cross-sectional daily returns within that month. Since there are usually only around 22 observations each month, the first PC is estimated using a much longer rolling window of 1 year (252 trading dates) previous to that month. Then, this estimated first PC is used to calculate the percentage of variance it explains within that month (around 22 trading dates).

The following graph plots the DIS, the co-movement level, and the rolling first PC of stock returns. Please note that the co-movement is in monthly frequency. Hence, DIS plotted is aggregated each month using the simple average. We can see that the co-movement is correlated to the DIS. From the graph, we observe that when DIS spikes, the co-movement of the stock return portfolios is likely to be high. We can observe the same phenomena from the historical series of the first PC of all the stock long-short portfolios: the volatility of the stock is relatively high when the DIS spikes.

To further estimate the correlation, I did the following regression. The regression coefficient is shown in Equation (3) and (4). The left-hand-side variable is the monthly co-movement level of portfolios. The right-hand-side variable is the level of monthly DIS. Like the previous section, regressions are done within each category and then all together, contemporaneously and predicatively.

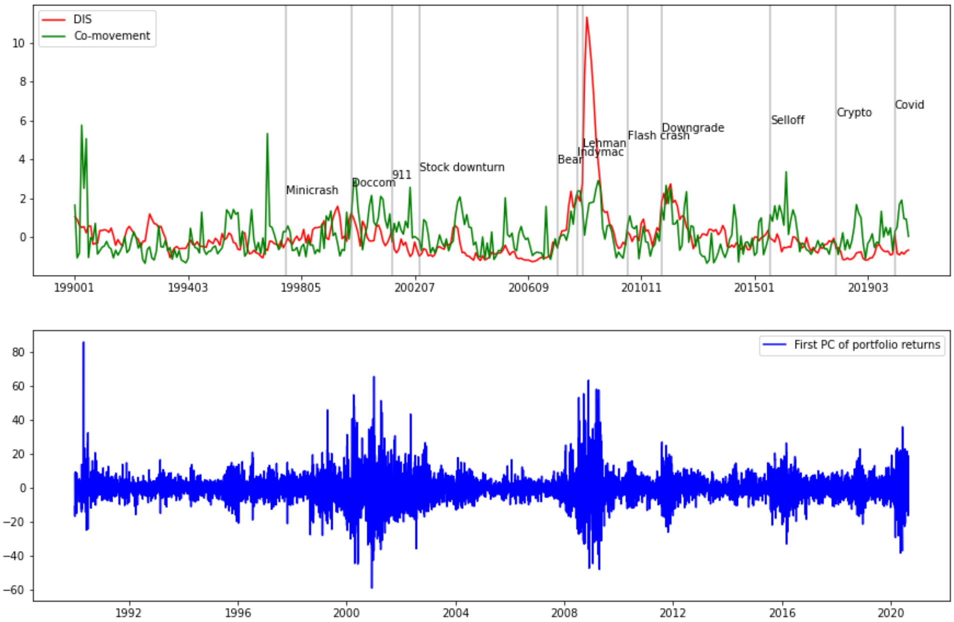

Figure 3: The monthly time series of DIS and portfolio co-movements (the explained variance of the first PC). Lower: The daily time series of the first PC of 169 stock long-short portfolios.

$$\text{Contemporaneous:} \quad \text{Co-movement}_{c,t} = \beta_{c,1}\text{DIS}_t + \beta_0 + \epsilon_{c,t} \tag{3}$$

$$\text{Predicative:} \quad \text{Co-movement}_{c,t} = \beta_c\text{DIS}_{t-1} + \beta_0 + \epsilon_{c,t} \tag{4}$$

c denotes categories.

The regression result is shown in Table V. DIS has a significant positive correlation with equity strategies' return co-movement, both concurrently and predicatively. The result implies that different equity strategies tend to co-move when market price dislocations are high. The predictive regression result shows that the price dislocation in the month before can predict the co-movement in the following month. The regression does not give causal inference, and price dislocation and stock portfolio co-movements are likely to be the expression of some deeper market factor. Nevertheless, asset managers need to be aware of the weakening of diversification.

Specifically, external financing, momentum, liquidity, profitability, and valuation portfolios co-move significantly with DIS, both concurrently and predictively. The liquidity portfolio's co-movement is the most sensitive to the level of DIS, which is in line with the analysis that DIS contains much information about market illiquidity. However, unlike the return analysis, the predictive power for liquidity co-movement is not less than concurrent explaining power, implying that the co-movement pattern is more persistent. For the portfolios building on the slow-changing fundamental variables, the strong correlation is likely to be affected by the embedded systematic risk factor instead of swift-changing day-to-day conditions since the DIS is aggregated within each month, and many of the day-to-day variations are averaged out.

There is a robust check worth pointing out for time-series tests, both for return and co-movement: the correlation is not only driven by the special case in 2008 when DIS spiked significantly.

Table V: **Portfolio Return Co-movements Regressed on Monthly DIS, Contemporaneously and Predicatively**

	Contemporaneous			Predictive		
	DIS_t β_p	β_0	R2(%)	DIS_{t-1} β_p	β_0	R2(%)
external financing	**0.11**	**0.23**	2.15	**0.09**	**0.23**	1.47
	(2.84)	**(4.38)**		**(2.34)**	**(4.4)**	
investment	0.00	0.05	0.00	0.03	0.05	0.15
	(0.03)	(0.98)		(0.73)	(1.02)	
liquidity	**0.20**	0.01	6.71	**0.21**	0.02	6.99
	(5.14)	(0.27)		**(5.24)**	(0.28)	
momentum	**0.14**	**0.15**	3.46	**0.15**	**0.16**	3.70
	(3.62)	**(2.88)**		**(3.75)**	**(2.93)**	
profitability	**0.10**	**0.16**	1.93	**0.11**	**0.16**	2.30
	(2.69)	**(3.03)**		**(2.93)**	**(3.06)**	
valuation	**0.15**	0.00	4.13	**0.17**	0.01	5.48
	(3.98)	(0.06)		**(4.61)**	(0.12)	
All	**0.22**	**0.11**	8.63	**0.25**	**0.11**	11.16
	(5.89)	**(2.16)**		**(6.78)**	**(2.09)**	

Reported are OLS regression coefficients with t-stat's in brackets, and R squared. Contemporaneous columns report coefficient for DIS_t in regression (3), and the predictive column reports coefficient and R squared for DIS_{t-1} in regression (4).

4 Cross-Sectional Predictability

The main idea of this section is to see how the DIS factor can explain cross-sectional return variations of assets. Much literature has pointed out that market price dislocations/market arbitrage can explain cross-sectional returns. So it is natural to first test if DIS is a risk factor and if it is priced within the 169 long-short strategies we have used so far. I did a portfolio sorting test to see if the cross-sectional return displays a clear pattern. Then to get a more general estimation of the risk premium, I applied the Fama Macbeth method to get the risk premium from long-short strategies and the overall market.

4.1 Portfolio sorting test

I followed the standard procedure of the portfolio sorting test. First, for each asset, the exposure on DIS is estimated by

$$r_{i,t} - r_{f,t} = \beta_i^F \Delta\text{DIS}_{t-1} + \beta_i^M (r_{M,t} - r_{f,t}) + \beta_i^S \text{SMB}_t + \beta_i^V \text{HML}_t + \beta_i^0 + \epsilon_{i,t} \tag{5}$$

where i denotes portfolios. $r_{i,t} - r_{f,t}$ is the portfolio's excess return at time t. ΔDIS_{t-1} is the change of DIS in time t-1 and β_i^F is the portfolio's exposure on DIS factor. $r_{M,t} - r_{f,t}$, SMB_t, HML_t are the Fama French 3 factors at time t and β_i^M, β_i^F and β_i^F are portfolio's corresponding exposure on the 3 factors[4] Please note that, unlike most related literature, I used the lagged factors instead of the factor at time t. FF3 factors are used concurrently to take out the effect of the 3 common risk factors to see how DIS picked up information left. There are two reasons for using the lagged variables: first, using the t-1 factor would examine the predictability power

[4]FF3 factors are from Ken French's website.

of DIS rather than the contemporaneous explaining power; second, empirically, lagged factor yields more significant results and clearer patterns than the concurrent one.

For each month t, the previous 6 months' daily returns are used to estimate the β_i^F using Equation (5). After that, I sorted the 169 portfolios into 10 by the estimated β_i^F, denoting the portfolio using the letter p. Then the post-ranking portfolio betas are estimated using the following equation

$$r_{p,t} - r_{f,t} = \beta_p^F \Delta\text{DIS}_{t-1} + \beta_p^M (r_{M,t} - r_{f,t}) + \beta_p^S \text{SMB}_t + \beta_p^V \text{HML}_t + \beta_p^0 + \epsilon_{p,t} \tag{6}$$

Where $r_{p,t}$ is the equal weighted excess return for portfolio p at time t. The regression is done over the entire sample.

Table VI: **DIS - Beta Sorted Portfolios, Returns and Betas**

	exret(%)	ret(%)	DIS_{t-1} β_i^F	Market_t β_i^M	SMB_t β_i^S	HML_t β_i^V	β_i^0	Adj-R2 (%)
1	5.09	7.41	**-0.07**	-0.12	-0.09	0.07	0.03	7.68
	(46.53)	(67.67)	**(-2.51)**	(-21.22)	(-7.75)	(6.75)	(3.82)	
2	2.88	5.20	**-0.08**	-0.12	-0.06	0.03	0.02	11.23
	(34.92)	(62.96)	**(-4.22)**	(-27.46)	(-7.69)	(4.44)	(3.35)	
3	2.23	4.55	**-0.03**	-0.09	-0.06	0.10	0.01	14.06
	(34.25)	(69.77)	**(-2.02)**	(-27.2)	(-8.43)	(17.8)	(3.22)	
4	0.23	2.54	**-0.06**	-0.09	-0.06	0.16	0.00	22.30
	(3.7)	(41.09)	**(-4.45)**	(-30.48)	(-10.31)	(30.67)	(1.17)	
5	0.86	3.17	**-0.04**	-0.08	-0.07	0.13	0.01	20.27
	(14.88)	(55.1)	**(-3.4)**	(-28.87)	(-13.32)	(26.7)	(1.95)	
6	1.92	4.23	**-0.03**	-0.08	-0.03	0.08	0.01	12.88
	(33.72)	(74.38)	**(-2.18)**	(-27.67)	(-4.68)	(15.8)	(3.18)	
7	-0.53	1.79	-0.01	-0.07	-0.05	0.08	0.00	10.03
	(-9.07)	(30.82)	(-0.6)	(-21.93)	(-7.59)	(15.19)	(0.12)	
8	-0.62	1.70	**-0.03**	-0.06	-0.00	0.06	-0.00	6.14
	(-9.99)	(27.59)	**(-2.07)**	(-19.27)	(-0.37)	(9.89)	(-0.03)	
9	-0.81	1.50	-0.01	-0.05	0.05	0.09	-0.00	4.32
	(-11.02)	(20.27)	(-0.6)	(-11.24)	(6.23)	(13.78)	(-0.46)	
10	-0.82	1.50	0.01	-0.01	0.06	0.03	-0.00	0.44
	(-7.76)	(14.24)	(0.36)	(-2.27)	(5.21)	(2.54)	(-0.46)	

Reported are post-ranking betas of 10 ΔDIS-beta-sorted portfolios estimated using Equation (6). The estimation is over the whole sample period from Jun 1991 to Dec 2020. ret denotes the annualized whole-sample average return, and exret denotes the annualized return over the risk-free rate. The t stat's are reported in the parenthesis.

Table VI reports expected returns of the 10 ΔDIS beta sorted portfolios and their post-ranking betas estimated from Equation (6). Seven of the ten portfolios have significant exposure to the lagged ΔDIS, indicating that the ΔDIS related risk is not completely picked up by Fama French three factor models. Portfolios 1 to 9 have negative betas: as the previous day's ΔDIS goes up, the average return goes down. These portfolios are likely to be exposed to risk factors correlated with DIS, such as liquidity and volatility. Compared to portfolio 1, portfolio 10 is a hedging asset under market stress since it has positive exposure to ΔDIS. The R squared of the model, however, is not very high. One of the reasons is that long-short portfolios are likely to be neutral in many factors by construction.

Now let us look at the average excess return patterns as we go down the table. The exposure on the DIS is roughly going up, and the average performance of these portfolios also decreases. Specifically, portfolios 1 and 2, which have the most negative exposures to the DIS factor (-0.07 and -0.08, respectively), earn an annualized excess return of 5.1% and 2.9%, respectively. However, portfolio 8, which has an exposure of -0.03, earns an average return of -0.6%, significantly under-performs portfolios with higher negative exposure to ΔDIS. The pattern implies that investors ask for compensation for risks they bear when the market is under stress. The Fama Macbeth estimation is conducted in the following session to estimate the risk premium.

Then to further understand the 10 ΔDIS sorted portfolios, I report in Table VII the average components of each of the 10 portfolios over the whole sample period. Numbers in the table indicate that, on average, what percentages of this portfolio are composed of each category. The sum of each column is not 100 because many long-short portfolios we used do not belong to these 6 categories reported. The components are also plotted in figure 4. The green line illustrates how many percentages each portfolio is composed of liquidity long-short portfolios. There are generally more liquidity category portfolios contained from portfolios 1 to 10. It shows that portfolio 10 is more liquid and portfolio 1 is more illiquid, exposing to more liquidity risks. For external financing, investment, and profitability portfolios, the proportion of them is low on the side and high in the middle. The portfolios on both sides have the most negative and positive exposure to the rapidly changing market prices; however, portfolios constructed on investment, financing, and profitability factors depend more on slow-moving fundamental variables. Therefore, portfolios based on those slow-changing variables are contained more within the middle of the 10 portfolios. For momentum categories, it is the opposite since momentum is based on many rapidly changing market information, so they are contained more within the extreme portfolios.

Table VII: **Percentages of each Category Portfolio within 10 DIS-Beta Sorted Portfolios**

	1	2	3	4	5	6	7	8	9	10
external financing	2.69	4.89	6.54	7.20	7.25	6.06	6.40	5.41	5.18	2.60
investment	8.14	9.92	10.70	11.17	11.60	11.22	11.57	11.75	11.45	8.75
liquidity	3.22	3.70	3.65	2.75	3.69	3.80	4.26	4.48	4.17	4.54
momentum	8.68	4.64	3.44	3.63	3.88	3.83	3.64	4.07	4.64	7.08
profitability	3.13	5.76	5.24	5.49	5.06	4.99	4.78	5.13	4.83	3.77
valuation	11.01	10.00	10.14	8.77	8.79	8.03	8.07	8.59	8.42	8.75

The percentage is taken as an average over the whole sample period. Numbers are in percentages. Long-short portfolios that do not belong to the 6 categories below are not reported.

The cross-sectional test I conducted here differs from most related literature in the following aspects. First, I used the daily data instead of the monthly data. The reason is that DIS is a fast-changing price factor, thus, aggregating into monthly measures may average out the frequent day-to-day changes. Meanwhile, the daily analysis would provide more insights and construction ideas for asset management since trade happens every day. Second, I used the lagged changes of the dislocation factor instead of the contemporaneous one. More interestingly, as I used the concurrent DIS instead of the lagged one, the cross-sectional test's performance is poor and displays a very weak pattern - this may be evidence that the information in the previous trading day is priced instead of the concurrent market factor.

The assumption that the market is frictionless obviously fails when there is DIS. Under the friction market condition, it is useful to understand more about the timing property of those

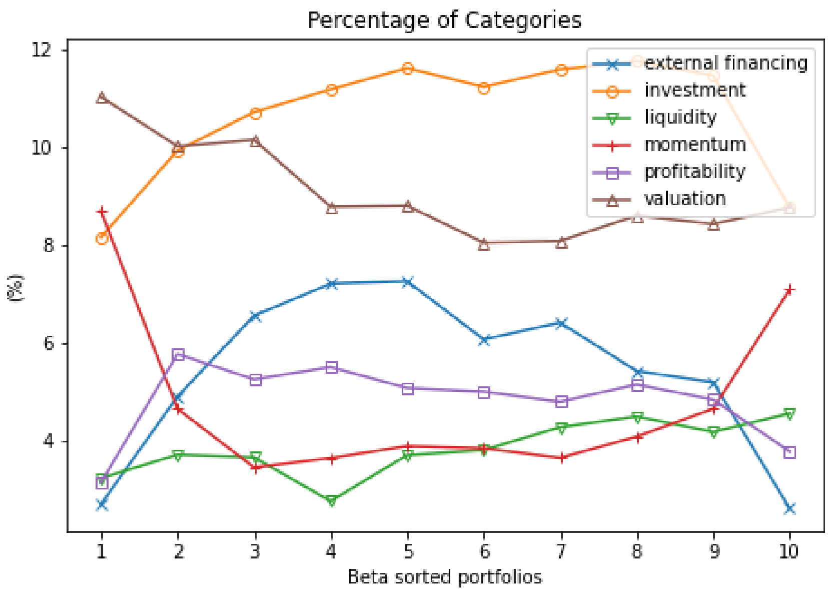

Figure 4: Percentages of each category portfolio within 10 beta sorted portfolios.

beta-sorted portfolios to see how they react to the DIS over a longer period. How do those portfolio returns react during a longer period after the DIS surges? How much will those returns reverse as the market conditions recover? I analyzed the timing property by conducting an event study. All dates with ΔDIS above the top 5% quantile are labeled as day 0. The following trading days are labeled as day x, and x is the number of trading dates between that day and day 0. Each trading day's abnormal return (AR) is the return component orthogonal to Fama French 3 factors. Day x's AR is the average AR of all days with label x. The cumulative abnormal return (CAR) of day x is the sum of the AR from day 0 to day x.

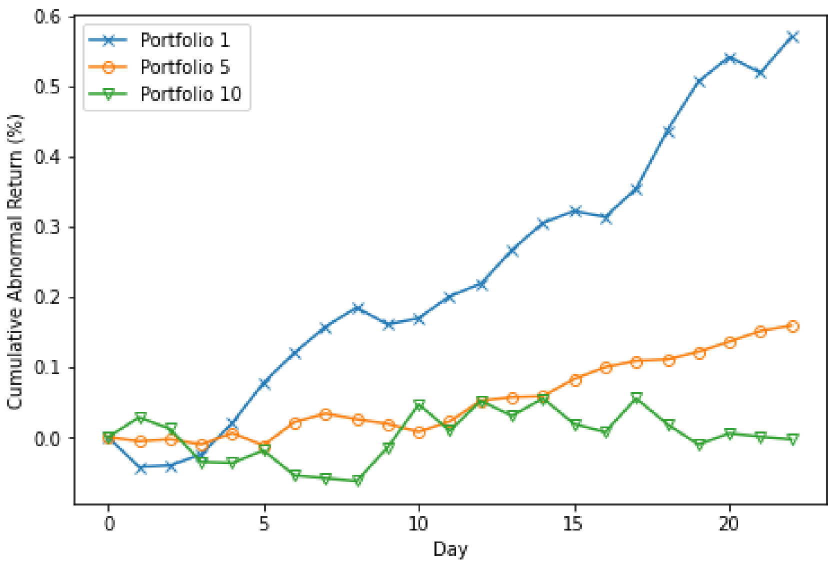

Figure 5: Cumulative abnormal return for days following big DIS shocks. Returns are re-centered to have 0 value at time 0 for clearer demonstration.

The ACR from day 0 to day 22 for portfolio 1, 5, and 10 is reported in Figure 5. The figure shows that portfolio 1, compared to portfolio 5, losses more after the DIS shock at time 0. Portfolio 10, on the opposite, has a higher return. This is consistent with the beta exposure on each portfolio. Before day 3, portfolio 10 keeps outperforming portfolios 1 and 5, and portfolio 5 outperforms portfolio 1. However, this trend reverts on day 3 and keeps reversing afterward. The CAR of portfolio 1 and 5 are both bouncing back, and portfolio 1 performs much better. Portfolio 10, though it performs well shortly after the shock, performs the worst as time goes further. The result supports the hypothesis that portfolio 1, though more exposed to short time liquidity shocks, is reverting quicker and stronger in the longer period going forward as market condition recovers.

4.2 Estimate the risk premium

Table VIII: **Annualized Risk Premium Estimation**

(a) Panel A - Long-short Portfolios

	λ^F	λ^M	λ^S	λ^V
ΔDIS	**-2.83**	8.79	-2.58	-2.04
	(-7.51)	(31.05)	(-15.43)	(-12.35)
Δ(DIS-VIX)	**-15.43**	9.25	-0.91	-2.09
	(-38.73)	(31.2)	(-5.04)	(-12.08)
Δ(DIS-Def)	**-10.02**	8.39	-2.70	-2.45
	(-27.09)	(28.35)	(-15.12)	(-14.03)
Δ(DIS-LIB)	**-12.49**	8.99	-2.65	-2.24
	(-30.23)	(30.34)	(-14.91)	(-12.99)
Δ(DIS-All)	**-15.23**	8.88	-1.94	-2.45
	(-38.65)	(30.05)	(-10.83)	(-14.12)

(b) Panel B - FF25 Portfolios

	λ^F	λ^M	λ^S	λ^V
ΔDIS	**-10.13**	12.29	0.91	-0.01
	(-19.28)	(49.83)	(7.07)	(-0.07)
Δ(DIS-VIX)	**-18.35**	13.04	2.06	-0.07
	(-39.24)	(50.34)	(15.1)	(-0.45)
Δ(DIS-Def)	**-10.95**	12.77	2.04	-0.09
	(-22.72)	(49.39)	(14.94)	(-0.61)
Δ(DIS-LIB)	**-17.79**	12.81	2.03	-0.02
	(-32.84)	(49.42)	(14.87)	(-0.16)
Δ(DIS-All)	**-19.92**	12.82	2.01	0.05
	(-41.72)	(49.48)	(14.69)	(0.34)

(c) Panel C - FF10 Portfolios

	λ^F	λ^M	λ^S	λ^V
ΔDIS	**-10.78**	12.11	6.40	-3.71
	(-11.59)	(48.38)	(17.11)	(-20.77)
Δ(DIS-VIX)	**-8.97**	12.46	0.06	-3.77
	(-10.29)	(47.28)	(0.15)	(-19.96)
Δ(DIS-Def)	**-6.08**	12.52	4.67	-2.95
	(-7.5)	(47.66)	(11.5)	(-15.25)
Δ(DIS-LIB)	**-21.44**	12.48	3.70	-3.50
	(-21.17)	(47.37)	(8.85)	(-18.13)
Δ(DIS-All)	**-14.36**	12.37	6.34	-3.54
	(-13.92)	(46.84)	(15.78)	(-18.55)

(d) Panel D - Individual Stocks

	λ^F	λ^M	λ^S	λ^V
ΔDIS	**-8.77**	10.73	6.13	3.86
	(-15.06)	(41.85)	(40.15)	(21.47)
Δ(DIS-VIX)	**0.64**	11.54	6.06	3.24
	(4.45)	(43.0)	(38.41)	(17.4)
Δ(DIS-Def)	**-1.64**	11.65	5.75	3.17
	(-13.05)	(43.26)	(36.39)	(17.01)
Δ(DIS-LIB)	0.08	11.62	5.99	3.24
	(0.64)	(43.16)	(37.81)	(17.35)
Δ(DIS-All)	-0.16	11.62	5.98	3.24
	(-1.29)	(43.18)	(37.88)	(17.41)

Reported are Fama Macbeth estimation results. λ^F is the risk premium corresponding to the factor in the "Factor" column, λ^M, λ^S, λ^V are risk premiums corresponding to FF 3 factors. DIS-x denotes the regression residual of DIS on variable x. Def, LIB denotes Default spread and LIBOR spread, respectively. Panel (a), (b), (c), and (d) report the estimation results from 169 long-short portfolios, Fama French 25 size-value sorted portfolios, Fama French 10 industry portfolios, and all individual stocks, respectively. All returns are daily from 1990 - 2020.

The next task is to estimate the risk premium. I estimated the risk premium following the conventional Fama Macbeth method. I first estimated the risk premium using the 169 long-short portfolios to see if the risk correlated to DIS is priced within those strategies. Table VIII Panel (a) reported the risk premium estimation using 169 long-short portfolios. We see that the risk corresponding to DIS is indeed priced among long-short portfolios since λ^F estimation is negative and statistically significant. The annualized risk premium is around - 3%. This negative number indicates that portfolios that lose money when DIS surges earn a premium on average. In other words, there is return compensation for those portfolios taking more risks correlated with DIS.

However, it is very hard for us to separate the effect of individual risk factors behind DIS. In Section 2, I showed that DIS mostly correlates with default spread, LIBOR spread, and VIX. So if we separate the shocks of these factors from ΔDIS, will ΔDIS still be significant? To test this, I took the orthogonalized component of the DIS factor to these factors and conducted the same estimation. The result is reported in the second to the last row of Table VIII Panel (a). We see that the orthogonalized DIS still has a significant negative risk premium.

However, risk premium estimation from long-short strategies does not necessarily mean the corresponding risk is priced in the overall market. Then, I checked if the risk correlated to DIS is priced in the overall market. Panel (b) and (c) reported the risk premium estimation using conventional portfolios, including Fama French 25 size-value sorted portfolios and 10 industry portfolios. Unlike the long-short strategies, which only include part of the stocks within the market, those Fama French portfolios are composed of all individual stocks in the market. The risk premium estimation shows that the DIS factor is priced, even after we take out the effect of VIX, Default premium, and LIBOR rate. We notice from Panel (b) that the DIS will somehow take out the value premium. Finally, I estimated the risk premium using all individual stocks with return data available in the WRDS CRSP database. The DIS factor is still significant, but as we take out VIX and LIBOR, the risk premium is either positive or insignificant, not as expected. However, this can be the result that the Fama Macbeth method using individual stocks contains more noise than using portfolios.

5 Conclusions

I proposed a DIS (dislocation) factor by taking the first principle component of 3 fixed-income dislocation measures, including CIP, on/off the run premium, and treasury noise measure. Like many market mispricing measures, DIS has the function of indicating market stress time. The connection of DIS and other market variables shows that it correlates with the market conditions in many aspects, including liquidity, volatility, credit, yield curve dynamics, etc.

I further explored how DIS affects returns on equity long-short strategies. I found that in the short-term, when DIS spikes, long-short strategies tend to underperform and co-move the following day. Furthermore, the exposure on DIS can help explain the cross-sectional variation of asset returns. Portfolios having more negative exposure on DIS earns a return premium for taking more risks correlated, such as liquidity. An event study shows that the return of the portfolio having more negative exposure to DIS will reverse stronger in a longer period after the DIS drops significantly.

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Appendix

A. Market stress time

Table IX: **Market Crisis Time**

	Crisis
Oct 1987	Black monday
Jun 1989	FIRREA
Oct 1989	Mini-crash
Jun 1990	Recession
Sep 1992	UK
Jul 1997	Asia
Oct 1997	Minicrash
Mar 2000	Doccom
Sep 2001	911
Sep 2002	Stock downturn
Oct 2007	Bear
Jun 2008	Indymac
Sep 2008	Lehman
May 2010	Flash crash
Aug 2011	Downgrade
Aug 2015	Selloff
Jan 2018	Crypto
Mar 2020	Covid

B. Factors that does not belong to categories

Advertising Expense, R&D over market cap, Organizational capital , Change in order backlog, Percent Operating Accruals, Percent Total Accruals, Accruals, Abnormal Accruals, Tangibility, Net Operating Assets, R&D capital-to-assets, Cash to assets, Real estate holdings, Cash-flow to price variance, Excluded Expenses, Pension Funding Status, Real dirty surplus, Piotroski F-score, Earnings announcement return, Earnings forecast revisions, Long-vs-short EPS forecasts, Predicted Analyst forecast error, EPS forecast revision, Long-term EPS forecast, Earnings consistency, Earnings Surprise, Earnings surprise streak , Earnings streak length, Firm age based on CRSP, Change in capital inv (ind adj), Change in capex (two years), Change in capex (three years), Customer momentum, Conglomerate return, Earnings surprise of big firms, Industry return of big firms, Price delay r square, Price delay coeff, Price delay SE adjusted, Market leverage, Book leverage (annual), Leverage component of BM, Net debt to price, Intangible return using BM, Intangible return using CFtoP, Intangible return using EP, Intangible return using Sale2P, Long-run reversal, Medium-run reversal, Volatility smirk near the money, Put volatility minus call volatility, Price, R&D ability, Takeover vulnerability, Analyst Optimism, Frazzini-Pedersen Beta, Momentum without the seasonal part, Off season long-term reversal, Off season reversal years 6 to 10, Off season reversal years 11 to 15, Off season reversal years 16 to 20, Return seasonality years 2 to 5, Return seasonality years 6 to 10, Return seasonality years 11 to 15, Return seasonality years 16 to 20, Return seasonality last year, Industry concentration (sales), Industry concentration (assets), Industry concentration (equity), Taxable income to income, Operating leverage, IPO and age, Change in Taxes, Inst own among high short interest, Breadth of ownership, Active shareholders, Cash Productivity, Change in recommendation, Coskewness using daily returns, Return skewness, Idiosyncratic skewness (3F model), CAPM beta, Coskewness, Tail risk beta, Sales growth over inventory growth, Sales growth over overhead growth, Revenue Surprise, Revenue Growth Rank, Order backlog, Change in Asset Turnover, Short Interest, Short term reversal, Size, Idiosyncratic risk (AHT), Systematic volatility, Idiosyncratic risk, Idiosyncratic risk (3 factor), Maximum return over month, EPS Forecast Dispersion, Past trading volume, Volume to market equity, Volume Trend, Option to stock volume, Option volume to average.