Financial Market Dislocations

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Dislocations occur when financial markets, operating under stressful conditions, experience large, widespread asset mispricings. This study documents systematic dislocations in world capital markets and the importance of their fluctuations for expected asset returns. Our novel, model-free measure of these dislocations is a monthly average of hundreds of individual abnormal absolute violations of three textbook arbitrage parities in stock, foreign exchange, and money markets. We find that investors demand statistically and economically significant risk premiums to hold financial assets performing poorly during market dislocations, that is, when both frictions to the trading activity of speculators and arbitrageurs and their marginal utility of wealth are likely to be high. (*JEL* G01, G12)

Financial market dislocations are circumstances in which financial markets, operating under stressful conditions, cease to price assets correctly on an absolute and relative basis. The goal of this empirical study is to document the aggregate, time-varying extent of dislocations in world capital markets and to ascertain whether their fluctuations affect expected asset returns.

The investigation of financial market dislocations is of pressing interest. When "massive" and "persistent," these dislocations pose "a major puzzle to classical asset pricing theory" (Fleckenstein, Longstaff, and Lustig 2013). The turmoil in both U.S. and world capital markets in proximity to the 2008 financial crisis is commonly referred to as a major "dislocation" (e.g., Goldman Sachs 2009; Matvos and Seru 2011). Policy makers have recently begun to treat such dislocations as an important, yet not fully understood, source of financial fragility and economic instability when considering macroprudential

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monitoring and regulation (Hubrich and Tetlow 2011; Kashyap, Berner, and Goodhart 2011; Adrian, Covitz, and Liang 2013).[1] Lastly, the recurrence of severe financial market dislocations over the last three decades (e.g., Mexico in 1994–1995; East Asia in 1997; Long-Term Capital Management [LTCM] and Russia in 1998; Argentina in 2001–2002) has prompted institutional investors and financial intermediaries to revisit their decision-making and risk-management practices (e.g., Banks 2003; Golub and Crum 2010; Goldman Sachs 2012).

Financial market dislocations are elusive to define, and difficult to measure. The assessment of absolute mispricings is subject to considerable debate and significant conceptual and empirical challenges (O'Hara 2008). The assessment of relative mispricings stemming from arbitrage parity violations is less controversial (Berk and DeMarzo 2007). According to the law of one price—a foundation of modern finance—arbitrage activity should ensure that prices of identical assets converge, lest unlimited risk-free profits may arise. Extant research reports frequent deviations from several arbitrage parities in the foreign exchange, stock, bond, and derivative markets, both during normal times and in correspondence with known financial crises; less often these observed deviations provide actionable arbitrage opportunities.[2] An extensive literature attributes these deviations to explicit and implicit "limits" to arbitrage activity.[3]

In this paper, we propose and construct a novel, model-free measure of financial market dislocations based on a large cross-section of observed violations of three textbook no-arbitrage conditions. The first one, known as the

[1] For instance, Kashyap, Berner, and Goodhart (2011) argue that a satisfactory "macroprudential toolkit" should include instruments to assess and prevent the occurrence of price dislocations in financial markets because they are likely to magnify the effects of a financial crisis on economic performance. Accordingly, new macroprudential authorities, such as the Financial Stability Board (FSB), the European Systemic Risk Board (ESRB), or the Financial Policy Committee (FPC), have been charged with the responsibility of identifying dislocations in financial markets and mitigating the risk of widespread financial distress (e.g., Agresti, Borgioli, and Poloni 2011; ESRB 2012; Brinkhoff et al. 2013).

[2] A comprehensive survey of this vast body of literature is beyond the scope of this paper. Recent studies find violations of the triangular arbitrage parity (Lyons and Moore 2009; Kozhan and Tham 2012), covered interest rate parity (Akram, Rime, and Sarno 2008; Coffey et al. 2009; Griffoli and Ranaldo 2011), cross-listed stock pairs parity (Pasquariello 2008; Gagnon and Karolyi 2010), Siamese twins parity (Mitchell, Pulvino, and Stafford 2002), closed-end fund parity (Pontiff 1996), exchange-traded fund parity (Chacko, Das, and Fan 2012), TIPS-Treasury arbitrage parity (Campbell, Shiller, and Viceira 2009; Fleckenstein, Longstaff, and Lustig 2013), off-the-run Treasury bond-note parity (Musto, Nini, and Schwarz 2011), CDS-bond yield parity (Duffie 2010; Garleanu and Pedersen 2011), convertible bond parity (Mitchell and Pulvino 2010), futures-cash parity (Roll, Schwartz, and Subrahmanyam 2007), and put-call parity (Lamont and Thaler 2003a; Ofek, Richardson, and Whitelaw 2004).

[3] Arbitrage activity may be impeded by such financial frictions as transaction costs, taxes, (inventory) holding costs, exchange controls, illiquidity, short-sale and other investment restrictions (surveyed in Gagnon and Karolyi [2010]), information problems (Grossman and Miller 1988), agency problems (De Long et al. 1990; Shleifer and Vishny 1997), idiosyncratic risk (Pontiff 2006), (counterparty) default risk (e.g., Adler and Dumas 1976), execution risk (Stein 2009; Kozhan and Tham 2012), noise trader risk (e.g., Shleifer 2000), opportunity cost of capital (Pontiff 1996) supply factors (Fleckenstein, Longstaff, and Lustig 2013), fire sales and market freezes (Kashyap, Berner, and Goodhart 2011; Shleifer and Vishny 2011; Acharya, Shin, and Yorulmazer 2013), competition (Kondor 2009), margin constraints (Garleanu and Pedersen 2011), and funding liquidity constraints and slow-moving capital (e.g., Brunnermeier and Pedersen 2009; Duffie 2010; Gromb and Vayanos 2010).

Covered Interest Rate Parity (CIRP), is a relationship between spot and forward exchange rates and the two corresponding nominal interest rates ensuring that riskless borrowing in one currency and lending in another in international money markets, while hedging currency risk, generates no riskless profit (e.g., Bekaert and Hodrick 2009). The second one, known as the Triangular Arbitrage Parity (TAP), is a relationship between exchange rates ensuring that cross-rates (e.g., yen per pounds) are aligned with exchange rates quoted relative to a "vehicle currency" (e.g., the dollar or the euro; Kozhan and Tham 2012). The third one, known as the American Depositary Receipt Parity (ADRP), is a relationship between exchange rates, local stock prices, and U.S. stock prices ensuring that the prices of cross-listed and home-market shares of stocks are aligned (e.g., Gagnon and Karolyi 2010). Focusing on these parities allows us to document systematic dislocations in multiple stock, foreign exchange, and money markets, among the largest and most liquid in the world, spanning nearly four decades (1973–2009).

Our measure of monthly financial market dislocations is a cross-sectional, equal-weighted average of hundreds of individual *abnormal* deviations from those arbitrage parities. Each parity's individual abnormal arbitrage violation is computed as the *standardized absolute* log difference between actual and theoretical prices. Absolute arbitrage parity violations are common, mostly (but not always) positively correlated, and often economically large over our sample period. At each point in time, individual deviations are standardized using exclusively their own current and past realizations. This procedure yields *innovations* in individual absolute violations (i.e., relative to their own time-varying *historical* means) and makes them comparable across different parities without introducing look-ahead and generated-regressor bias in the measure. The resulting market dislocation index (MDI) is higher when marketwide arbitrage parity violations are greater than normal (i.e., when such violations are, on average, historically larger). The index is easy to calculate and displays sensible properties as a gauge of financial market dislocations. It exhibits cycle-like dynamics—for example, rising and falling in proximity of well-known episodes of financial turmoil in the 1970s, 1980s, and 1990s—and reaches its height during the most recent financial crisis. It is higher during U.S. recessions, in the presence of greater fundamental uncertainty, lower systematic liquidity, and greater financial instability, but also in calmer times. Yet, a wide array of state variables can only explain a fraction of its dynamics. These properties suggest that MDI is a good candidate proxy for the *commonality* in the many frictions affecting the ability of global financial markets to correctly price traded assets.

Financial market dislocation risk is potentially important for asset pricing. As observed by Fleckenstein, Longstaff, and Lustig (2013), sizeable and recurring arbitrage parity violations indicate the presence of forces driving asset prices that are absent in standard, frictionless asset pricing models. Many studies relate individual barriers, biases, and impediments to investors' trading activity (e.g., liquidity, information, sentiment, noise, financial distress) to asset prices.[4] Others emphasize the role of rare events, crashes, and crises for the cross-section of asset returns (e.g., Veronesi 2004; Barro 2006, 2009; Bollerslev and Todorov 2011). The direct measurement of these frictions, at both the market and asset-specific levels, is however notoriously difficult. Studying the aggregate, time-varying intensity of arbitrage parity violations across assets and markets—that is, encompassing multiple possible sources of mispricings—may help us establish the empirical relevance of these elusive forces for asset pricing in both tranquil and turbulent times. As such, financial market dislocations may be a priced state variable.

The literature suggests that cross-sectional differences in expected asset returns may be related to differences in assets' vulnerability to dislocations due to observable and unobservable asset characteristics. For example, securities that are "difficult to value" (e.g., small, distressed, unprofitable, or extreme sales growth stocks), "risky" (e.g., highly volatile), or "hard to trade" (e.g., illiquid, expensive to short) may be more vulnerable to fluctuations in the aggregate intensity of frictions to arbitrage (see Baker and Wurgler 2006 and references therein). Acharya, Shin, and Yorulmazer (2013) argue that such vulnerability may be "contagious" (i.e., may propagate to other, even unrelated, assets and markets) if there are opportunity costs of idle arbitrage capital waiting "on the sidelines" and the provision of arbitrage capital is from a common pool (see also Pontiff 1996, 2006; Brunnermeier and Pedersen 2009; Gromb and Vayanos 2010).

The literature also suggests that investors may require a compensation (in the form of higher expected returns) for holding those assets with greater sensitivity to dislocation risk. Intuitively, the current price of an asset should be lower (and its expected return higher) if the asset has a low payoff during future dislocations (a *negative* sensitivity to dislocation risk), that is, when frictions to the trading activity of speculators and arbitrageurs are high (for example, impeding their ability to accommodate selling pressure or to hold the asset when investment opportunities are good). Such an asset may be especially undesirable to those speculators and arbitrageurs whose wealth is more likely to drop (i.e., with higher marginal utility of wealth) during dislocations, e.g., because of tightening solvency or margin constraints. For instance, Garleanu and Pedersen (2011) argue that deviations from the law of one price may depend on the product of margin requirements and speculators' shadow cost of funding constraints (i.e., the general shadow cost of capital); according to Brunnermeier and Pedersen (2009, their Equation (31)), securities with *negative* beta with

[4] For example, Amihud and Mendelson (1986), Constantinides (1986), Brennan and Subrahmanyam (1996), Brennan et al. (1998), Vayanos (1998), Shleifer (2000), Amihud (2002), Huang (2003), Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Duffie, Garleanu, and Pedersen (2005, 2007), Baker and Wurgler (2006), Sadka and Scherbina (2007), Brunnermeier and Pedersen (2009), Avramov et al. (2010), Stambaugh, Yu, and Yuan (2011), Hu, Pan, and Wang (2013), and Alti and Tetlock (2013), among others. See also the survey in Harvey, Liu, and Zhu (2013).

respect to marketwide funding liquidity shocks (i.e., shocks to "commonality of fragility" affecting speculators' capital and margin requirements) should have *high* required returns.

We investigate this possibility within both the United States and a sample of developed and emerging stocks and foreign exchange. Our evidence indicates that these assets' sensitivities to MDI have significant effects on the cross-sectional properties of their returns. We find that stock and currency portfolios with *more negative* "financial market dislocation betas"—that is, experiencing *lower realized* returns when MDI is *higher*—exhibit *higher expected* returns. Reflecting the above intuition, MDI betas are generally more negative for portfolios of more "speculative" assets (e.g., Baker and Wurgler 2007; Brunnermeier and Pedersen 2009; Lustig, Roussanov, and Verdelhan 2011): smaller U.S. stocks, U.S. stocks with higher book-to-market, illiquid U.S. stocks, stocks of emerging countries, high interest rate currencies. However, MDI is not redundant relative to popular risk factors based on those asset characteristics. Between 1973 and 2009, the estimated market dislocation risk premium for U.S. stock portfolios formed on size and book-to-market sorts is about −2% per annum, even after controlling for their sensitivities to the market and additional risk factors. Similarly, the market price of MDI risk for portfolios of currencies sorted by their interest rates is −1.5% per annum when assessed over the available sample period 1983–2009. The estimated MDI (dollar) risk premium for country stock portfolios is smaller, ranging between −0.5% and −0.7% (when net of global risk factors). These estimates are both statistically and economically significant, for they imply nontrivial compensation per average MDI beta, for example, as high as 7.5% per annum for U.S. stock portfolios, 6.1% and 5.4% for the U.S. (high-minus-low) book-to-market and illiquidity stock portfolios, 6.0% for international stock portfolios, and 7.4% for a zero-cost carry trade portfolio (long high-interest rate currencies and short low-interest rate currencies). Furthermore, MDI betas alone explain up to 51% (20%) of the samplewide cross-sectional variation in expected U.S. (international) excess stock returns, and 80% of the cross-sectional variation in excess currency returns.

Consistently, when sorting U.S. stocks into portfolios according to their historical MDI betas, we find that stocks with more *negative* (positive) ex ante sensitivity to market dislocation risk tend to be more (less) speculative and to exhibit both *higher* (lower) expected returns and smaller ex post sensitivity to MDI. A spread between the bottom and top deciles of historical MDI beta stocks earns annualized abnormal returns ("alphas") of 5.3% after accounting for sensitivities to the market, size, value, momentum, and liquidity factors. Dislocation spread alphas are even higher (ranging between 7.2% and 10% per annum) in the recent, more turbulent subperiod of 1994–2009. Intuitively, more speculative, worse-performing stocks during prior financial market dislocations (e.g., in decile 1, with the most negative historical MDI betas, when MDI realizations are positive and frictions to speculation are high) may subsequently fail to recover those losses during more normal times (i.e., with small, insignificant postranking MDI betas, when MDI realizations are small or negative but speculation faces the risk of future dislocations); however, less speculative, better-performing stocks during past dislocations (e.g., in decile 10, with the most positive historical MDI betas) may subsequently preserve those gains during more normal times (i.e., with small, or negative postranking MDI betas). Hence, investors demand (offer) sizeable compensation to hold low (high) decile stocks in the form of positive (negative) alphas.

Overall, this evidence suggests that investors earn a premium on financial assets performing poorly during market dislocations (i.e., with negative sensitivity to our index), but pay a premium on financial assets providing insurance against that risk (i.e., with positive sensitivity to our index). These results are in line with the notion of priced dislocation risk discussed earlier. Thus, they provide additional validation of our index of abnormal arbitrage parity violations as a measure of dislocation risk.

We proceed as follows. In Section 1, we construct our measure of financial market dislocations and describe its empirical properties. In Section 2, we examine the relationship between expected asset returns and dislocation risk. We conclude in Section 3.

1. The Financial Market Dislocation Index

Financial market dislocations entail large, widespread mispricings of traded financial securities. Motivated by their frequent occurrence, over the last few decades, financial economics has advocated the important role of numerous frictions for the process of price formation in capital markets to explain why mispricings may arise, persist, and wane. Measuring the direct extent of these frictions—and their relevance for asset pricing—is challenging, and often practical only "in the context of a series of 'special cases'" (Gagnon and Karolyi 2010, 54; see also Barberis and Thaler 2003; Lamont and Thaler 2003b). In this study, we circumvent this issue by constructing a composite index of relative mispricings in global stock, foreign exchange, and money markets. The index captures the commonality in a large cross-section of potential violations of three textbook arbitrage parities in those markets. Hence, it aims to assess the systematic significance of those observable and unobservable, explicit and implicit forces behind their occurrence. Next, we describe each of these parities, the procedure for the construction of our index, and the index's basic properties.

1.1 Arbitrage parities

1.1.1 Covered interest rate parity. The first set of arbitrage deviations in our study stems from violations of the Covered Interest Rate Parity (CIRP). According to the CIRP, in absence of arbitrage borrowing in any currency A for $T-t$ days (at interest cost $r_{A,t,T}$), exchanging the borrowed amount to currency B at the spot exchange rate $S_{t,A/B}$, lending in currency B (at interest

$r_{B,t,T}$), and hedging the foreign exchange risk of repaying the original loan plus interest at the forward exchange rate $F_{t,T,A/B}$ generates no profits. The absence of covered interest rate arbitrage in international money markets implies the following theoretical ("*"), no-arbitrage forward exchange rate between any two currencies A and B:

$$F^{*}_{t,T,A/B} = S_{t,A/B}\left(\frac{1+r_{A,t,T}}{1+r_{B,t,T}}\right), \tag{1}$$

where $S_{t,T,A/B}$ ($F_{t,T,A/B}$) is the spot (forward) exchange rate on day t expressed as units of currency A for one unit of currency B.

Although conceptually simple, the actual implementation of nonconvergence CIRP arbitrage if the CIRP in Equation (1) is violated ($F_{t,T,A/B} \neq F^{*}_{t,T,A/B}$) is more involved. For instance, if $F_{t,T,EUR/USD} < F^{*}_{t,T,EUR/USD}$, one would profit by buying USD for EUR in the forward market at a low price and then selling USD for EUR at a high synthetic forward price using the spot and money markets (i.e., borrowing the initial amount of USD, converting them into EUR, and lending EUR). This strategy requires accounting for synchronous prices and rates, transaction costs, and borrowing and lending on either secured terms (at "repo" and "reverse repo" rates) or unsecured terms (at overnight bid and offer rates, with accompanying index swaps to hedge interest rate risk; see, e.g., Griffoli and Ranaldo 2011). Both funding and trading costs and explicit and implicit limits to arbitrage typically create no-arbitrage bands around theoretical CIRP levels. Both have been shown to vary during "tranquil versus turbulent periods" (e.g., Frenkel and Levich 1975, 1977; Coffey et al. 2009). Data and structural limitations (e.g., nonbinding pricing) make measurement of actual CIRP arbitrage *profits* challenging and feasible only over a few, most recent years (e.g., Akram, Rime, and Sarno 2008; Fong, Valente, and Fung 2010; Griffoli and Ranaldo 2011).[5]

Instead, in this study we intend to measure daily CIRP *violations* across the broadest spectrum of currencies and maturities over the longest feasible sample period. To that purpose (as in the literature), our sample is made of daily indicative spot and forward prices (midquotes, as observed at 4 p.m. GMT) of nine exchange rates among five of the most liquid (and relatively free-floating) currencies in the foreign exchange market (CHF/USD, GBP/USD, EUR/USD, JPY/USD, CHF/EUR, GBP/EUR, JPY/EUR, CHF/GBP, JPY/GBP), and the corresponding LIBOR rates at seven maturities (7, 30, 60, 90, 180, 270, and 360 days), gross of transaction costs, between May 1, 1990, and December 31, 2009.[6] The former is the earliest available date for forward

5 For instance, Griffoli and Ranaldo (2011) report evidence of sizable actual CIRP profits (i.e., at actionable quotes and net of execution costs) during the 2008 financial crisis.

6 LIBOR rates are computed by the British Bankers Association (BBA) as arithmetic averages of contributor banks' interbank offers at around 11 a.m. GMT. For simplicity and uniformity across exchange rates (e.g., when considering national holidays, weekends, special circumstances for fixing and value dates, as well as evolving

Table 1
Arbitrage parity violations: Summary statistics

Parity	N_p	N	Mean	Median	SD	Min	Max	Correlation matrix CIRP	TAP	ADRP	MDI
Panel A: Absolute arbitrage parity violations											
$CIRP_m$	63	236	21.22	19.58	8.76	8.76	84.27	1	−0.116	0.314	0.901
TAP_m	122	444	0.14	0.14	0.01	0.12	0.19	−0.116	1	−0.140	0.182
$ADRP_m$	410	441	218.87	200.86	78.16	121.94	673.86	0.314	−0.140	1	0.292
Panel B: Standardized absolute arbitrage parity violations											
$CIRP_m^z$	63	235	−0.02	−0.10	0.42	−0.55	3.33	1	−0.140	0.558	0.917
TAP_m^z	122	444	0.08	0.04	0.13	−0.15	0.78	−0.140	1	−0.025	0.203
$ADRP_m^z$	410	441	−0.16	−0.17	0.25	−1.28	1.47	0.558	−0.025	1	0.825
MDI_m	595	444	−0.03	−0.05	0.17	−0.65	1.47	0.917	0.203	0.825	1

This table reports summary statistics for monthly averages of daily equal-weighted means of observed (Panel A, in basis points, i.e., multiplied by 10,000) and standardized (Panel B) absolute log violations of the Covered Interest Rate Parity described in Section 1.1.1 ($CIRP_m$ and $CIRP_m^z$, respectively), of the Triangular Arbitrage Parity described in Section 1.1.2 (TAP_m and TAP_m^z), of the ADR Parity described in Section 1.1.3 ($ADRP_m$ and $ADRP_m^z$), as well as for the ensuing Market Dislocation Index described in Section 1.2 (MDI_m), between January 1973 and December 2009. Each individual absolute log difference between actual and theoretical prices is standardized by its historical mean and standard deviation over at least 22 observations up to (and including) its current realization. The market dislocation index is constructed as an equal-weighted average of $CIRP_m^z$, TAP_m^z, and $ADRP_m^z$, when available. N is the number of monthly observations. N_p is the total number of parities.

prices in the sample; the latter is the latest available date for all variables in the analysis. This dataset comes from Thomson Reuters Datastream (Datastream).[7] For each of the resulting 63 CIRP permutations (i), we compute daily (t) absolute log differences (in basis points [bps], i.e., multiplied by 10,000) between actual and CIRP-implied forward exchange rates: $CIRP_{i,t} = \left|\ln\left(F_{t,T,A/B}\right) - \ln\left(F^*_{t,T,A/B}\right)\right| \times 10{,}000$.[8]

Panel A of Table 1 reports summary statistics for $CIRP_m$, the monthly average of daily mean observed CIRP violations $CIRP_{i,t}$ across all available currency-maturity permutations. We plot its time series in Figure 1a. During most circumstances, CIRP violations are low. Mean absolute percentage deviations of market forward exchange rates from their theoretical levels average 21 bps (i.e., 0.21%), fluctuate between 10 and 15 bps during the late 1990s, and are as low as 9 bps by the end of 2006. Yet, CIRP violations also display meaningful intertemporal dynamics. Over our sample period, $CIRP_m$ trends first upward and then downward. It also often spikes in proximity of well-known episodes of financial turmoil. Most notably, mean CIRP deviations

day-count conventions [and their different, possibly conflicting interpretations] over the sample period; see, e.g., Miron and Swannell 1991; Deng et al. 2012), interest rates are compounded using a 30/360 convention. The effect of employing "market" day-count conventions (when feasible) on our analysis is immaterial.

7 Exchange and money market rates for EUR/USD, GBP/EUR, CHF/EUR, and JPY/EUR are available in Datastream since the introduction of the euro in 1999; prior forward and LIBOR data for such European currencies as DEM, FRF, or ITL is not.

8 We filter this dataset for potential data errors and exclude daily CIRP deviations of 10% or more,that is, when $CIRP_{i,t} \geq 1{,}000$ bps. The evidence that follows is unaffected by our filtering procedure.

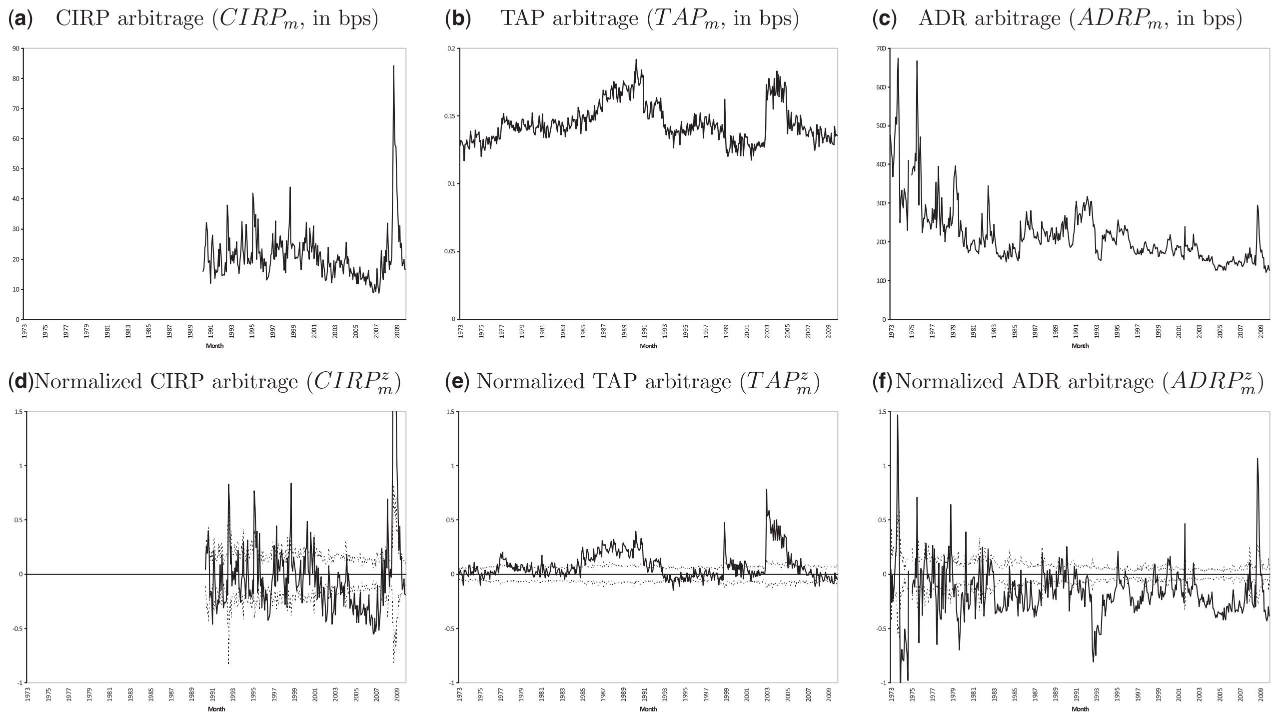

Figure 1
Arbitrage parity violations
This figure plots monthly averages of daily equal-weighted means of observed (solid lines; in basis points, i.e., multiplied by 10,000) and standardized (solid lines, with their 90% confidence intervals around zero [dotted lines] based on within-month sample variation) absolute log violations across 63 permutations of the Covered Interest Rate Parity described in Section 1.1.1 ($CIRP_m$, Figure 1a, 236 months m; $CIRP^z_m$, Figure 1d, 235 months), across 122 permutations of the Triangular Arbitrage Parity described in Section 1.1.2 (TAP_m, Figure 1b, 444 months; TAP^z_m, Figure 1e, 444 months), and across 410 permutations of the ADR Parity described in Section 1.1.3 ($ADRP_m$, Figure 1c, 441 months; $ADRP^z_m$, Figure 1f, 441 months), between January 1973 and December 2009.

reach a maximum (84 bps) in October 2008 (immediately following the Lehman bankruptcy) and remain higher than the historical averages for many months afterward.[9]

1.1.2 Triangular arbitrage parity. The second set of arbitrage deviations in our study stems from violations of the Triangular Arbitrage Parity (TAP). Triangular arbitrage is a sequence of contemporaneous transactions keeping cross-rates—exchange rates not involving vehicle currencies (USD or EUR), for example, JPY/GBP—in line with exchange rates quoted versus vehicle currencies (e.g., JPY/USD and USD/GBP). According to the TAP, in absence of arbitrage, the spot cross-rate between any two currencies A and B should satisfy the following relation with the spot exchange rates of each with a third, vehicle currency (V):

$$S^{*}_{t,A/B} = S_{t,A/V} \times S_{t,V/B}. \tag{2}$$

When Equation (2) is violated ($S_{t,A/B} \neq S^{*}_{t,A/B}$), implementation of the triangular arbitrage is straightforward because it involves simultaneously selling and buying three currencies in the spot market. For instance, if $S_{t,JPY/GBP} < S^{*}_{t,JPY/GBP}$ and $V = USD$, one would simultaneously buy GBP for JPY, sell the ensuing units of GBP for USD, and sell those USD for JPY; this strategy would be profitable because it implies buying GBP at a low JPY price and selling GBP at a high JPY price (e.g., Bekaert and Hodrick 2009). This trading strategy does not rely on convergence to parity and is typically unimpeded by taxes, short-selling, or other regulatory constraints. Similar data limitations as for the CIRP prevent the large-scale measurement of actual TAP arbitrage profits. Rather, we focus on measuring daily TAP violations for the most cross-rates (with respect to either USD or EUR [DEM before January 1, 1999]) among the most liquid, relatively free-floating currencies over the longest feasible sample period, between January 1, 1973 (the earliest available date), and December 31, 2009: AUD, CAD, CHF, FRF, GBP, ITL, JPY. These daily indicative spot exchange rates (as observed at 12 p.m. EST) come from the Pacific Exchange Rate Service database (Pacific). For each of the resulting 122 TAP permutations (i), we compute daily (t) absolute log differences (in bps) between actual and TAP-implied spot cross-rates: $TAP_{i,t} = \left| \ln\left(S_{t,A/B}\right) - \ln\left(S^{*}_{t,A/B}\right) \right| \times 10{,}000.$[10]

[9] Investigations by media and regulators suggest that some of the LIBOR contributor banks may have under-reported their offer rates to the BBA during the recent financial crisis (e.g., see the coverage of the LIBOR probe on the *Wall Street Journal* Web site, at http://stream.wsj.com/story/the-libor-investigation/SS-2-32262/). This is unlikely to meaningfully affect our analysis. Griffoli and Ranaldo (2011) compute similarly large CIRP violations in 2008 and 2009 to those in Figure 1a when using alternative (secured and unsecured) interest rates (in the repo and overnight index swap [OIS] markets, respectively). Furthermore, all of our ensuing inference is insensitive to removing 2008 and 2009 from the sample (see Section 1.3).

[10] We filter this dataset for errors (and unreasonably large TAP deviations) using the same procedure employed for CIRP deviations in Section 2.1.1. We also verify that observed TAP violations in our dataset are not due to rounding

Transaction costs are minimal in the highly liquid spot foreign exchange market (BIS, 2010). Not surprisingly, the literature finds that TAP violations are small, yet persistent, and often larger than the corresponding bid-ask spreads (e.g., Lyons and Moore 2009; Kozhan and Tham 2012). Consistently, Panel A of Table 1 reports that mean monthly absolute percentage TAP deviations across all available cross-rate permutations, TAP_m, average 0.14 bps (i.e., 0.0014%). TAP_m's plot (in Figure 1b), however, shows TAP violations to ebb and flow in long cycles, for example, first steadily increasingly during the 1970s and 1980s and then markedly declining in the 1990s. Figure 1b also points to two noteworthy upward shocks to TAP_m. The first one is short-lived and occurs in December 1998, a month *before* the official launch of the euro; the second one begins in early 2003, lasts roughly two years (in correspondence with a protracted appreciation of the euro), and rapidly dissipates afterward.[11] Interestingly, these dynamics appear to be only weakly related to those of average cross-currency CIRP violations (e.g., a correlation of −0.116 with $CIRP_m$ in Table 1). Thus, TAP violations may provide distinct information on financial market dislocations (and the frictions driving them) over our sample period.

1.1.3 ADR parity. The last set of arbitrage deviations in our study stems from violations of the American Depositary Receipt Parity (ADRP). Companies can list shares of their stock for trading in several markets (especially in the United States) besides their domestic ones in several forms, from global registered offerings to direct listings (e.g., Karolyi 2006). Of these cross-listing mechanisms, American Depositary Receipts (ADRs) are the most common. ADRs are dollar-denominated, negotiable certificates traded on U.S. stock markets representing a prespecified amount ("bundling ratio") of a foreign company's publicly traded equity held on deposit at a U.S. depositary bank.[12] Depositary banks (e.g., Bank of New York Mellon, JPMorgan Chase) charge small custodial fees for converting all stock-related payments in USD and, more generally, facilitating ADRs' convertibility into the underlying foreign market shares and vice versa. The holder of an ADR can redeem that certificate into the

of prices from Equation (2) and/or from direct-to-indirect quote conversion (i.e., from $S_{t,A/B} = (S_{t,B/A})^{-1}$). We accommodate any deviation from the latter in the dataset by considering TAP violations of either $S^*_{t,A/B}$ or $S^*_{t,B/A}$ separately.

[11] We note here that DEM, FRF, and ITL exit our database only on the first trading day of the euro (January 4, 1999), leaving 60 TAP permutations in TAP_m. Removing cross-rates relative to FRL and ITL from the full sample has little impact on TAP_m. Kozhan and Tham (2012) report TAP violations (net of bid-ask spreads) of comparable magnitude from 2003–2004 using tick-by-tick data from the Reuters Dealing 3000 trading system.

[12] A minority of companies, mostly Canadian, cross-list their stock in the U.S. in the form of ordinary shares. "Canadian" ordinaries are identical certificates trading in both the U.S. and a foreign market (i.e., with a bundling ratio of one; see Bekaert and Hodrick 2009); "global registered shares" (GRSs) are ordinaries trading in multiple foreign markets. In the U.S., ordinaries trade like U.S. firms' stock, require no depositary bank, but are subject to specific clearing and transfer arrangements. The literature typically groups ordinaries together with ADRs (e.g., Gagnon and Karolyi 2010).

underlying shares from the depositary bank at any time for a fee; conversely, new ADRs can be created at any time by depositing the ratio of foreign shares at the depositary bank. If ADRs and the underlying equity are perfect substitutes, absence of arbitrage implies that the unit price of an ADR, $P_{i,t}$, should, at any time, be equal to the dollar price of the corresponding amount (i.e., bundling ratio) q_i of home-market shares, as follows:

$$P^*_{i,t} = S_{t,USD/H} \times q_i \times P^H_{i,t}, \tag{3}$$

where $P^H_{i,t}$ is the unit stock price of the underlying foreign shares in their local currency H.

Implementation of a literal ADR arbitrage when Equation (3) is violated ($P_{i,t} \neq P^*_{i,t}$) is complex. For instance, if $P_{i,t} < P^*_{i,t}$, one would simultaneously buy the ADR, retrieve the underlying foreign shares from the depositary bank (a process known as "cancellation"), sell those shares in their home market, and convert the foreign currency sale proceeds to USD. Alternatively, simpler convergence-based trading strategies would involve, for example, buying the "cheap" asset (in this case the ADR at $P_{i,t}$) and selling the "expensive" one (in this case the underlying foreign shares at $P^H_{i,t}$). Several studies (exhaustively surveyed in Karolyi 2006) provide evidence of significant deviations of observed ADR prices from their theoretical parities. Any of the many aforementioned frictions to trading in the literature may impede the successful exploitation of both types of ADR arbitrage.

ADRs' fungibility, as captured by Equation (3), is also limited by such additional factors as conversion fees, holding fees, custodian safekeeping fees, foreign exchange transaction costs, service charges, transfer arrangements, or (one-way and two-way) cross-border ownership restrictions (Gagnon and Karolyi 2010).[13] In particular, one-way restrictions may impede ADR arbitrage (and yield ADR parity violations) by restricting foreign ownership of local shares or local ownership of foreign shares; two-way restrictions may preclude arbitrage by restricting both. As noted in Gagnon and Karolyi (2010), several emerging economies liberalized their financial markets over the last two decades, especially during the late 1990s, by fully or partially relaxing capital controls. Yet, many studies (e.g., Edison and Warnock 2003; Chinn and Ito 2006) show that financial liberalizations are not "one-time events," as the intensity of capital controls, albeit generally declining, varies over time and often increases during times of distress (e.g., Malaysia in 1998; Argentina in 2001–2002; Brazil in 2008–2009). Both the introduction and removal of these restrictions and uncertainty about either may affect the trading activity of speculators and arbitrageurs and hence the extent and

13 Consistently, Gagnon and Karolyi (2010, 79) observe that "the mechanics of arbitrage in the market for cross-listed stocks is complex and the institutional features of this marketplace make it difficult to judge the actual profitability of such trading strategies."

dynamics of asset mispricings (e.g., Auguste et al. 2006; Garleanu and Pedersen 2011).[14]

As the above discussion makes clear, measuring ADR parity violations has the potential to shed light on the intensity of a wide array of (current or expected) limits to arbitrage in the U.S. stock market, in international stock markets for the underlying stocks, and/or in the corresponding foreign exchange markets. As for CIRP and TAP violations, data availability and structural limitations (e.g., imperfect price synchronicity, stale pricing) preclude a comprehensive investigation of actual ADR arbitrage profits.[15] Accordingly, in this study we aim to measure daily ADRP violations across the broadest spectrum of stocks (and currencies) over the longest feasible sample within the period 1973–2009 (as in Sections 1.1.1 and 1.1.2). To that end, we obtain the complete sample of all foreign stocks cross-listed in the United States either as ADRs or as ordinary shares compiled by Datastream at the end of December 2009. Consistent with the literature (e.g., Pasquariello 2008; Gagnon and Karolyi 2010), we exclude from this sample non-exchange-listed ADRs (Level I, trading over-the-counter in the "pink sheet" market), SEC Regulation S shares, private placement issues (Rule 144A ADRs), and preferred shares, as well as ADRs and foreign shares with missing Datastream pair codes.[16] Our final sample is made of 410 home-U.S. pairs of closing stock prices (and bundling ratios) for exchange-listed (on NYSE, AMEX, or NASDAQ; sponsored or unsponsored) Level II and Level III (capital raising) ADRs from 41 developed and emerging countries between January 1, 1973, and December 31, 2009.[17]

For each of these pairs (i), we use Equation (3) and exchange rates from Pacific and Datastream to compute daily (t) absolute log differences (in bps) between actual and theoretical ADR prices: $ADRP_{i,t} = \left|\ln(P_{i,t}) - \ln\left(P^*_{i,t}\right)\right| \times 10,000$.[18] Panel A of Table 1 contains descriptive statistics for $ADRP_m$, the

[14] The number of cross-listings from emerging markets prior to their financial liberalizations is small in our sample. Accordingly, excluding from the analysis cross-listings from those countries over the portion of the sample when these restrictions were in place has virtually no effect on our inference. In addition, as we explain in Section 1.2, our index of financial market dislocations is based on *differences* between observed arbitrage parity violations and their historical means, as the latter may capture the persistent effect of those direct barriers to arbitrage. We examine the relation between financial market dislocations and explicit measures of time-varying capital controls in Section 1.3 (footnote 25).

[15] For instance, Gagnon and Karolyi (2010) address nonsynchronicity between foreign stock and ADR prices by employing available intraday price and quote data for the latter (from TAQ) at a time corresponding to the closing time of the equity market for the underlying (if their trading hours are at least partially overlapping). However, the trading hours of Asian markets do not overlap with U.S. trading hours. In addition, TAQ data is available only from January 1, 1993.

[16] We cross-check the accuracy of Datastream pairings by comparing them with those reported in the Bank of New York Mellon Depositary Receipts Directory (available at www.adrbnymellon.com/dr_directory.jsp).

[17] Sponsored ADRs are initiated by the foreign company of the underlying shares; unsponsored ADRs are initiated by a depositary bank. Most developed cross-listings in our sample are from Canada (67), the Euro area (58), the United Kingdom (43), Australia (30), and Japan (24); emerging cross-listings include stocks traded in Hong Kong (54, a third of which are H-shares of firms incorporated in mainland China), Brazil (23), South Africa (14), and India (10), among others.

[18] As for CIRP and TAP violations in Sections 1.1.1 and 1.1.2, we filter this dataset for errors and unreasonably large ADRP deviations. We also exclude deviations in correspondence with ADR prices below \$5 or above \$1,000.

monthly average of daily mean ADRP violations among all available pairs in the sample. Average absolute deviations from ADR parity are large, about 219 bps (i.e., 2.19%), and subject to large fluctuations.[19] As displayed in Figure 1c (and reported in Gagnon and Karolyi 2010), $ADRP_m$ is generally declining over our sample period, hinting at a broad trend for lower barriers to (arbitrage) trading and greater global financial market integration. Yet, in correspondence with episodes of financial turmoil, ADR parity deviations tend to increase and become more volatile (e.g., in the 1970s, during the Mexican Peso and Asian crises, or in 2008).[20] Some of these dynamics appear to relate to those of CIRP violations in Figure 1a (a correlation of 0.314 with $CIRP_m$ in Table 1), presumably via mispricings in the foreign exchange market, but not to the time series of TAP violations in Figure 1b (a correlation of −0.140 with TAP_m).

1.2 Index construction

The three textbook arbitrage parities described in Sections 1.1.1 to 1.1.3 yield 595 daily potential mispricings in the global stock, foreign exchange, and money markets. Each is only an imprecise estimate of the extent of dislocations in the market(s) in which it is observed (as well as of the explicit and implicit frictions behind its occurrence). However, Table 1 indicates that their realizations are only weakly correlated across parities. Figures 1a to 1c further suggest that observed mispricings tend to persist over time, perhaps reflecting the permanent nature of some impediments to arbitrage or data and structural limitations to their accurate measurement. This discussion suggests that an average of all "abnormal" arbitrage parity violations may measure financial market dislocation risk more precisely.

We construct our novel index of dislocation risk in three steps. First, on any day t, we standardize each parity's individual arbitrage deviation ($CIRP_{i,t}$, $TAP_{i,t}$, $ADRP_{i,t}$) relative to its historical distribution on that day: $CIRP^z_{i,t}$, $TAP^z_{i,t}$, $ADRP^z_{i,t}$.[21] This step allows us to assess the extent to which each realized individual absolute arbitrage parity violation was *historically large* (small) relative to its up-to-current mean (i.e., *abnormally* so) on the day it occurred, from its *positive* (negative) normalized value, without introducing look-ahead and generated-regressor bias, while making these violations comparable across and within different parities. Equivalently, each so-defined standardized arbitrage parity violation represents

[19] Summary statistics for $ADRP_m$ are similar to (albeit slightly smaller than) those reported in Gagnon and Karolyi (2010, their Table 2) for *signed* log-price differences based on synchronous prices when possible.

[20] Consistently, Pasquariello (2008) finds evidence of greater ADRP violations for stocks of emerging markets during the financial crises of the 1990s and early 2000s (Mexico, East Asia, Russia, Brazil, Turkey, and Argentina).

[21] To that end, on any day t, we exclude parity deviations with less than twenty-two past and current realizations.

an *innovation* with respect to its historical, time-varying mean (i.e., *expected*) mispricing.

Second, on any day t we compute the equal-weighted average of all standardized violations within each parity available on that day: $CIRP_t^z$, TAP_t^z, $ADRP_t^z$. This step allows to isolate the *common*, systematic force(s) behind *each* cross-section of innovations in (i.e., abnormal) absolute arbitrage parity violations in our sample at each point in time. Their paritywide monthly means ($CIRP_m^z$, TAP_m^z, $ADRP_m^z$; plotted in Figures 1d to 1f, with their 90% confidence intervals around zero) are frequently negative, often statistically significant, and subject to large intertemporal fluctuations.[22] These variables are also not highly correlated (see Panel B of Table 1), suggesting that each of them may convey nonredundant information about the forces impeding the trading activity of speculators and arbitrageurs.

Third, we compute a monthly index of financial market dislocation risk, MDI_m, as the cross-parity, equal-weighted average of these three monthly means. This step allows us to retain *all* common, systematic forces behind *each* of the three cross-sections of abnormal arbitrage parity violations in our sample at each point in time parsimoniously, while preserving their time-series properties. By construction, the index (plotted in Figure 2, with its 90% confidence interval around zero) is positive in correspondence with *greater-than-normal* marketwide mispricings, that is, in the presence of historically large financial market dislocations.

1.3 Index properties

The composite index MDI_m, based on minimal manipulations of observed model-free mispricings in numerous equity, foreign exchange, and money markets, is easy to calculate and displays sensible properties as a measure of financial market dislocation risk.

Estimated correlations in Panel B of Table 1 indicate that MDI_m loads positively on average abnormal violations in each of the three textbook arbitrage parities (CIRP, TAP, and ADRP). Saliently, its plot (in Figure 2) displays several significant, short-lived upward and downward spikes, as well as meaningful longer-lived, cycle-like dynamics over our sample period 1973–2009. Many of these spikes and cycles occur in proximity to well-known episodes of financial turmoil in the last four decades: the Mideast oil embargo in the fall of 1973, the oil crisis in the late 1970s, the emerging debt crisis in 1982, the U.S. stock market crash in October 1987, the European currency crisis in 1992–1993, the

[22] For instance, several recent studies use equal-weighted cross-sectional averages of stock-level liquidity measures (i.e., potentially affected by idiosyncratic shocks) to produce a more precise assessment of commonality in liquidity (Amihud 2002; Pastor and Stambaugh 2003; Acharya and Pedersen 2005). Monthly averaging smooths potentially spurious daily variability in these normalized arbitrage parity violations (e.g., due to price staleness or nonsynchronicity), but at the potential cost of aggregating away shorter-lived abnormal mispricings (i.e., of underestimating dislocation risk). According to Figures 1d to 1f, $CIRP_m^z$, TAP_m^z, and $ADRP_m^z$ are statistically significant, at the 10% level, in 47% (and also positive in 11%), 46% (41%), and 72% (8%) of all available months over the sample period 1973–2009, respectively.

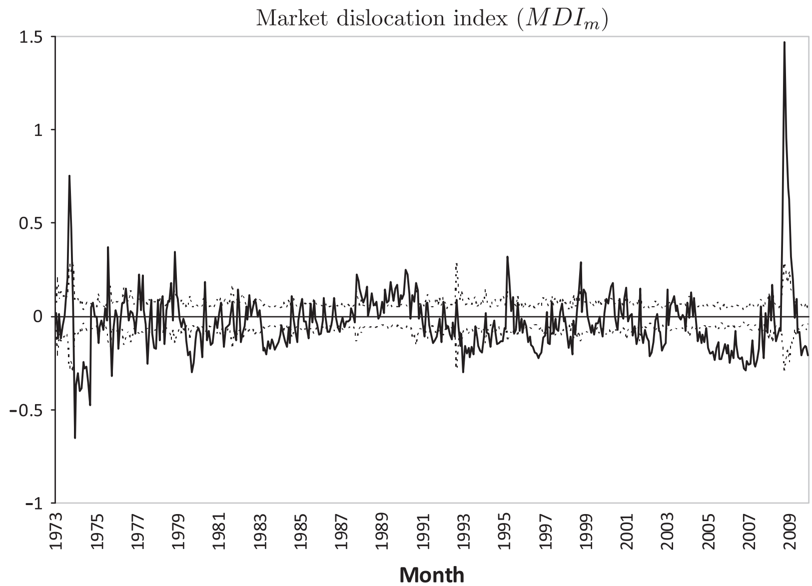

Figure 2
The market dislocation index (MDI_m)
This figure plots the Market Dislocation Index described in Section 1.2 (MDI_m; solid line). The index is constructed as a monthly average of equal-weighted means of daily abnormal (i.e., standardized), absolute log violations (in basis points, i.e., multiplied by 10,000) across 63 permutations of the Covered Interest Rate Parity described in Section 1.1.1 ($CIRP_m^z$; Figure 1d), 122 permutations of the Triangular Arbitrage Parity described in Section 1.1.2 (TAP_m^z; Figure 1e), and 410 permutations of the ADR Parity described in Section 1.1.3 ($ADRP_m^z$; Figure 1f), between January 1973 and December 2009. Each individual absolute log difference between actual and theoretical prices is standardized by its historical mean and standard deviation over at least twenty-two observations up to (and including) its current realization. This figure also plots MDI_m's 90% confidence interval around zero (dotted lines; based on within-month sample variation of its components).

collapse of bond markets in 1994, the Mexican peso crisis in 1994–1995, the Asian crisis in 1997, the Russian default and LTCM "debacle" in the fall of 1998, the internet bubble during the late 1990s, 9/11, the quant "meltdown" in August 2007, and the global financial crisis of 2008–2009.

Consistent with this chronology, most sizably positive realizations of our index (i.e., most abnormal mispricings) occur in the latter portion of our sample.[23] The index is highest in October 2008, in the wake of Lehman's default and in the midst of the most significant recession and financial freeze since the Great Depression. It is plausible to conjecture that in those circumstances, impediments to speculation and arbitrage may have become more severe, and asset mispricings larger and more widespread. All of the ensuing inference is nonetheless robust to (and often stronger when) excluding this most recent, turbulent period (2008–2009) from the sample. In addition, a regression of

[23] Overall, as shown in Figure 2, MDI_m is statistically significant, at the 10% level, in 62% (and also positive in 19%) of the 444 months in the sample period 1973–2009.

MDI_m on a dummy equal to one during the aforementioned crisis periods and zero otherwise yields a R^2 of less than 6%.

Further insight on the nature and properties of our market dislocation index comes from regressing its realizations on the change in several U.S. and international, economic and financial market variables, in Table 2.[24] Regressors include monthly U.S. stock returns (from French's Web site), official NBER recession dummy, world market returns (from MSCI), innovations in Pastor and Stambaugh's (2003) liquidity measure (based on volume-related return reversals, from Pastor's Web site), as well as monthly changes in Chauvet and Piger's (2008) historical U.S. recession probabilities (from Piger's Web site), VIX (monthly average of daily S&P 500 VIX, from CBOE), world market return volatility (its annualized 36-month rolling standard deviation), U.S. risk-free rate (one-month Treasury-bill rate, from Ibbotson Associates), slope of U.S. yield curve (average of ten-year minus one-year constant-maturity Treasury yields, from the Board of Governors), U.S. bond yield volatility (annualized average of 22-day rolling standard deviation of five-year constant-maturity Treasury yields, as in Hu, Pan, and Wang 2013), "TED" spread (average of three-month USD LIBOR minus constant maturity Treasury yields, from Datastream), default spread (average of Baa minus Aaa corporate bond yields, from Moody's), and innovations in Adrian, Etula, and Muir's (Forthcoming) broker-dealer leverage (from Muir's Web site).

Variable selection is driven by the earlier observation that mispricings are more likely during periods of U.S. and/or global economic and financial uncertainty, illiquidity, and overall financial distress. Accordingly, we find MDI_m to be higher during U.S. recessions (in Columns (1) and (4) of Table 2) and periods of economic uncertainty (e.g., higher default risk; Columns (3) and (4)), as well as in correspondence with higher world stock market volatility (Columns (1) and (4)), lower U.S. systematic liquidity (Column (4)), and higher financial instability (e.g., lower balance sheet capacity of financial intermediaries [hence, deteriorating funding conditions], as postulated by Garleanu and Pedersen (2011); Column (4)). Yet, we find MDI_m to be (weakly) higher during more tranquil times as well (e.g., lower TED spread; Columns (3) and (4)).

Ceteris paribus, average abnormal arbitrage parity violations also increase (albeit not significantly so) in correspondence with lower marketwide sentiment or "risk appetite" (higher CBOE VIX index, Columns (1) and (4); e.g., Whaley 2000; Bollerslev et al. 2009) or a steeper U.S. Treasury yield curve (higher slope; Columns (2) and (4)) but are insensitive to U.S. and world stock market

[24] Unreported analysis indicates that most of these variables (listed next) are persistent, or highly autocorrelated, time series over our sample period. Regressions in changes help mitigate biases caused by the presence of such regressors (see, e.g., Jansson and Moreira 2006 and references therein). Regressing MDI_m on either raw or similarly normalized levels of these variables yields similar inference.

Table 2
MDI: Time-series regression analysis

	MDI_m				$CIRP_m^z$	TAP_m^z	$ADRP_m^z$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	−0.069***	−0.033**	−0.025	−0.059***	−0.057	0.075***	−0.198***
	(−4.97)	(−2.53)	(−1.55)	(−3.86)	(−1.63)	(3.81)	(−11.78)
U.S. stock return	0.004			0.003	−0.002	0.004	0.005
	(0.50)			(0.63)	(−0.18)	(1.13)	(0.56)
NBER recession dummy	0.166**			0.131***	0.332**	−0.045	0.114***
	(2.35)			(2.72)	(2.56)	(−1.08)	(2.78)
Change in U.S. recession probability	−0.032			−0.014	−0.279	0.253*	−0.056
	(−0.20)			(−0.07)	(−0.64)	(1.77)	(−0.38)
Change in VIX	0.007			0.005	0.012	−0.003	0.007*
	(1.04)			(1.10)	(1.07)	(−0.66)	(1.76)
World market return	−0.006			−0.006	−0.003	−0.004	−0.007
	(−0.94)			(−1.07)	(−0.23)	(−0.92)	(−0.75)
Change in world market return volatility	0.081***			0.057***	0.125***	−0.011	0.057***
	(2.69)			(2.89)	(2.78)	(−0.57)	(2.86)
Innovations in U.S. liquidity	−0.289			−0.376**	−0.790	−0.024	−0.342**
	(−1.50)			(−2.05)	(−1.63)	(−0.15)	(−2.32)
Change in U.S. risk-free rate		−0.108		0.151	0.107	0.137	0.064
		(−1.14)		(0.65)	(0.20)	(0.80)	(0.26)
Change in slope of U.S. Treasury yield curve		0.050		0.083	0.085	0.015	0.138**
		(1.64)		(1.37)	(0.59)	(0.24)	(2.32)
Change in U.S. Treasury yield volatility		−0.002		0.001	−0.005	−0.007	0.018*
		(−0.29)		(0.13)	(−0.18)	(−0.59)	(1.79)
Change in TED spread (Libor – Treasury Bill)			−0.008	−0.048	−0.036	0.026	−0.142*
			(−1.10)	(−0.62)	(−0.21)	(0.83)	(−1.97)
Change in default spread (Aaa – Baa)			0.454*	0.402**	0.745	0.014	0.454***
			(1.82)	(2.16)	(1.64)	(0.18)	(3.39)
Innovations in broker-dealer leverage			−0.003	−0.003*	−0.006*	0.0003	−0.003***
			(−1.49)	(−1.96)	(−1.77)	(0.38)	(−2.80)
Number of observations	239	443	335	239	235	239	239
R_a^2	31.87%	0.75%	15.81%	42.47%	37.96%	−2.27%	38.14%

This table reports OLS coefficients from time-series regressions of the financial market dislocation index described in Section 1.2, MDI_m (Columns (1) to (4)) and its components ($CIRP_m^z$, Column (5); TAP_m^z Column (6); $ADRP_m^z$ Column (7)). Regressors include monthly U.S. stock returns (from French's Web site), official NBER recession dummy, world market returns (from MSCI), innovations in liquidity (from Pastor and Stambaugh 2003), Adrian, Etula, and Muir's (Forthcoming) innovations in broker-dealer leverage (from Muir's Web site), as well as monthly changes in Chauvet and Piger's (2008) U.S. recession probability (from Piger's Web site), S&P500 VIX (from CBOE), world market return volatility (its rolling standard deviation), U.S. risk-free rate (one-month Treasury-bill rate, from Ibbotson), slope of U.S. yield curve (ten-year minus one-year constant-maturity Treasury yields, from Board of Governors), U.S. bond yield volatility (rolling standard deviation of five-year constant-maturity Treasury yields), TED spread (three-month USD LIBOR minus constant maturity Treasury yields, from Datastream), and default spread (Aaa minus Baa corporate bond yields, from Moody's). R_a^2 is the adjusted R^2. Newey-West t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

downturns (and the accompanying illiquidity, as argued by Chordia, Roll, and Subrahmanyam (2001); Columns (1) and (4)), higher volatility of U.S. interest rates (Column (4)), or flight to quality (e.g., lower U.S. risk-free rates, Column (2); see Hu, Pan, and Wang 2013). Lastly, in untabulated regressions of MDI_m on each of the variables listed in Table 2 separately, we find that its sensitivity to innovations in U.S. stock market liquidity is the most statistically significant (a slope coefficient of −0.393 [$t = -2.22$]), but changes in VIX have the greatest explanatory power (R^2 of 10.92%). We explore the impact of either measure on whether MDI_m is a priced state variable in Sections 2.1.2 and 2.1.3.

Insight on MDI_m can also be drawn from regressing each of its components ($CIRP^z_m$, TAP^z_m, and $ADRP^z_m$) on these variables (in Columns (5), (6), and (7) of Table 2). Not surprisingly, U.S. financial market conditions play an important role in explaining ADR parity deviations but play a lesser one for CIRP and TAP deviations. For instance, $ADRP^z_m$ (in Column (7)) is increasing in frictions in the U.S. intermediation sector (lower broker-dealer leverage), U.S. stock market illiquidity (stronger volume-related return reversals) and volatility (higher VIX), and deteriorating U.S. bond market conditions (higher default spread, Treasury bond yield slope and volatility), but also in calmer times (lower TED spread). Whereas $CIRP^z_m$ displays some similar sensitivities (Column (5)), TAP^z_m shares only a few (but rarely significantly; see Column (6)). This is consistent with the notion, suggested by the correlation matrices in Table 1 (and the literature discussed in Section 1.1.2), that abnormal cross-rate mispricings may be driven by distinct (possibly unobservable) forces. In aggregate, all of these proxies can only explain up to 42% of MDI_m's dynamics (in Column (4)), and no more than 38% of each of its components (in Columns (5) to (7)); the adjusted R^2 (R^2_a) of these regressions are even lower when the most recent period of financial turmoil (2008–2009) is removed from the sample (in this case, dropping to less than 9% in Column (4), and to 4%, −2%, and 14% in Columns (5) to (7)).[25]

These properties suggest our index of abnormal arbitrage parity violations to be a reasonable, nonredundant proxy for financial markets' ability to correctly price traded assets.

1.4 Alternative index specifications

In general, there is no commonly accepted way to construct state variables (or factors) that may be relevant for asset returns. Recent surveys of the

[25] The above inference is unaffected by the further inclusion of the difference between the VIX index and realized S&P 500 return volatility (a proxy for time-varying variance risk premiums in the U.S. stock market; Bollerslev et al. 2009) or the Federal Reserve Bank of St. Louis' financial stress index (capturing the comovement of 18 financial variables such as stock and bond returns and return volatility, various yield spreads, and TIPS breakeven inflation rates) in the regressions of Table 2. In unreported analysis, we also find MDI_m to be only weakly related to the measure of U.S. investor sentiment introduced by Baker and Wurgler (2006, 2007; e.g., a slope coefficient of −0.014 [$t = -1.42$] over 1973–2009) and to either cross-country averages of the unsmoothed or price-smoothed proxy for the intensity of capital controls in emerging markets proposed by Edison and Warnock (2003; e.g., slope coefficients of 0.027 [$t = 0.04$] and −0.066 [$t = -0.09$], respectively, over the available sample period 1989–2006).

literature list numerous alternative procedures and methodologies (e.g., Harvey, Liu, and Zhu 2013; McLean and Pontiff 2013). According to Cochrane (2001), 110, 150), risk factors in linear asset pricing models neither need to be "returns (though they may be)," nor do they need to be made "orthogonal," "serially uncorrelated," "totally unpredictable," or "conditionally or unconditionally mean zero," as long as they are expressed in the "right units" because these models (as in Section 2 next) are often applied to excess returns without identifying the conditional mean of the discount factor.

The market dislocation index MDI_m is not highly persistent (e.g., an untabulated first-order autocorrelation of 0.68) and, by measuring innovations in relative mispricings with respect to their historical levels, avoids look-ahead and generated-regressor bias in asset pricing tests from those transformations. In addition, only weak predictive evidence in unreported analysis suggests that inference from these tests is unlikely to be contaminated by correlation between MDI_m and future excess returns (e.g., Campbell 1996). Alternatively, month-to-month changes in the index, ΔMDI_m (with an untabulated first-order autocorrelation of -0.17), measure innovations in relative mispricings only with respect to their most recent levels. Hence, ΔMDI_m may not capture long-lasting dislocations (like those observed during the last quarter of 2008 and the first quarter of 2009, in the aftermath of Lehman Brothers' default), leading to a less salient assessment of dislocation risk. The correlation between MDI_m and ΔMDI_m is 0.40. Accordingly, our inference is weaker, yet qualitatively robust to replacing MDI_m with ΔMDI_m; these unreported results are available on request.

As noted earlier, our index MDI_m is an equal-weighted average of three paritywide monthly means of standardized arbitrage parity violations, $CIRP_m^z$, TAP_m^z, and $ADRP_m^z$. The literature has also used principal components analysis to summarize the common information in multiple time series of variables of interest (e.g., see Baker and Wurgler 2006). Principal components analysis may not be adequate in our setting because correlations among $CIRP_m^z$, TAP_m^z, and $ADRP_m^z$ (in Panel B of Table 1) are relatively low. Accordingly, their first principal component (with an eigenvalue of 1.4, loading nearly equally on $CIRP_m^z$ and $ADRP_m^z$) accounts for 45% of their variance; their second principal component (with an eigenvalue of 1, loading almost exclusively on TAP_m^z) accounts for an additional 33% of that variance. Furthermore, their computation requires the entire time series of $CIRP_m^z$, TAP_m^z, and $ADRP_m^z$, thus introducing look-ahead bias in any resulting aggregation. Nonetheless, the correlation between an equal-weighted (or variance explained-weighted) average of the first two principal components and MDI_m is 0.97.

We conclude that the above alternative specifications of our index, while yielding similar results, exhibit features making them less appealing as measures of dislocation risk.

2. Is Financial Market Dislocation Risk Priced?

Our measure of financial market dislocation risk, MDI_m, is based on a large cross-section of arbitrage parity violations in global stock, foreign exchange, and money markets over nearly four decades. It has several desirable properties. It is parsimonious and easy to compute; it relies on model-free assessment of asset mispricings; it is free of look-ahead and generated-regressor bias; and it displays sensible time-series features, consistent with commonly held notions of market dislocations. In this section, we investigate whether so-defined financial market dislocation risk is a priced state variable. We concentrate on equity and foreign exchange markets, because of the potential sensitivity of stock and currency returns to systematic mispricings and the availability of established pricing benchmarks. We test whether MDI_m is related to the cross-section of U.S. and international stock portfolio returns, the cross-section of U.S. stock returns, and the cross-section of currency portfolio returns.

2.1 Financial market dislocations and risk premiums: Stocks

2.1.1 Univariate MDI beta estimation. We begin by exploring the exposure of equity market portfolios to financial market dislocation risk. Preliminarily, we follow the standard cross-sectional approach by proceeding in two steps (e.g., Campbell, Lo, and MacKinlay 1997; Lettau and Ludvigson 2001; Petkova 2006). First, we run full-sample time-series regressions to estimate the sensitivity of the monthly excess dollar return of each portfolio i, $R_{i,m}$, to our aggregate abnormal mispricing index MDI_m:

$$R_{i,m}=\beta_{i,0}+\beta_{i,MDI}MDI_m+\varepsilon_{i,m}. \tag{4}$$

Second, we estimate the dislocation risk premium λ_{MDI} by running a cross-sectional regression of the average excess returns of all portfolios on their MDI betas $\beta_{i,MDI}$ from Equation (4):

$$E(R_{i,m})=\lambda_0+\lambda_{MDI}\beta_{i,MDI}+\eta_i. \tag{5}$$

We consider two samples of 25 U.S. and 49 international equity portfolios over the period 1973–2009. The U.S. sample is made of 25 portfolios formed on size (market equity) and book-to-market (book equity to market equity) from French's Web site.[26] The international sample is unbalanced and includes 23 developed and 26 emerging country portfolios (listed in Table 4) from MSCI.[27]

[26] Unreported analysis yields similar inference from studying either a larger (100) or a smaller (10) number of portfolios sorted on size and book-to-market. Lewellen, Nagel, and Shanken (2010) argue that the strong factor structure of size and book-to-market portfolios makes asset pricing tests based on the cross-section of their returns potentially misleading, and suggest (among others) constructing portfolios of stocks sorted by their loadings on the proposed factor. We do so in Section 2.1.3.

[27] World and developed country portfolio returns are available from January 1973, with the exception of Finland (January 1982), Greece, Ireland, New Zealand, and Portugal (January 1988). Emerging country returns are available from January 1988, with the exception of China, Colombia, India, Israel, Pakistan, Peru, Poland, South Africa, and Sri Lanka (January 1993) and Czech Republic, Egypt, Hungary, Morocco, and Russia (January 1995). Hence, these countries are excluded from the OLS estimation of Equations (4) and (5) over earlier subperiods.

Table 3
MDI betas: U.S. stock portfolios

	25 U.S. portfolios				
$\beta_{i,MDI}$	Low B/M	2	3	4	High B/M
Small M	−3.05	−3.09	−3.92**	−3.81**	−6.37***
	(−1.32)	(−1.57)	(−2.36)	(−2.44)	(−3.76)
2	−2.26	−3.37**	−3.10**	−4.53***	−5.65***
	(−1.07)	(−1.98)	(−2.03)	(−3.07)	(−3.33)
3	−2.79	−3.14**	−3.56**	−4.18***	−4.11***
	(−1.43)	(−1.99)	(−2.54)	(−3.06)	(−2.66)
4	−2.31	−3.23**	−4.35***	−4.29***	−4.82***
	(−1.32)	(−2.14)	(−2.98)	(−3.14)	(−3.15)
Large M	−1.91	−2.25*	−3.04**	−3.95***	−3.95***
	(−1.37)	(−1.71)	(−2.37)	(−3.15)	(−2.85)

This table reports OLS estimates of MDI betas $\beta_{i,MDI}$, the slope coefficients from time-series regressions of percentage monthly excess returns of each of 25 U.S. stock portfolios i on MDI_m, the financial market dislocation index described in Section 1.2 (Equation (4)), over the full sample period (January 1973 to December 2009, 444 observations). The sample includes the intersections of five U.S. stock portfolios formed on size (market equity, M), from small to large, and five portfolios formed on book-to-market (book equity to market equity, B/M), from low to high, $R_{i,m}$, from French's Web site. t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Tables 3 and 4 report estimated MDI betas from Equation (4) for U.S. and international portfolios, respectively. Figures 3a and 3b display scatter plots of their annualized mean percentage excess (dollar) returns versus these MDI betas.

Estimates of $\beta_{i,MDI}$ in Tables 3 and 4 are large, mostly (and often highly) statistically significant, and always negative: excess returns of U.S. and international stock portfolios tend to be lower in correspondence with abnormally high financial market dislocations—that is, when arbitrage parity violations are (in aggregate) greater than their historical means ($MDI_m > 0$).[28] MDI betas are more negative for portfolios of relatively smaller, or higher book-to-market U.S. stocks, as well as for emerging market portfolios—that is, for portfolios of securities commonly deemed to be riskier, more difficult to value, or harder to arbitrage (e.g., Baker and Wurgler (2006)). We report estimates of the cross-sectional regression of Equation (5) for U.S. and international stock portfolios in Panel A of Tables 5 and 6, respectively.

Figures 3a and 3b suggest that stock portfolios with more negative MDI betas have higher average excess returns. Accordingly, Panel A of Tables 5 and 6 indicate that the annualized price of financial market dislocation risk is negative ($\lambda_{MDI} < 0$) and statistically significant within both the U.S. and international samples.[29] Dislocation risk premiums are economically significant, amounting

[28] For instance, the estimates of MDI betas in Tables 3 and 4 imply that monthly excess returns of U.S. and international stock portfolios decline on average by 0.62% and 1.61%, respectively, from a one-standard-deviation shock to MDI_m (in Panel B of Table 1). Estimating Equation (4) using country-level returns in local currency yields similar inference. We examine the relationship between financial market dislocations and currency returns in Section 2.2.

[29] Annualized risk premium estimates are computed multiplying monthly estimates by 12. Their t-statistics are obtained by applying the errors-in-variables correction described in Shanken's (1992) to the corresponding

Table 4
MDI betas: International stock portfolios

Developed countries				Emerging countries			
	$\beta_{i,MDI}$		$\beta_{i,MDI}$		$\beta_{i,MDI}$		$\beta_{i,MDI}$
Australia	−6.38***	Netherlands	−6.21***	Argentina	−12.74**	Mexico	−7.81**
	(−3.12)		(−3.99)		(−2.55)		(−2.42)
Austria	−9.80***	New Zealand	−11.81***	Brazil	−18.13***	Morocco	−7.41***
	(−5.22)		(−4.78)		(−3.38)		(−3.64)
Belgium	−6.76***	Norway	−9.38***	Chile	−7.98***	Pakistan	−10.99**
	(−3.90)		(−4.17)		(−3.31)		(−2.56)
Canada	−5.26***	Portugal	−9.12***	China	−9.14**	Peru	−11.99***
	(−3.18)		(−4.15)		(−2.36)		(−3.48)
Denmark	−6.41***	Singapore	−5.96**	Colombia	−12.57***	Philippines	−8.14***
	(−4.11)		(−2.54)		(−3.72)		(−2.59)
Finland	−10.97***	Spain	−5.71***	Czech Republic	−14.86***	Poland	−18.23***
	(−3.88)		(−3.02)		(−4.83)		(−3.87)
France	−4.62***	Sweden	−7.17***	Egypt	−15.96***	Russia	−20.33***
	(−2.49)		(−3.64)		(−4.79)		(−3.26)
Germany	−7.25***	Switzerland	−4.11***	Hungary	−19.92***	South Africa	−10.65***
	(−4.08)		(−2.75)		(−5.08)		(−3.64)
Greece	−11.45***	United Kingdom	−4.44**	India	−14.04***	South Korea	−9.89***
	(−3.41)		(−2.50)		(−4.44)		(−2.67)
Hong Kong	−5.38*	United States	−3.21**	Indonesia	−15.19***	Sri Lanka	−10.01***
	(−1.87)		(−2.52)		(−3.19)		(−2.69)
Ireland	−11.95***			Israel	−4.90*	Taiwan	−8.46**
	(−5.67)				(−1.89)		(−2.31)
Italy	−6.42***			Jordan	−9.04***	Thailand	−8.54**
	(−3.10)				(−4.98)		(−2.19)
Japan	−3.60**			Malaysia	−5.89**	Turkey	−13.32**
	(−2.06)				(−2.02)		(−2.36)

This table reports OLS estimates of MDI betas $\beta_{i,MDI}$, the slope coefficients from time-series regressions of percentage monthly excess dollar returns of each of 49 international stock portfolios i on MDI_m, the financial market dislocation index described in Section 1.2 (Equation (4)). The sample includes 23 developed and 26 emerging country portfolios, from MSCI. Developed country returns are available from January 1973 to December 2009 (444 observations), with the exception of Finland, New Zealand (January 1982, 336 observations), Greece, Ireland, and Portugal (January 1988, 264 observations). Emerging country returns begin on January 1988, with the exception of China, Colombia, India, Israel, Pakistan, Peru, Poland, South Africa, Sri Lanka (January 1993, 204 observations), Czech Republic, Egypt, Hungary, Morocco, and Russia (January 1995, 180 observations). t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

to −2.03% and −0.46% per unit of MDI beta—that is, 7.41% (t=4.49, in Panel A of Table 5) and 4.45% (t=3.40, in Panel A of Table 6) per average MDI beta $\lambda_{MDI}\overline{\beta_{i,MDI}}$—for U.S. and international stock portfolios, respectively. The accompanying cross-sectional R^2 of 51% and 20% suggest that financial market dislocation risk alone can explain a meaningful portion of the cross-section of equity portfolio returns.[30] These properties are generally robust across sample subperiods, although absolute estimated λ_{MDI} and Equation (5)'s

conventional standard errors. Because of MDI_m's relatively large variance (see, e.g., Panel B of Table 1), this correction has virtually no effect on the inference. The joint GMM estimation of $\beta_{i,MDI}$ and λ_{MDI} in Section 2.1.2 (and Tables A1 and A2 and footnote 39) yields heteroscedasticity-robust inference as well (e.g., Cochrane 2001).

30 For instance, the corresponding cross-sectional R^2 relative to the U.S. and world market alone (or the U.S. and global market, size, and value factors) are 23% and 15% (or 75% and 21%), respectively. We consider multivariate MDI beta estimation and pricing in Section 2.1.2.

(a) MDI betas and U.S. stock returns (b) MDI betas and country stock returns (c) MDI betas and currency returns

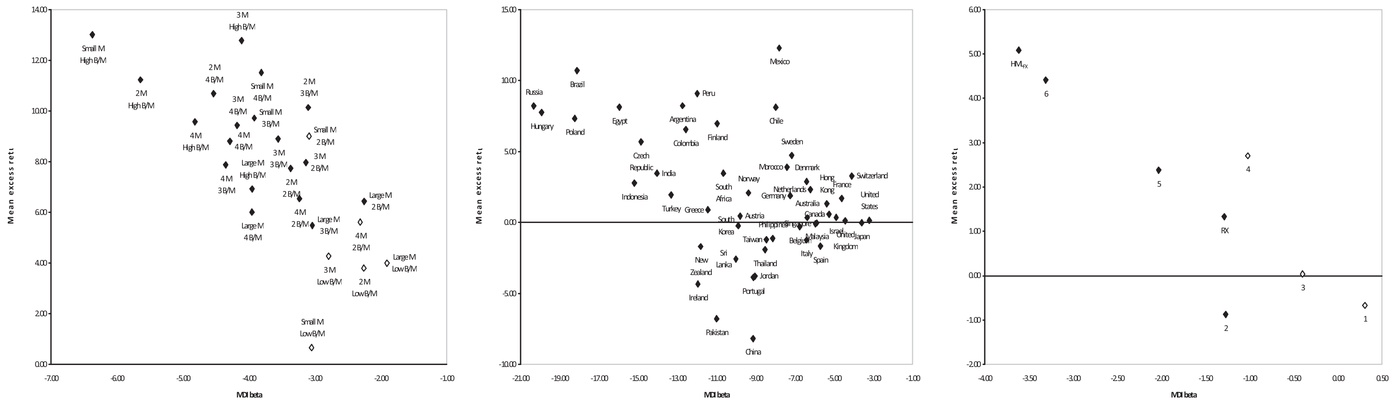

Figure 3
MDI betas and stock and currency portfolios' excess returns
This figure presents labeled scatter plots of annualized mean percentage excess stock and currency returns (i.e., multiplied by 12, left axis) versus their financial market dislocation risk betas ($\beta_{i,MDI}$) estimated in Equation (4). Figure 3a is based on 25 U.S. stock portfolios: The intersection of five portfolios formed on size (M, market equity) and five portfolios formed on book-to-market (B/M, book equity divided by market equity), from French's Web site. MDI betas and mean excess returns are estimated for each U.S. portfolio over the full sample 1973–2009. Figure 3b is based on 49 international stock portfolios: 23 developed and 26 emerging country portfolios, from MSCI. MDI betas and mean excess dollar returns are estimated for each country over the longest span of available data within the full sample 1973–2009. Figure 3c is based on eight currency portfolios: Six portfolios formed on interest rates (from low [1] to high [6]), a portfolio going long a basket of developed and emerging currencies against the dollar (RX), and a carry trade portfolio going long high-interest rate currencies and short low-interest rate currencies (HML_{FX}), from Verdelhan's Web site. MDI betas and mean excess (dollar) returns are estimated for each currency portfolio over the full sample 1983–2009. Scatters with dark (white) background refer to statistically (in)significant MDI betas, at the 10% level or less.

Table 5
MDI risk premiums: U.S. stock portfolios

	1973–2009				1973–1993				1994–2009			
	λ_0	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	R^2	λ_0	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	R^2	λ_0	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	R^2
Panel A: Univariate regressions												
	0.52	−2.03***	7.41***	51%	12.71***	−2.36***	−4.58***	65%	2.19	−0.70	5.45	9%
	(0.23)	(−3.51)	(4.49)		(9.53)	(−4.08)	(−3.36)		(0.57)	(−1.43)	(1.48)	
Panel B: Multivariate regressions												
CAPM	6.34	−1.75***	0.69**	56%	11.36**	−2.48***	1.43	66%	0.96**	−0.49	0.33	30%
	(1.25)	(−3.09)	(2.01)		(2.12)	(−3.26)	(0.41)		(2.23)	(−1.11)	(1.04)	
3-factor	14.91**	−0.09	−0.06	75%	5.69	−0.82	−0.15	80%	23.46***	0.13	0.12	66%
	(2.77)	(−0.14)	(−0.14)		(0.87)	(−1.24)	(−1.00)		(4.39)	(0.23)	(0.24)	
4-factor	9.09	−0.38	−0.23	77%	5.16	−0.99	−0.13	82%	16.16**	−0.10	−0.08	70%
	(1.14)	(−0.48)	(−0.52)		(0.77)	(−1.42)	(−0.36)		(2.15)	(−0.18)	(−0.19)	
5-factor	8.88	−0.44	−0.28	79%	3.43	−0.90	−0.11	82%	17.42**	−0.23	−0.23	71%
	(1.09)	(−0.55)	(−0.19)		(0.48)	(−1.25)	(−1.47)		(2.22)	(−0.38)	(−0.41)	
3-factor°	6.67	−2.26**	1.09**	58%	9.60	−1.47**	1.39**	79%	16.30***	−1.32**	0.96**	58%
	(0.94)	(−2.11)	(2.10)		(1.48)	(−2.26)	(2.47)		(3.04)	(−2.43)	(2.02)	

This table reports estimates of annualized percentage MDI risk premiums (λ_{MDI}, multiplied by 12) for univariate and multivariate MDI betas ($\beta_{i,MDI}$) of 25 U.S. stock portfolios. The U.S. portfolios include the intersections of five U.S. stock portfolios formed on size and five portfolios formed on book-to-market (from French's Web site). Annualized OLS estimates of λ_{MDI} (and of zero-beta portfolio returns λ_0) are obtained from univariate (Equation (5), Panel A) and multivariate (Equation (7), Panel B) cross-sectional regressions of portfolio-level, mean excess percentage monthly dollar returns $R_{i,m}$ on previously estimated MDI betas $\beta_{i,MDI}$ from univariate (Equation (4)) and multivariate (Equation (6)) time-series regressions, as well as the risk premium per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$), over the full sample 1973–2009 and two subperiods (1973–1993, 1994–2009). Multivariate time-series regressions include the U.S. market factor (MKT_m, CAPM), three traded Fama-French factors (U.S. market plus size [SMB_m] and book-to-market [HML_m], from French's Web site), four traded factors (three factors plus momentum [MOM_m, also from French's Web site]), five traded factors (four factors plus liquidity [PS_m, from Pastor's Web site]), or three traded factors (five factors minus size and book-to-market; "°"). R^2 is the cross-sectional R^2. t-statistics are in parentheses; in the case of λ_0 and λ_{MDI}, t-statistics are computed by applying Shanken's (1992) errors-in-variables correction to the corresponding conventional standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6
MDI risk premiums: International stock portfolios

	1973–2009§				1973–1993§				1994–2009			
	λ_0	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	R^2	λ_0	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	R^2	λ_0	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	R^2
Panel A: Univariate regressions												
	−2.44*	−0.46***	4.45***	20%	6.74***	0.06	−0.20	0%	−4.61*	−0.52***	6.02***	14%
	(−1.68)	(−3.40)	(3.40)		(2.87)	(0.21)	(−0.21)		(−1.95)	(−2.73)	(2.72)	
Panel B: Multivariate regressions												
WCAPM	−5.79**	−0.53***	1.66**	24%	17.18***	0.34	−0.72	21%	−4.51*	−0.53**	1.50**	14%
	(−2.61)	(−2.69)	(2.59)		(3.95)	(1.02)	(−0.98)		(−1.69)	(−2.37)	(2.26)	
GCAPM	−5.34**	−0.37**	1.44*	22%	16.97***	0.43*	−3.40*	12%	−4.58*	−0.52**	1.71**	14%
	(−2.44)	(−2.05)	(1.97)		(2.87)	(1.93)	(−1.86)		(−1.74)	(−2.31)	(2.24)	
3-factor	−5.44**	−0.34	1.04	23%	7.01	0.25	−0.96	50%	−4.23	−0.73***	1.93**	19%
	(−2.46)	(−1.57)	(1.54)		(1.22)	(1.27)	(−1.02)		(−1.53)	(−2.77)	(2.61)	
4-factor	−4.46**	−0.24	0.74	36%	9.24*	0.37***	−1.40	47%	−3.24	−0.59**	1.55**	26%
	(−2.15)	(−1.18)	(0.40)		(1.92)	(4.51)	(−0.52)		(−1.19)	(−2.22)	(2.15)	

This table reports estimates of annualized percentage MDI risk premiums (λ_{MDI}, multiplied by 12) for univariate and multivariate MDI betas ($\beta_{i,MDI}$) of 49 international stock portfolios. The international portfolios include 23 developed and 26 emerging country portfolios (from MSCI). Annualized OLS estimates of λ_{MDI} (and of zero-beta portfolio returns λ_0) are obtained from univariate (Equation (5)) and multivariate (Equation (7)) cross-sectional regressions of portfolio-level, mean excess percentage monthly dollar returns $R_{i,m}$ on previously estimated MDI betas $\beta_{i,MDI}$ from univariate (Equation (4), Panel A) and multivariate (Equation (6), Panel B) time-series regressions, as well as the risk premium per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$), over the full sample 1973–2009 and two subperiods (1973–1993, 1994–2009). Multivariate time-series regressions include the world market factor ($WMKT_m$, from MSCI), the global market factor ($GMKT_m$, from French's Web site), three traded Fama-French global factors (global market, size [$GSMB_m$], and book-to-market [$GHML_m$], from French's Web site), or four traded global factors (three factors plus global momentum [$GMOM_m$, also from French's Web site]). The three (four) global factors are jointly available only from July (November) 1990 and onward; over the resulting subperiods ("§"), the corresponding OLS estimation is restricted to 35 country portfolios for which data is available (i.e., excluding China, Colombia, Czech Republic, Egypt, Hungary, India, Israel, Pakistan, Peru, Poland, South Africa, and Sri Lanka). R^2 is the cross-sectional R^2. t-statistics are in parentheses; in the case of λ_0 and λ_{MDI}, t-statistics are computed by applying Shanken's (1992) errors-in-variables correction to the corresponding conventional standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

cross-sectional explanatory power are greater in the first subperiod (1973–1993) for U.S. portfolios, and in the second subperiod (1994–2009) for country portfolios.[31]

Intuitively, this evidence is consistent with the notion (discussed earlier) that investors find financial market dislocations undesirable. Thus, they require a compensation for holding stock portfolios with greater exposure to that risk, that is, performing more poorly when asset mispricings are abnormally large.

2.1.2 Multivariate MDI beta estimation. Financial market dislocation risk may be related to (or subsumed by) other priced risk factors. For instance, Figures 3a and 3b (and Tables 3 and 4) show that well-known portfolios of arguably "riskier" U.S. and international stocks are highly sensitive to our index MDI_m.

We investigate this possibility in several ways. We begin by estimating the MDI betas of several "traded" factors—stock portfolios commonly interpreted as capturing popular sources of U.S. and global systematic risk. U.S. traded factors include the market (MKT_m), size (SMB_m), and book-to-market (HML_m) factors of Fama and French (1993; from French's Web site), the momentum factor (MOM_m) of Carhart (1997); from French's Web site), and the liquidity factor (PS_m) of Pastor and Stambaugh (2003; from Pastor's Web site). The World (or Global) CAPM is the most common international asset pricing model (Bekaert and Hodrick 2009); yet, there is evidence of size, book-to-market, and momentum effects in international stock returns (e.g., Fama and French 1998, 2012; Hou, Karolyi, and Kho 2011). Global traded factors therefore include the world market ($WMKT_m$, net of the U.S. risk-free rate; from MSCI), and the four global (developed) market ($GMKT_m$), size ($GSMB_m$), value ($GHML_m$), and momentum ($GMOM_m$) factors of Fama and French (2012; also from French's Web site, over the available sample period 1990–2009).[32] Table 7 reports estimated dislocation betas from Equation (4) for each of these ten portfolios.

Tables 7 highlights important similarities and differences in the relationship between U.S. and global traded factors and our index MDI_m. In both cases, estimates of $\beta_{i,MDI}$ are nearly always negative (as for all portfolios in Tables 3 and 4). Exposure to dislocation risk does not wane in aggregation: dislocation betas for MKT_m and $WMKT_m$ (or $GMKT_m$) are large and statistically significant, especially in the later subperiod 1994–2009. The relative performance of small stocks over large ones (SMB_m and $GSMB_m$) and past losers over past winners (MOM_m and $GMOM_m$) is unrelated to MDI_m within all sample partitions. However, HML_m and PS_m (but not $GHML_m$)

[31] Those uneven subperiods are chosen to correspond to the even subperiods (1978–1993, 1994–2009) stemming from the analysis of the cross-section of U.S. stock returns in Section 2.2.

[32] Specifically, returns on the three (four) global Fama-French portfolios, formed by sorting stocks of twenty-three developed countries, are jointly available exclusively from July (November) 1990 and onward.

Table 7
MDI betas: U.S. and global traded factors

	U.S. factors					Global factors				
$\beta_{i,MDI}$	MKT	SMB	HML	MOM	PS	WMKT	GMKT	GSMB	GHML	GMOM
1973–2009§	−3.12**	−0.61	−2.69***	−0.87	−2.91***	−4.21***	−7.73***	−0.81	−1.29	−0.51
	(−2.39)	(−0.68)	(−3.13)	(−0.67)	(−2.89)	(−3.47)	(−5.16)	(−1.01)	(−1.47)	(−0.33)
1973–1993§	2.35	−0.35	−2.09*	−2.24	−2.81**	0.88	−13.76**	−2.42	−3.39	−1.42
	(1.15)	(−0.29)	(−1.78)	(−1.46)	(−2.01)	(0.47)	(−2.21)	(−0.81)	(−1.50)	(−0.35)
1994–2009	−7.13***	−0.82	−3.20**	0.02	−2.87*	−7.95***	−7.39***	−0.69	−1.19	−0.49
	(−4.36)	(−0.59)	(−2.49)	(0.01)	(−1.95)	(−5.11)	(−4.79)	(−0.81)	(−1.24)	(−0.29)

This table reports OLS estimates of univariate MDI betas $\beta_{i,MDI}$, the slope coefficients from time-series regressions of percentage monthly excess returns of each of ten U.S. and global traded factors on MDI_m, the financial market dislocation index described in Section 1.2 (Equation (4) in Section 2.1.1), over the full sample period (January 1973 to December 2009 [444 observations]) and two subperiods (1973–1993 [252 observations], 1994–2009 [192 observations]). The sample includes the three traded Fama-French factors (U.S. market [MKT_m], size [SMB_m], and book-to-market [HML_m], from French's Web site), the traded momentum factor (MOM_m, from French's Web site), the traded liquidity factor of Pastor and Stambaugh (2003) (PS_m, from Pastor's Web site), the world market factor ($WMKT_m$, from MSCI), and the four traded Fama-French global factors (global market [$GMKT_m$], size [$GSMB_m$], book-to-market [$GHML_m$], and momentum [$GMOM_m$], also from French's Web site). $GMKT_m$, $GSMB_m$, and $GHML_m$ ($GMOM_m$) are available only from July (November) 1990 onward (234 [230] observations; "§"). t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

tend to perform poorly during market dislocations, even after controlling for their (small) market betas.[33] These estimates are consistent with the notion, discussed earlier, that the extent of dislocations in world capital markets (as measured by MDI_m) may be a state variable of concern to market participants holding distressed, difficult-to-value, or illiquid assets, that is, assets that are particularly vulnerable to frictions to the trading activity of speculators and arbitrageurs.

In light of these estimates, we next assess the marginal contribution of MDI_m to the cross-section of equity portfolio returns, while accounting for their sensitivities to those other factors—that is, whether MDI_m has additional information for average equity returns relative to those well-known priced sources of risk. To that purpose, we consider a multivariate extension of Equations (4) and (5). We first find estimates of the dislocation beta of each portfolio from the following multivariate time-series regressions (e.g., Fama and French 1993; Cochrane 2001):

$$R_{i,m} = \beta_{i,0} + B_i F_m + \beta_{i,MDI} MDI_m + \varepsilon_m, \tag{6}$$

where F_m is a $K \times 1$ vector of traded factors, and B_i is a $1 \times K$ vector of factor loadings. We then estimate the dislocation risk premium from a cross-sectional regression of the average excess returns of all portfolios on both their traded factor betas and their MDI betas from Equation (6):

$$E(R_{i,m}) = \lambda_0 + B_i \lambda_F + \lambda_{MDI} \beta_{i,MDI} + \eta_i. \tag{7}$$

We report the ensuing estimated MDI risk premiums for U.S. and international portfolios in Panel B of Tables 5 and 6, respectively.

The estimation of Equations (6) and (7) is meant to facilitate the interpretation of the relationship between U.S. and international portfolios' dislocation betas and their average excess returns (as displayed in Figures 3a and 3b), rather than as a "horse race" among alternative sources of risk or factor models. In particular, Table 7 motivates us to examine several factor specifications for the 25 U.S. size and book-to-market portfolios and the 49 developed and emerging equity portfolios in our sample. We first characterize the vector F_m in Equation (6) as including the U.S. market alone (MKT_m) for the former and either the world ($WMKT_m$) or the global (developed) market factor ($GMKT_m$) for the latter. Market-adjusted estimates of λ_{MDI} in Panel B of Tables 5 and 6 suggest that full-period and subperiod dislocation risk premiums for both U.S. and international stock portfolios are nearly always negative, statistically significant, and large (e.g., as high as -2.48% [$t = -3.26$] for U.S. portfolios) even after accounting for the effect of market risk. MDI

[33] For instance, Tables 1 and 7 imply that the monthly returns of both HML_m and PS_m decline on average by roughly 0.5% in correspondence with a one-standard-deviation shock to MDI_m over the full sample 1973–2009. The (untabulated) market-adjusted dislocation betas of HML_m and PS_m are discussed next.

risk premiums per average MDI beta $\lambda_{MDI}\overline{\beta_{i,MDI}}$ are unsurprisingly smaller than their univariate counterparts in Panel A of Tables 5 and 6, given market portfolios' negative sensitivity to our index MDI_m in Table 7. Yet, they remain economically meaningful, for example, ranging between 1.50% ($t = 2.26$) and 1.66% ($t = 2.59$) for country portfolios (relative to WCAPM).

The evidence in Table 7 also suggests that CAPM-adjusted dislocation betas and risk premiums (in Panel B of Table 5) may help interpret the "value" and "liquidity" premiums documented by Fama and French (1993) and Pastor and Stambaugh (2003) in the U.S. stock market—that is, HML_m and PS_m's high average excess returns given market betas (see, e.g., Fama and French 2006).[34] In unreported analysis, MDI betas for HML_m and PS_m relative to CAPM ($F'_m = MKT_m$ in Equation (6)) are $\beta_{i,MDI} = -3.46$ ($t = -4.31$) and -3.06 ($t = -3.02$) from 1973–2009, -1.52 ($t = -1.42$) and -2.53 ($t = -1.83$) from 1973–1993, -5.18 ($t = -4.09$) and -2.49 ($t = -1.61$) from 1994–2009. These estimates imply nontrivial dislocation premiums when multiplied by the annualized, CAPM-adjusted λ_{MDI} in Panel B of Table 5, for instance, amounting to $\lambda_{MDI}\beta_{i,MDI} = 6.07\%$ per annum for HML_m and 5.36% for PS_m over 1973–2009.[35] Accordingly, estimated premiums per unit of (and average) dislocation betas of U.S. portfolios in Panel B of Table 5 are small and uniformly statistically insignificant relative to three conventional traded factor specifications, including the book-to-market factor: Fama-French ($F'_m = (MKT_m \;\; SMB_m \;\; HML_m)$), Fama-French plus momentum ($F'_m = (MKT_m \;\; SMB_m \;\; HML_m \;\; MOM_m)$), and Fama-French plus momentum and liquidity ($F'_m = (MKT_m \;\; SMB_m \;\; HML_m \;\; MOM_m \;\; PS_m)$). However, those premiums remain large, negative, and significant relative to the market, momentum, and liquidity factors alone ($F'_m = (MKT_m \;\; MOM_m \;\; PS_m)$).

Table 7 further shows that global (developed) size, book-to-market, and momentum factors are only weakly related to MDI_m. Thus, estimates of dislocation risk premiums for eligible international stock portfolios relative to global three- ($F'_m = (GMKT_m \;\; GSMB_m \;\; GHML_m)$) and four-factor models ($F'_m = (GMKT_m \;\; GSMB_m \;\; GHML_m \;\; GMOM_m)$) in Panel B of Table 6 remain statistically significant over the later subperiod, when all country-level and factor data are available. For instance, annualized, factor-adjusted MDI risk premiums per average MDI beta $\lambda_{MDI}\overline{\beta_{i,MDI}}$ are as high as 1.93% ($t = 2.61$) over 1994–2009. The single-stage GMM estimation of $\beta_{i,MDI}$ and λ_{MDI} in the multivariate asset pricing model of Pastor and Stambaugh (2003; where $\lambda_0 = 0$

[34] For instance, Cochrane (2001, 441) observes that a typical value firm "has a price that has been driven down from a long string of bad news, and is now in or near financial distress. Stocks bought on the verge of bankruptcy have come back more often than not, which generates the high average returns of this strategy. This observation suggests a natural interpretation of the value premium: If a credit crunch, liquidity crunch, flight to quality or similar financial event comes along, stocks in financial distress will do very badly, and this is just the sort of time at which one particularly does not want to hear that one's stocks have become worthless!"

[35] The estimation of Equation (6) also produces lower, but still positive and significant intercepts (as in Fama and French [2006]);for instance, $\beta_{i,0} = 5.27\%$ per annum ($t = 3.16$) for HML_m (versus a CAPM-only 6.56% [$t = 3.93$]) and 5.44% ($t = 2.60$) for PS_m (versus 6.58% [$t = 3.16$]) over 1973–2009.

and, since MDI_m is not a traded factor, $\beta_{i,0} = \beta_{i,MDI}[\lambda_{MDI} - E(MDI_m)]$ in Equations (6) and (7)), albeit problematic for our unbalanced international sample (see Section 2.1.1), yields even stronger evidence that dislocation risk may be priced. This evidence is reported in the Appendix (Tables A1 and A2). For example, GMM estimates of the annualized dislocation risk premium per unit MDI beta are larger—e.g., $\lambda_{MDI} = -7.26\%$ ($t = -2.85$) (-3.92% [$t = -4.94$]) in Table A1 (A2) for the 25 U.S. (35 available international) stock portfolios relative to the five U.S. (four global) traded factors from 1973–2009 (1990–2009)—and statistically significant with respect to most factor specifications in all sample partitions.

Lastly, MDI_m may be redundant in understanding the cross-section of assets' mean excess returns if the intercept from regressing MDI_m on other conventional factors is zero. According to (Cochrane 2001, 2011), this test is equivalent to replacing MDI_m with an appropriately orthogonalized factor in Equation (6) and testing whether the ensuing $\lambda_{MDI} = 0$ in Equation (7); yet, as noted in Section 1.4, the latter would suffer from look-ahead and generated-regressor bias. Table 8 reports estimates of the intercept from the following regression (e.g., Petkova 2006):

$$MDI_m = c_0 + CF_m + \varepsilon_m, \tag{8}$$

where F_m includes all the factor specifications considered in Panel B of Tables 5 and 6.

Consistent with the above evidence, estimates of c_0 in Table 8 are statistically significant under all U.S. and global factor specifications and most sample partitions. For instance, estimated intercepts in Equation (8) are $c_0 = -0.024$ ($t = -2.99$) relative to Fama-French (and -0.017 [$t = -2.04$] relative to Fama-French plus momentum and liquidity) from 1973–2009, and -0.030 ($t = -2.53$) relative to global Fama-French plus global momentum from 1990–2009. Untabulated intercept estimates from a *six*-factor specification including the S&P100 VIX "mimicking" factor of Ang et al. (2006) are similarly significant: $c_0 = -0.030$ ($t = -3.21$) over the available sample period 1986–2009, 0.006 ($t = 0.47$) from 1986-1993, and -0.050 ($t = -4.00$) from 1994–2009.

Overall, the sensitivities of U.S. and international stock portfolios to financial market dislocations appear to explain a nontrivial portion of their risk, one that is *not fully* captured by fluctuations in U.S. and global factors and for which investors require meaningful compensation.

2.1.3 Portfolio construction by financial market dislocation betas. The evidence in Tables 3 to 8 provides support to the notion that financial market dislocation risk may be priced in the cross-section of U.S. and international stock portfolio returns. In this section we investigate further whether the cross-section of U.S. stocks' expected returns is related to those stocks' sensitivities to abnormal marketwide mispricings, that is, to their MDI betas. We follow a parsimonious portfolio-based approach, similar to the one used by Pastor

Table 8
MDI: Redundant factor tests

	1973–2009§	1973–1993§	1994–2009
	c_0	c_0	c_0
		U.S. factors	
CAPM	−0.031***	−0.027***	−0.036***
	(−3.84)	(−2.89)	(−2.63)
3-factor	−0.024***	−0.023**	−0.028**
	(−2.99)	(−2.41)	(−2.15)
4-factor	−0.020**	−0.018*	−0.023*
	(−2.49)	(−1.79)	(−1.75)
5-factor	−0.017**	−0.016	−0.018
	(−2.04)	(−1.59)	(−1.37)
3-factor°	−0.026***	−0.020**	−0.030**
	(−3.12)	(−2.13)	(−2.40)
		Global factors	
WCAPM	−0.033***	−0.026***	−0.041***
	(−4.08)	(−2.80)	(−3.05)
GCAPM	−0.042***	−0.068***	−0.036***
	(−3.69)	(−4.23)	(−2.69)
3-factor	−0.035***	−0.063***	−0.028**
	(−3.04)	(−4.01)	(−2.08)
4-factor	−0.030**	−0.081***	−0.021
	(−2.53)	(−5.00)	(−1.49)

This table reports OLS estimates of the intercept c_0 of regressions of MDI_m on various conventional U.S. and global factor specifications (Equation (8) in Section 2.1.2), over the full sample period (January 1973 to December 2009 [444 observations]) and two subperiods (1973–1993 [252 observations], 1994–2009 [192 observations]). U.S. factor specifications include the U.S. market factor (MKT_m, CAPM), three traded Fama-French factors (U.S. market plus size [SMB_m] and book-to-market [HML_m]), four traded factors (three factors plus momentum [MOM_m]), five traded factors (four factors plus liquidity [PS_m]), or three traded factors (five factors minus size and book-to-market, "°"). Global factor specifications include the world market factor ($WMKT_m$), the global market factor ($GMKT_m$), three traded Fama-French global factors (global market, size [$GSMB_m$], and book-to-market [$GHML_m$]), or four traded global factors (three factors plus global momentum [$GMOM_m$]). The three (four) global factors are jointly available only from July (November) 1990 and onward (234 [230] observations; "§"). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

and Stambaugh (2003), that allows for each stock's factor loadings (including its MDI betas) to vary through time. At the end of each year in our sample, starting with 1977, we sort all stocks into ten portfolios based on stocks' estimated MDI betas over the previous five years. We then regress the ensuing stacked, postformation returns on standard asset pricing factors. According to the literature, estimated nonzero intercepts (alphas) would suggest that MDI betas explain a component of expected stock returns not captured by standard factor loadings.

Our dataset comes from the monthly tape of the Center for Research in Security Prices (CRSP). It comprises monthly stock returns and values for all domestic ordinary common stocks (CRSP share codes 10 and 11) traded on the NYSE, AMEX, and NASDAQ between January 1, 1973, and December 31, 2009.[36] At the end of each year (e.g., on month m), for each stock j with 60 months of available data through m we estimate its MDI beta as the slope

[36] As is customary, this restriction excludes Real Estate Investment Trusts (REITs), closed-end funds, Shares of Beneficial Interest (SBIs), certificates, units, Americus Trust Components, companies incorporated outside the

coefficient $\beta_{j,MDI}$ on MDI_m in the following multiple regression of its monthly excess return $R_{j,m}$:

$$R_{j,m} = \beta_{j,0}+\beta_{j,M}MKT_m+\beta_{j,S}SMB_m+\beta_{j,B}HML_m \qquad (9)$$
$$+\beta_{j,M}MOM_m+\beta_{j,L}PS_m+\beta_{j,MDI}MDI_m+\eta_{j,m},$$

which includes all the popular traded factors described in Section 2.1.2 (Fama-French [MKT_m, SMB_m, HML_m], momentum [MOM_m], and liquidity [PS_m]). Our results are stronger when excluding either PS_m alone or both MOM_m and PS_m (following Pastor and Stambaugh 2003) from Equation (9). We then sort all stocks by their preranking, *historical* MDI betas $\beta_{j,MDI}$ into ten portfolios (from the lowest, 1, to the highest, 10), and compute their value-weighted returns for the next twelve months.[37] Equally weighted portfolios yield similar inference. Repeating this procedure over our sample and stacking decile returns across years generates ten monthly return series from January 1978 to December 2009.

Panel A of Table 9 reports postranking MDI betas from running Equation (9) for each historical MDI beta-decile portfolio i, as well as for the 1–10 *spread* portfolio going long stocks with the lowest (i.e., most negative) preranking MDI betas (decile 1) and short stocks with the highest (i.e., most positive) preranking MDI betas (decile 10). Focus on this spread portfolio is motivated by the evidence in the previous sections that stock portfolios with the most negative exposure to financial market dislocation risk experience the highest mean excess returns. Panel B of Table 9 reports additional features of these portfolios: their average market capitalization and sensitivities to those standard risk factors.

No clear pattern emerges in Table 9 across MDI beta deciles. However, as postulated previously, their properties suggest that lower decile stocks (i.e., with more negative historical MDI betas) are generally more “speculative.” According to Pastor and Stambaugh (2003), smaller, more volatile stocks may produce noisier historical beta estimates. Consistently, whereas stocks in low MDI beta deciles are somewhat larger, smaller (higher MKT beta) firms populate the two extremes of the MDI sorts, and the SMB (MKT) beta of the 1–10 spread is insignificant (positive). Low decile portfolios weakly tilt toward value stocks (positive HML betas, as in Table 3) and past losers (negative MOM betas), but are insensitive to liquidity risk (small, insignificant PS betas). In unreported analysis, similar inference ensues from including the VIX mimicking factor of Ang et al. (2006). Monthly returns of low MDI beta

United States, and American Depositary Receipts (ADRs). The latter is important because ADR mispricings contribute to our financial market dislocation index. When forming MDI beta-sorted portfolios, we also exclude stocks with prices below \$5 or above \$1,000.

[37] The ten portfolios contain an approximately equal number of stocks in each month. On average, each portfolio contains 124 stocks. No portfolio contains less (more) than 71 (181) stocks. Notably, on each portfolio formation month, this procedure sorts stocks using exclusively information available up to that month.

Table 9
Value-weighted portfolios of U.S. stocks sorted on historical MDI betas

Preranking	1	2	3	4	5	6	7	8	9	10	1-10
Panel A: Postranking MDI betas											
1978–2009	0.15	0.43	0.18	0.09	0.23	0.89	0.78*	1.24**	0.87	−1.29*	1.45
	(0.77)	(0.71)	(0.56)	(−0.27)	(0.25)	(1.49)	(1.69)	(2.28)	(1.36)	(−1.74)	(1.23)
1978–1993	−1.19	−0.99	−2.21**	0.41	0.31	−0.19	−0.13	1.21	0.79	0.14	−1.33
	(−0.81)	(−0.92)	(−2.34)	(0.49)	(0.45)	(−0.26)	(−0.15)	(1.29)	(0.81)	(0.12)	(−0.64)
1994–2009	0.78	1.20	1.15	−0.03	0.00	1.24*	0.71	0.79	0.70	−1.92*	2.71*
	(0.68)	(1.18)	(1.52)	(−0.04)	(0.00)	(1.69)	(0.98)	(1.18)	(0.81)	(−1.93)	(1.77)
Panel B: Additional properties 1978–2009											
Market Cap	$24.11	$37.58	$40.91	$45.77	$41.09	$37.63	$37.87	$35.89	$35.11	$14.72	
MKT beta	1.17***	1.08***	0.97***	0.99***	0.97***	0.96***	0.95***	0.90***	0.95***	1.05***	0.12***
	(35.69)	(39.83)	(44.00)	(49.74)	(54.66)	(49.41)	(45.23)	(44.29)	(40.35)	(37.48)	(2.65)
SMB beta	0.15***	−0.12***	−0.22***	−0.23***	−0.22***	−0.15***	−0.14***	−0.08***	−0.09***	0.14***	0.01
	(3.37)	(−3.41)	(−7.54)	(−8.51)	(−9.27)	(−5.84)	(−4.83)	(−3.03)	(−2.82)	(3.72)	(0.14)
HML beta	−0.05	0.02	0.07**	0.03	0.15***	0.11***	0.14***	0.13***	−0.01	−0.08*	0.02
	(−1.10)	(0.44)	(2.09)	(0.97)	(5.38)	(3.75)	(4.32)	(4.14)	(−0.23)	(−1.83)	(0.34)
MOM beta	−0.23***	−0.07***	−0.04**	0.04**	0.04**	0.04**	0.02	0.03	0.05**	0.05*	−0.27***
	(−7.93)	(−2.88)	(−2.16)	(2.54)	(2.41)	(2.13)	(0.95)	(1.54)	(2.25)	(1.89)	(−6.97)
PS beta	0.02	0.03	−0.01	0.03	0.005	0.01	−0.06***	−0.01	−0.03	−0.05	0.07
	(0.52)	(1.16)	(−0.40)	(1.59)	(0.25)	(0.63)	(−2.61)	(−0.61)	(−1.11)	(−1.54)	(1.34)

This table reports postranking properties of value-weighted portfolios of U.S. stocks sorted by their historical MDI betas into ten approximately equal portfolios from the lowest (1) to the highest (10), as well as for the 1–10 spread portfolio going long decile 1 stocks and short decile 10 stocks, over the full sample 1978–2009 and two subperiods (1978–1993, 1994–2009). Specifically, at the end of each year (between 1977 and 2008), all eligible NYSE, AMEX, and NASDAQ stocks with 60 months of available data through then are sorted in ten deciles of their estimated MDI betas ($\beta_{j,MDI}$ of Equation (9), in Section 2.1.3) from a multivariate regression of their percentage monthly excess returns on our financial market dislocation index MDI_m (described in Section 1.2), the three traded Fama-French factors (U.S. market [MKT_m], size [SMB_m], and book-to-market [HML_m], from French's Web site), the traded momentum factor (MOM_m, also from French's Web site), and the traded liquidity factor of Pastor and Stambaugh (2003) (PS_m, from Pastor's Web site). The resulting value-weighted decile portfolio returns for the next 12 months are stacked across years to generate postranking return series. Panel A reports their estimated postranking MDI betas from the aforementioned multivariate regression model. Panel B reports the time-series mean of each of these portfolios' value-weighted average market capitalization (in billions of U.S. dollars), as well as their postranking factor betas (B of Equation (6), in Section 2.1.2). t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

portfolios (and the 1–10 spread) tend to be either statistically unrelated or negatively related to this factor.

Postranking MDI betas are broadly consistent with the preranking sorts, but are smaller and considerably less dispersed; the spread portfolio's MDI beta is also small, and significant (but positive) only over the subperiod 1994–2009. Stocks doing relatively poorly during past financial market dislocations (large and negative MDI betas when $MDI_m > 0$) may subsequently do poorly or fail to recover those losses during normal times (small, insignificant postranking MDI betas when $MDI_m \leq 0$). As discussed earlier, more speculative securities are more likely to trade at low prices, both because speculators may not be able to accommodate selling pressure when frictions are high and because speculators require additional compensation for the risk that frictions may be high in the future (e.g., while facing order imbalance in those assets or incurring losses on them when their investment opportunities are good; see Brunnermeier and Pedersen 2009; Garleanu and Pedersen 2011). However, less speculative stocks doing relatively better during past financial market dislocations (large and positive MDI betas when $MDI_m > 0$), may preserve or add to those gains afterwards (small positive, or negative and significant postranking MDI betas when $MDI_m \leq 0$). In light of MDI_m's cycle-like dynamics over our sample period (see Figure 2), these properties suggest stocks in lower (i.e., more negative) preranking MDI beta decile portfolios to be riskier than their high decile counterparts.

Our analysis reveals that investors demand sizeable compensation to hold those riskier stocks. Table 10 reports postranking annualized raw returns and alphas for each preranking MDI beta portfolio and the 1–10 spread with respect to four conventional traded factor specifications: CAPM (the market factor: MKT_m), Fama-French (the market, size, and book-to-market factors: MKT_m, SMB_m, HML_m), Fama-French plus momentum (MKT_m, SMB_m, HML_m, MOM_m), and Fama-French plus momentum and liquidity (MKT_m, SMB_m, HML_m, MOM_m, PS_m).

Raw returns and alphas are generally *declining* across ex ante MDI beta deciles—and alphas of the *lowest* (highest) MDI beta decile portfolio are generally *positive* (negative)—except in the earlier, more tranquil subperiod (1978–1993). These estimates suggest that investors require stocks with the highest *negative* sensitivity to abnormal mispricings to earn a *positive* premium (e.g., a four-factor alpha of 2.85% [$t = 1.75$] from 1978–2009) but are willing to receive a *negative* premium from stocks providing insurance against that risk, that is, with the highest *positive* such sensitivity (e.g., a four-factor alpha of −2.88% [$t = 2.06$]).[38]

[38] In unreported analysis, we also find that the null hypothesis that all decile portfolio alphas in Table 10 are jointly zero is always rejected by the F-statistic of Gibbons, Ross, and Shanken (1989), except for CAPM alphas and in the earlier subperiod (1978–1993). Postranking MDI betas and alphas are more often statistically significant, but less disperse, for equally weighted decile portfolios.

Table 10
Alphas of value-weighted portfolios of U.S. stocks sorted on historical MDI betas

Preranking	1	2	3	4	5	6	7	8	9	10	1-10
					1978–2009						
Raw return	8.70**	8.58***	8.17***	6.53**	6.28**	5.76**	7.71***	6.28**	7.19**	4.65	4.05*
	(2.25)	(2.63)	(2.88)	(2.30)	(2.32)	(2.13)	(2.83)	(2.42)	(2.51)	(1.37)	(1.76)
CAPM alpha	0.66	1.68	2.17*	0.42	0.45	−0.07	1.91*	0.75	1.10	−2.54*	3.20
	(0.39)	(1.25)	(1.86)	(0.40)	(0.45)	(−0.07)	(1.77)	(0.74)	(0.96)	(−1.82)	(1.40)
3-factor alpha	0.29	1.65	2.01*	0.69	0.04	−0.33	1.41	0.30	1.44	−2.31*	2.60
	(0.17)	(1.23)	(1.86)	(0.70)	(0.04)	(−0.34)	(1.36)	(0.30)	(1.24)	(−1.68)	(1.12)
4-factor alpha	2.85*	2.43*	2.49**	0.19	−0.38	−0.70	1.24	0.03	0.95	−2.88**	5.73**
	(1.75)	(1.80)	(2.27)	(0.19)	(−0.43)	(−0.73)	(1.18)	(0.03)	(0.81)	(−2.06)	(2.56)
5-factor alpha	2.72*	2.19	2.57**	−0.07	−0.41	−0.77	1.73	0.19	1.21	−2.57*	5.29**
	(1.65)	(1.60)	(2.31)	(−0.07)	(−0.45)	(−0.78)	(1.63)	(0.18)	(1.01)	(−1.82)	(2.34)
					1978–1993						
Raw return	8.57*	8.45**	8.61**	7.27*	6.87*	7.82**	9.08**	6.71*	8.58**	9.22**	−0.65
	(1.72)	(1.96)	(2.17)	(1.79)	(1.76)	(2.05)	(2.26)	(1.70)	(2.08)	(2.03)	(−0.22)
CAPM alpha	−0.31	0.59	1.32	−0.24	−0.51	0.73	1.60	−0.52	0.96	0.99	−1.30
	(−0.15)	(0.38)	(0.97)	(−0.18)	(−0.51)	(0.63)	(1.28)	(−0.39)	(0.72)	(0.58)	(−0.44)
3-factor alpha	−0.21	0.62	1.44	0.90	−0.81	0.39	1.62	−1.15	0.96	1.54	−1.75
	(−0.10)	(0.41)	(1.05)	(0.74)	(−0.83)	(0.38)	(1.29)	(−0.86)	(0.70)	(0.88)	(−0.58)
4-factor alpha	0.81	0.96	1.46	0.27	−0.74	0.88	1.87	−0.20	1.06	−0.42	1.24
	(0.38)	(0.61)	(1.02)	(0.21)	(−0.72)	(0.82)	(1.43)	(−0.14)	(0.74)	(−0.25)	(0.40)
5-factor alpha	0.82	1.05	1.91	−0.07	−0.83	0.84	1.56	−0.23	1.25	−0.26	1.08
	(0.38)	(0.66)	(1.36)	(−0.06)	(−0.81)	(0.78)	(1.20)	(−0.16)	(0.87)	(−0.15)	(0.35)
					1994–2009						
Raw return	8.83	8.70*	7.74*	5.79	5.68	3.69	6.34*	5.85*	5.79	0.07	8.76**
	(1.49)	(1.78)	(1.90)	(1.46)	(1.52)	(0.96)	(1.73)	(1.73)	(1.45)	(0.01)	(2.47)
CAPM alpha	1.83	2.86	2.96	0.98	1.24	−0.93	2.02	1.79	1.10	−5.97***	7.81**
	(0.68)	(1.31)	(1.55)	(0.60)	(0.73)	(−0.58)	(1.18)	(1.23)	(0.59)	(−2.74)	(2.23)
3-factor alpha	1.35	2.78	2.77*	0.84	0.86	−1.23	1.29	1.33	1.58	−5.88***	7.23**
	(0.50)	(1.27)	(1.67)	(0.56)	(0.63)	(−0.79)	(0.83)	(0.94)	(0.86)	(−2.77)	(2.05)
4-factor alpha	3.98	3.54	3.44**	0.52	0.52	−1.71	1.31	1.05	1.12	−6.05***	10.04***
	(1.63)	(1.62)	(2.09)	(0.35)	(0.38)	(−1.09)	(0.83)	(0.74)	(0.60)	(−2.82)	(3.04)
5-factor alpha	3.79	3.14	2.79*	0.26	0.20	−1.79	2.29	1.11	1.15	−5.47**	9.26***
	(1.52)	(1.41)	(1.68)	(0.17)	(0.14)	(−1.12)	(1.45)	(0.77)	(0.61)	(−2.51)	(2.76)

This table reports annualized raw percentage excess returns as well as intercepts (percentage alphas, multiplied by 12) from the regression of monthly excess postranking returns of twelve-month value-weighted portfolios (constructed by sorting U.S. stocks by their preranking, 60-month historical MDI betas; see Section 2.1.3) on the U.S. market factor (MKT_m, CAPM), three traded Fama-French factors (U.S. market plus size [SMB_m] and book-to-market [HML_m]), four traded factors (three factors plus momentum [MOM_m]), or five traded factors (four factors plus liquidity [PS_m]). t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Accordingly, all four 1–10 spread portfolio alphas are positive over the full sample (1978–2009), and especially large and statistically significant in the later subperiod (1994–2009) — when large dislocations (i.e., sizably positive realizations of MDI_m) occur more often (see Figure 2). For instance, five-factor alpha for the 1–10 spread portfolio is 5.29% (t=2.34) from 1978–2009, 1.08% (t=0.35) from 1978–1993 (during which MDI_m is considerably less volatile), and 9.26% (t=2.76) from 1994–2009 (in correspondence with the most well-known episodes of financial turmoil).[39] Table 2 suggests that MDI_m may be related to changes in stock return volatility. However, augmenting the five-factor model to include the VIX-mimicking factor of Ang et al. (2006) yields nearly identical inference. For example, the resulting (untabulated) six-factor alpha for the 1–10 spread portfolio is 6.15% (t=2.30) from 1986–2009, 0.31% (t=0.08) from 1986–1993, and 9.02% (t=2.53) from 1994–2009.

In summary, this evidence supports the conclusion that stocks with greater sensitivity to dislocation risk offer higher expected returns, even after controlling for their exposure to standard priced sources of risk.

2.2 Financial market dislocations and risk premiums: Currencies

Individual violations of each of the three textbook arbitrage parities entering our composite index MDI_m (CIRP, TAP, and ADRP) may stem from foreign exchange markets. Thus, these markets are a potentially important source of dislocations as measured by MDI_m. Accordingly, it is intuitive to consider whether exposure to dislocation risk can explain the cross-section of returns to currency speculation.

To that purpose, we study the performance of the currency portfolios developed by Lustig, Roussanov, and Verdelhan (2011) from the perspective of a U.S. investor. Lustig, Roussanov, and Verdelhan (2011) compute monthly excess foreign exchange returns as the return on buying a foreign currency (and selling USD) in the forward market and then selling it (and buying USD) in the spot market, net of transaction costs (bid-ask spreads), for up to 34 developed and emerging currencies between November 1983 and December 2009. Excluding emerging currencies produces similar results. These (dollar) returns are then sorted into six equal-weighted portfolios on the basis of foreign currencies' interest rates. The first portfolio ($i=1$) is made of currencies with the lowest interest rates, whereas the last ($i=6$) contains currencies with the highest interest rates. These portfolios (from Verdelhan's Web site) have appealing

[39] Similar insights on the dislocation risk premium come from its direct estimation using *all ten* MDI beta decile portfolios, via the multivariate GMM procedure of Pastor and Stambaugh (2003). For instance, untabulated GMM estimates of λ_{MDI} and $\beta_{i,MDI}$ after accounting for priced sensitivities to the three, four, or five aforementioned traded factors in Equation (6) yield annualized MDI risk premiums per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$) of no less than 0.48% (t=2.37) over the full sample (1978–2009) and as high as 0.82% (t=2.06) over the later subperiod (1994–2009), in line with those estimated for the 25 size and book-to-market stock portfolios in Panel B of Table 5. The MDI risk premiums for the 1–10 spread portfolio ($\lambda_{MDI}\left(\beta_{1,MDI}-\beta_{10,MDI}\right)$) are larger—for instance, ranging between 6.85% (t=2.89) with five traded factors and 7.80% (t=2.87) with three traded factors from 1994-2009—and comparable with the estimates reported in Table 10.

properties. Currency speculation via forward contracts is easy to implement and yields Sharpe ratios comparable to those offered by international equity markets (see, e.g., Lustig, Roussanov, and Verdelhan 2011, their Table 1). The difference between the first and last portfolio returns, HML_{FX}, can be interpreted as the return of *carry trades*, going long high-interest rate currencies and short low-interest rate currencies. Lustig, Roussanov, and Verdelhan (2011) also find that both the *slope* factor HML_{FX} and the average *level* of excess foreign exchange returns, RX—that is, the return for a U.S. investor to investing in a broad basket of currencies—explain most of the time-series variation in currency portfolio returns.

We estimate MDI betas and MDI risk premiums for currency portfolios from the standard cross-sectional approach described in Section 2.1.1 (Equations (4) and (5)), in Table 11. As for U.S. and international equity markets, most estimated MDI betas ($\beta_{i,MDI}$ in Equation (4)) for excess currency returns are large, negative, and often statistically significant.[40] Portfolios made of currencies carrying higher interest rates tend to exhibit more negative sensitivity to dislocation risk, as do both the basket currency (RX) and the carry trade (HML_{FX}) portfolios, especially in the later subperiod (1994–2009).[41] Hence, both excess returns to speculating in foreign currencies against the dollar or to zero-cost carry trading tend to decline in correspondence with abnormally high relative mispricings.

Investors in foreign currencies require a meaningful compensation for exposure to such risk. The scatter plot in Figure 3c shows that—as for U.S. and international stock portfolios in Figures 3a and 3b—currency portfolios' average excess returns are inversely related to their MDI betas. Thus, although this is a weak test (because of the small number of assets), Equation (5) yields negative estimates of the annualized price of MDI risk: $\lambda_{MDI} < 0$ in Table 11. For instance, the estimated λ_{MDI} between 1983 and 2009 is large (-1.46% per unit MDI beta) and statistically significant at the 1% level ($t = -3.74$), implying a dislocation premium of 2.30% per average MDI beta (and $\lambda_{MDI}\beta_{i,MDI} = 5.28\%$ for the carry trade portfolio). Dislocation premiums rise to nearly 4% (more than 7%) from 1994–2009. In addition, MDI betas in Equation (5) can explain up to 80% of the cross-sectional variation in currency portfolio returns.

These results suggest that returns to speculation in foreign exchange markets may reflect their sensitivity to financial market dislocation risk.

[40] For example, these estimates imply that monthly excess returns of the currency portfolios in Table 11 decline on average by 0.27% from a one-standard-deviation shock to MDI_m.

[41] Consistently, Brunnermeier, Nagel, and Pedersen (2008), Lustig, Roussanov, and Verdelhan (2011), Menkhoff et al. (2012), and Hu, Pan, and Wang (2013) find returns to carry trades to be related to such potential sources of systematic risk as shocks to Treasury yield curve noise, U.S. and global equity volatility, and global foreign exchange volatility. However, the unreported estimation of Equation (8) indicates that MDI_m is not redundant relative to RX and HML_{FX}, for instance, yielding an intercept $c_0 = -0.022$ ($t = -2.35$) from 1983–2009.

Table 11
MDI betas and risk premiums: Currency portfolios

	OLS estimates of MDI betas $\beta_{i,MDI}$								MDI risk premiums			
	1	2	3	4	5	6	RX	HML_{FX}	λ_0	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	R^2
1983–2009	0.31	−1.27*	−0.40	−1.02	−2.03**	−3.31***	−1.29*	−3.62***	−0.50	−1.46***	2.30***	77%
	(0.38)	(−1.78)	(0.54)	(−1.40)	(−2.53)	(−3.63)	(−1.94)	(−4.29)	(−0.63)	(−3.74)	(3.54)	
1983–1993	0.93	1.27	3.48*	1.55	0.74	1.67	1.61	0.74	3.12**	−0.75	−1.13	20%
	(0.42)	(0.63)	(1.66)	(0.70)	(0.31)	(0.67)	(0.83)	(0.33)	(2.75)	(−1.14)	(−0.77)	
1994–2009	0.12	−1.85***	−1.17*	−1.58**	−2.62***	−4.31***	−1.90***	−4.43***	−2.05*	−1.68***	3.72***	80%
	(0.15)	(−2.64)	(−1.65)	(−2.42)	(−3.51)	(−4.72)	(−3.02)	(−5.09)	(−1.83)	(−4.15)	(4.34)	

This table reports OLS estimates of univariate MDI betas $\beta_{i,MDI}$, the slope coefficients from time-series regressions of percentage monthly excess returns of each of the eight currency portfolios i in Lustig, Roussanov, and Verdelhan (2011) on MDI_m, the financial market dislocation index described in Section 1.2 (Equation (4) in Section 2.1.1), over the full sample period November 1983–December 2009 (314 observations) and two subperiods (1983–1993, 1994–2009). The sample includes six currency portfolios formed on interest rates, from low (P1) to high (P6), as well as a portfolio going long a basket of developed and emerging currencies against the dollar (RX) and a carry trade portfolio (HML_{FX}) going long high-interest rate currencies and short low-interest rate currencies (from Verdelhan's Web site). The table also reports OLS estimates of λ_0 and the percentage MDI risk premium λ_{MDI} (annualized, i.e., multiplied by 12) from regressing currency portfolios' mean excess percentage monthly (dollar) returns $R_{i,m}$ on those previously estimated univariate MDI betas $\beta_{i,MDI}$ (Equation (5), in Section 2.1.1), as well as the risk premium per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$). t-statistics are in parentheses; in the case of λ_0 and λ_{MDI}, t-statistics are computed by applying Shanken's (1992) errors-in-variables correction to the corresponding conventional standard errors. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

3. Conclusions

Dislocations occur when financial markets experience abnormal and widespread asset mispricings. This study argues that dislocations are a recurrent, systematic feature of financial markets, one with important implications for asset pricing.

We measure financial market dislocations as the monthly average of innovations in hundreds of observed violations of three textbook arbitrage parities in global stock, foreign exchange, and money markets. Our novel, model-free market dislocation index (MDI) has sensible properties, for example, rising in proximity of U.S. recessions and well-known episodes of financial turmoil over the past four decades, in correspondence with greater fundamental uncertainty, illiquidity, and financial instability, but also in tranquil periods.

Financial market dislocations indicate the presence of forces impeding the trading activity of speculators and arbitrageurs. The literature conjectures these forces to affect equilibrium asset prices. Accordingly, we find that investors demand significant risk premiums to hold stock and currency portfolios performing poorly during financial market dislocations, even after controlling for exposures to market returns and such popular traded factors as size, book-to-market, momentum, and liquidity. This evidence provides further validation of our index.

Our analysis contributes original insights to the understanding of the process of price formation in financial markets in the presence of frictions. It also proposes an original and easy-to-compute macroprudential policy tool for overseeing the integrity of financial markets and for detecting systemic risks to markets' orderly functioning.

Appendix

Table A1
GMM estimation of MDI risk premiums: U.S. stock portfolios

	1973–2009			1973–1993			1994–2009		
	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	J-test	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	J-test	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	J-test
CAPM	−4.54***	2.25**	26.98	−5.66***	2.31**	25.19	−4.17***	2.47*	23.21
	(−5.00)	(2.52)	0.31	(−3.46)	(2.14)	0.40	(−6.32)	(1.75)	0.51
3-factor	−7.88***	−0.57	36.25*	−5.89***	0.12	24.57	−5.32***	−1.36**	32.84
	(−2.86)	(−1.62)	0.05	(−2.71)	(0.35)	0.43	(−5.01)	(−2.40)	0.11
4-factor	−7.79***	−0.36	37.90**	−23.65	0.14	23.25	−5.60***	−0.91	34.88*
	(−2.84)	(−1.00)	0.04	(−0.61)	(0.30)	0.51	(−5.14)	(−1.53)	0.07
5-factor	−7.26***	−0.37	38.12**	−15.86	0.26	24.35	−5.42***	−1.18*	34.25*
	(−2.85)	(−0.97)	0.03	(−1.01)	(0.71)	0.44	(−5.09)	(−1.80)	0.08
3-factor°	−4.72***	2.79***	27.91	−6.62***	3.60***	24.80	−4.04***	3.04**	23.84
	(−4.59)	(3.11)	0.26	(−3.04)	(2.72)	0.42	(−5.94)	(2.23)	0.47

This table reports GMM estimates of annualized percentage MDI risk premiums (λ_{MDI}, multiplied by 12) for multivariate MDI betas ($\beta_{i,MDI}$) of U.S. stock portfolios over the full sample 1973–2009 and two subperiods (1973–1993, 1994–2009). The U.S. portfolios include the intersections of five U.S. stock portfolios formed on size and five portfolios formed on book-to-market (from French's Web site). Joint GMM estimation of Equations (6) and (7) after assuming that $\lambda_0=0$ and $\beta_{i,0}=\beta_{i,MDI}[\lambda_{MDI}-E(MDI_m)]$ (as in Pastor and Stambaugh [2003]), yields dislocation risk premiums both per unit MDI beta (λ_{MDI}) and per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$) after accounting for excess returns' sensitivity to either the U.S. market factor (MKT_m, CAPM), three traded Fama-French factors (U.S. market plus size [SMB_m] and book-to-market [HML_m], from French's Web site), four traded factors (three factors plus momentum [MOM_m, also from French's Web site]), five traded factors (four factors plus liquidity [PS_m, from Pastor's Web site]), or three traded factors (five factors minus size and book-to-market; "°"). Following Pastor and Stambaugh (2003), the GMM estimator of the set γ of $2+N(K+1)$ unknown parameters λ_{MDI}, β_{MDI}, B, and $E(MDI_m)$ minimizes $g(\gamma)'Wg(\gamma)$, where $g(\gamma)=(1/M)\sum_{m=1}^{M} f_m(\gamma)$, the $[N(K+2)+1]\times 1$ moment vector function $f_m(\gamma)=\binom{h_m\otimes\varepsilon_m}{MDI_m-E(MDI_m)}$, $h'_m=\begin{pmatrix}1 & F'_m & MDI_m\end{pmatrix}$, the $N\times 1$ vector $\varepsilon_m=R_m-\beta_{MDI}[\lambda_{MDI}-E(MDI_m)]-BF_m-\beta_{MDI}MDI_m$ (where R_m is a $N\times 1$ vector of excess portfolio returns, F_m is a $K\times 1$ vector of traded factors, B is a $N\times K$ matrix of factor loadings, and β_0 and β_{MDI} are $N\times 1$ vectors), W is the inverse of $(1/M)\sum_{m=1}^{M} f_m(\widehat{\gamma})f_m(\widehat{\gamma})'$, and $\widehat{\gamma}=\text{argmin}\, g(\gamma)'g(\gamma)$. Asymptotic t-statistics are in parentheses. J-test is the asymptotic chi-square statistic for overidentifying restrictions; the corresponding p-values are below. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A2
GMM estimation of MDI risk premiums: International stock portfolios

	1973–2009§			1973–1993§			1994–2009		
	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	J-test	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	J-test	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	J-test
WCAPM	−0.75	0.85	6.74	−1.57**	0.53	5.62	−3.97***	4.03**	34.36
	(−1.24)	(1.25)	0.99	(−1.99)	(0.57)	1.00	(−5.82)	(2.34)	0.82
GCAPM	−8.80***	−0.54	34.03	5.39	2.14***	26.13	−5.47***	0.78	39.59
	(−2.66)	(−0.26)	0.47	(1.13)	(2.68)	0.83	(−6.27)	(0.36)	0.62
3-factor	−2.10***	5.12***	97.67***	3.11	−0.31	12.61	−3.72	8.23	102.15***
	(−2.93)	(3.26)	0.00	(1.23)	(−0.84)	1.00	(−0.30)	(−0.29)	0.00
4-factor	−3.92***	9.80***	158.46***	2.46	2.91	15.83	−1.67***	4.17**	120.16***
	(−4.94)	(4.87)	0.00	(1.03)	(1.24)	1.00	(−4.70)	(2.27)	0.00

This table reports GMM estimates of annualized percentage MDI risk premiums (λ_{MDI}, multiplied by 12) for multivariate MDI betas ($\beta_{i,MDI}$) of 49 international stock portfolios over the full sample 1973–2009 and two subperiods (1973–1993, 1994–2009). The international portfolios include 23 developed and 26 emerging country portfolios (from MSCI). Joint GMM estimation of Equations (6) and (7) after assuming that $\lambda_0=0$ and $\beta_{0,i}=\beta_{i,MDI}[\lambda_{MDI}-E(MDI_m)]$ (as in Pastor and Stambaugh [2003]), yields dislocation risk premiums both per unit MDI beta (λ_{MDI}) and per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$) after accounting for excess returns' sensitivity to the world market factor ($WMKT_m$, from MSCI), the global market factor ($GMKT_m$, from French's Web site), three traded Fama-French global factors (global market, size [$GSMB_m$], and book-to-market [$GHML_m$], from French's Web site), or four traded global factors (three factors plus global momentum [$GMOM_m$, also from French's Web site]). Because the MSCI panel is unbalanced, GMM estimation for the WCAPM is limited to 18 developed country portfolios (excluding Finland, Greece, Ireland, New Zealand, and Portugal) over 1973–2009 and 1973–1993, and to 44 country portfolios (excluding Czech Republic, Egypt, Hungary, Morocco, and Russia) over 1994–2009. The three (four) global factors are jointly available only from July (November) 1990 onward; over the resulting subperiods ("§"), the corresponding GMM estimation is restricted to 35 of the 44 country portfolios (i.e., further excluding China, Colombia, India, Israel, Pakistan, Peru, Poland, South Africa, and Sri Lanka). Following Pastor and Stambaugh (2003), the GMM estimator of the set γ of $2+N(K+1)$ unknown parameters λ_{MDI}, β_{MDI}, B, and $E(MDI_m)$ minimizes $g(\gamma)'Wg(\gamma)$, where $g(\gamma)=(1/M)\sum_{m=1}^{M} f_m(\gamma)$, the $[N(K+2)+1]\times 1$ moment vector function $f_m(\gamma)=\binom{h_m\otimes\varepsilon_m}{MDI_m-E(MDI_m)}$, $h_m'=(1 \;\; F_m' \;\; MDI_m)$, the $N\times 1$ vector $\varepsilon_m=R_m-\beta_{MDI}[\lambda_{MDI}-E(MDI_m)]-BF_m-\beta_{MDI}MDI_m$ (where R_m is a $N\times 1$ vector of excess portfolio returns, F_m is a $K\times 1$ vector of traded factors, B is a $N\times K$ matrix of factor loadings, and β_0 and β_{MDI} are $N\times 1$ vectors), W is the inverse of $(1/M)\sum_{m=1}^{M} f_m(\widehat{\gamma})f_m(\widehat{\gamma})'$, and $\widehat{\gamma}=\operatorname{argmin} g(\gamma)'g(\gamma)$. Asymptotic t-statistics are in parentheses. J-test is the asymptotic chi-square statistic for overidentifying restrictions; the corresponding p-values are below. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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