Financial Market Dislocations

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August 7, 2012

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Abstract

Dislocations occur when financial markets, operating under stressful conditions, experience large, widespread asset mispricings. This study documents systematic financial market 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 six hundred abnormal absolute violations of three textbook arbitrage parities in stock, foreign exchange, and money markets. We find that investors demand economically and statistically significant risk premiums to hold financial assets performing poorly during market dislocations.

JEL classification: G01; G12

Keywords: Asset Pricing; Dislocations; Expected Returns; Financial Crisis; Arbitrage; Law of One Price

1 Introduction

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 financial market dislocations in world capital markets and to investigate 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 et al., 2010). The turmoil in both U.S. and world capital markets in proximity of the 2008 financial crisis is commonly referred to as a major "dislocation" (e.g., 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 macro-prudential regulation (Kashyap et al., 2010; Hubrich and Tetlow, 2011). Lastly, the recurrence of severe financial market dislocations over the last three decades (e.g., Mexico in 1994-1995; East Asia in 1997; LTCM and Russia in 1998; Argentina in 2001-2002) has prompted institutional investors to revisit their decision-making and risk-management practices.

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. 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 in 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.[1] An extensive literature attributes these deviations to explicit and implicit "limits" to arbitrage activity.[2]

In this paper, we propose and construct a model-free measure of financial market dislocations based on *innovations* in daily observed violations of six hundred permutations of three textbook no-arbitrage conditions. The first one, known as the 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 British pounds) are aligned with exchange rates quoted relative to a "vehicle currency" (e.g., the dollar or the euro; Kozhan and Tham, 2010). 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). Focus on these parities allows us to document systematic market dislocations in multiple stock, foreign exchange, and money markets spanning nearly four decades (1973-2009).

Our aggregate measure of monthly financial market dislocations is a cross-permutation, equal-weighted average of *abnormal* individual deviations from their arbitrage parities. Each parity's

[1] A comprehensive survey of this vast literature is beyond the scope of this paper. Recent studies find violations of the triangular arbitrage parity (Marshall et al., 2008; Kozhan and Tham, 2010), covered interest rate parity (Akram et al., 2008; Coffey et al., 2009; Griffoli and Ranaldo, 2011), cross-listed stock pairs parity (Pasquariello, 2008; Gagnon and Karolyi, 2010), Siamese twins parity (Mitchell et al., 2002), closed-end fund parity (Pontiff, 1996), exchange-traded fund parity (Chacko et al., 2012), TIPS-Treasury arbitrage parity (Campbell et al., 2009; Fleckenstein et al., 2010), off-the-run Treasury bond-note parity (Musto et al., 2011), CDS-bond yield parity (Duffie, 2010; Garleanu and Pedersen, 2011), convertible bond parity (Mitchell and Pulvino, 2010), futures-cash parity (Roll et al., 2007), and put-call parity (Lamont and Thaler, 2003; Ofek et al., 2004).

[2] Arbitrage activity may be impeded by such financial frictions as transaction costs, taxes, holding costs, 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), risk factors (e.g., Pontiff, 1996, 2006), execution risk (Stein, 2009; Kozhan and Tham, 2010), noise trader risk (e.g., Shleifer, 2000), supply factors (Fleckenstein et al., 2010), fire sales (Kashyap et al., 2010; Shleifer and Vishny, 2011), competition (Kondor, 2009), margin constraints (Garleanu and Pedersen, 2011), funding liquidity constraints and slow-moving capital (e.g., Brunnermeier and Pedersen, 2009; Duffie, 2010; Gromb and Vayanos, 2010).

individual arbitrage deviation 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.[3] At each point in time, individual deviations are standardized using exclusively their current and past realizations. This procedure ensures comparability of innovations in absolute deviations across different parities without introducing a look-ahead bias in the measure. The resulting market dislocation index (MDI) is higher the greater-than-normal marketwide arbitrage parity violations. The index is easy to calculate and displays sensible properties as a gauge of aggregate financial market dislocations. It exhibits cycle-like dynamics — e.g., 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 up to 42% of its dynamics. These properties suggest MDI to be a good candidate proxy for the many frictions and barriers affecting the ability of global financial markets to correctly price traded assets.

Accordingly, it seems natural to conjecture the risk of financial market dislocations to be important for asset pricing. As observed by Fleckenstein et al. (2010), sizeable and time-varying arbitrage parity violations indicate the presence of forces driving asset prices that are absent in standard, frictionless asset pricing models. A copious literature relates several frictions to (and biases in) investors' trading activity to asset prices.[4] The direct measurement of these forces is however notoriously difficult. Studying the extent of arbitrage parity violations across assets and markets may help us establish these forces' empirical relevance for asset returns.

[3] For instance, absolute log deviations average 21 basis points (bps) for CIRP, 0.14 bps for TAP, and 219 bps for ADRP.

[4] See, e.g., 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 et al. (2005, 2007), Baker and Wurgler (2006), and Sadka and Scherbina (2007).

As such, financial market dislocations may be a priced state variable. Investors may require a compensation (in the form of higher expected returns) for holding assets with greater sensitivity to dislocation risk.

We investigate this possibility within both the U.S. 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-section and time-series properties of their returns. We find that stock and currency portfolios with higher *negative* "financial market dislocation betas" — i.e., experiencing *lower realized* returns when MDI is *higher* — exhibit *higher expected* returns. For example, between 1973 and 2009, the estimated market dislocation risk premium for U.S. stock portfolios formed on size and book-to-market sorts is up to -4.5% (-1.4%) 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 risk premium for country stock portfolios is smaller, ranging between -1.7% and -0.5% (when net of four global factors). These estimates are both statistically and economically significant, for they imply non-trivial compensation per average MDI beta: E.g., as high as 7.5% per annum for U.S. stock portfolios, 5.9% 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, the MDI betas explain 51% (20%) of the samplewide cross-sectional variation in expected U.S. (international) excess stock returns, and up to 77% of the cross-sectional variation in excess currency returns.

This evidence suggests that investors require a positive premium to hold asset portfolios performing poorly during financial market dislocations (i.e., with negative MDI betas), but are willing to pay a negative premium to hold portfolios providing insurance against that risk (i.e., with positive MDI betas). Consistently, when sorting U.S. stocks into portfolios according to their historical MDI betas, we find that stocks with higher *ex ante* negative (positive) sensitivity to market dislocation risk tend to exhibit both higher (lower) expected returns and small positive (negative) *ex post* such sensitivity. 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. Intuitively, stocks doing poorly during prior financial market dislocations (i.e., with large negative historical MDI betas when MDI realizations are positive) may subsequently do poorly or fail to recover those losses during more normal times (i.e., with small positive post-ranking MDI betas when MDI realizations are small or negative). Investors demand sizeable compensation to hold these stocks, especially in the recent, more turbulent sub-period 1994-2009: GMM-estimated market dislocation risk premium after controlling for the aforementioned five traded factors is roughly 2.4% per annum, implying a statistically and economically significant compensation of 6.8% for the spread's positive and significant post-ranking MDI beta. Lastly, in the time-series, MDI has some predictive power for future asset returns over both short and longer horizons. For instance, a one standard deviation positive shock to MDI predicts (an average of) 1.1% *lower* excess returns next month but 3.6% *higher* six-month-ahead cumulative excess returns (consistent with our cross-sectional results) for several developed and emerging stock portfolios between 1973 and 2009.

Numerous empirical studies document the relation between empirical measures of individual frictions absent from classical finance theory (e.g., liquidity, information, sentiment, noise, financial distress) and expected asset returns, hedge fund returns, or asset pricing anomalies (e.g., Pastor and Stambaugh, 2003; Baker and Wurgler, 2006; Sadka and Scherbina, 2007; Avramov et al., 2010; Fleckenstein et al., 2010; Hu et al., 2010; Alti and Tetlock, 2011; Stambaugh et al., 2011).[5] Others emphasize the potential importance of rare events and crises for the cross-section

[5]For instance, Hu et al. (2010) show that a measure of "noise" constructed as the difference between actual and *interpolated* Treasury bond yields spikes during episodes of marketwide illiquidity (see also Musto et al., 2011) and is related to cross-sectional returns of hedge funds and currency carry trades. The literature proposes several alternative yield curve interpolation models, but finds all of them to be plagued by errors both in normal times and during periods of financial turmoil (e.g., Gürkaynak et al., 2007). This raises the question of whether yield differentials from these models are akin to mispricings and can be conceptually attributed to liquidity effects.

of asset returns (e.g., Veronesi, 2004; Barro, 2006; 2009; Gabaix, 2007; Bianchi, 2010; Bollerslev and Todorov, 2011). Our novel, model-free analysis of systematic financial market dislocation risk — one encompassing both observable and unobservable sources of mispricings — and its role in asset pricing in both tranquil and turbulent times complements (rather than competing with) these insights.

We proceed as follows. In Section 2, we construct our measure of financial market dislocations and describe its empirical properties. In Section 3, we present and discuss the results of a wide array of asset pricing tests. We conclude in Section 4.

2 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 frictions and biases for the process of price formation in capital markets. As previously mentioned, it has proposed and tested several explanations for why mispricings may arise, persist, and wane. Measuring the direct extent of these frictions and biases — 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, p. 54).

In this study, we circumvent this issue by constructing a composite index of price dislocations in global stock, foreign exchange, and money markets. The index captures the systematic component of six hundred potential violations of three textbook arbitrage parities in those markets. Hence, it measures the systematic significance of observable and unobservable factors behind their occurrence. Next, we describe each of these parities, the procedure for the construction of our index, and the index's basic properties. In Section 3, we then investigate whether financial market dislocation risk — i.e., the risk that frictions and biases in capital markets may lead to mispricings — is priced in currency and U.S. and international stock returns.

2.1 Arbitrage parities

We estimate the observed magnitude of mispricings in global capital markets by measuring violations of the Covered Interest Rate Parity, the Triangular Arbitrage Parity, and the American Depositary Receipt Parity. There are several advantages to focusing on these parities. Assessing their violations does not require us to take a stance on any asset pricing model. Their violations imply impediments to the enforcement of the law of one price via arbitrage within some of the largest, most liquid financial markets in the world. The literature surveyed in the Introduction attributes these violations to such explicit and implicit barriers to arbitrage as taxes, (inventory) holding costs, transaction costs, short-sale restrictions, opportunity cost of capital, idiosyncratic risk, liquidity risk, slow moving capital, funding liquidity, market freezes, rollover risk, (counterparty) default risk, execution risk, exchange controls, information problems, agency problems, or political risk. Ample data availability for these violations allows us to assess the systematic, time-varying extent of those (often difficult to measure) impediments over a sample period spanning almost four decades.

2.1.1 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.

While conceptually simple, the actual implementation of non-convergence CIRP arbitrage if the CIRP in Eq. (1) is violated ($F_{t,T,A/B} \neq F^*_{t,T,A/B}$) is more involved. E.g., 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).[6] 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; Griffoli and Ranaldo, 2011). Data and structural limitations (e.g., non-binding pricing) make measurement of actual CIRP arbitrage profits challenging and feasible only over a few, most recent years (e.g., see Akram et al., 2008; Fong et al., 2010; Griffoli and Ranaldo, 2011).

We intend to capture the systematic component of CIRP violation levels and dynamics 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. Greenwich Mean Time [GMT]) of nine exchange rates among five of the most liquid (and relatively free-floating) currencies in the global for-

[6] See Griffoli and Ranaldo (2011) for further details and evidence of actual CIRP profits during the 2008 financial crisis.

eign 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), void of transaction costs, between May 1, 1990 and December 31, 2009.[7] This dataset comes from Thomson Reuters Datastream (Datastream).[8] 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: $CIRP_{i,t} = \left|\ln\left(F_{t,T,A/B}\right) - \ln\left(F^{*}_{t,T,A/B}\right)\right| \times 10,000$.[9]

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. Systematic 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, then downward. It also often spikes in proximity of well-known episodes of financial turmoil. Most notably (and consistent with recent aforementioned studies), average CIRP deviations reach a maximum (84 bps) in October 2008 (immediately following the Lehman bankruptcy) and remain higher than the historical averages for many months afterwards.[10]

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[7] CHF is the Swiss franc; EUR is the European euro; GBP is the British pound; JPY is the Japanese yen; USD is the U.S. dollar. LIBOR rates are computed by the British Bankers Association (BBA) as arithmetic averages of contributor banks' interbank offers at around 11 a.m. GMT.

[8] Exchange and money market rates for EUR/USD, GBP/EUR, CHF/EUR, and JPY/EUR are available in Datastream from the date the euro is officially introduced (January 1, 1999); prior forward and LIBOR data for such European currencies as the German mark (DEM), the French franc (FRF), or the Italian lira (ITL) is not. For simplicity and uniformity across exchange rates (e.g., when considering national holidays, special circumstances for fixing and value dates, as well as evolving day-count conventions [and their possibly conflicting interpretations] over the sample period), interest rates are compounded using a 30/360 convention. The effect of employing "market" day-count conventions, when feasible, on our analysis is immaterial.

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

[10] Investigations by media and regulators suggest that some of the LIBOR contributor banks may have underreported 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 website, 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

2.1.2 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), e.g., 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 Eq. (2) is violated ($S_{t,A/B} \neq S^*_{t,A/B}$), implementation of the triangular arbitrage is straightforward for it involves simultaneously selling and buying three exchange rates in the spot market. E.g., 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 for 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 extracting the systematic component of 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 and December 31, 2009: AUD, CAD, CHF, FRF, GBP, ITL, JPY.[11] These

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 2.3).

[11] AUD is the Australian dollar; CAD is the Canadian dollar.

daily indicative spot exchange rates (as observed at 3 p.m. Eastern Standard Time [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: $TAP_{i,t} = \left|\ln\left(S_{t,A/B}\right) - \ln\left(S^*_{t,A/B}\right)\right| \times 10,000$.[12]

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 (e.g., Aiba et al., 2002; Marshall et al., 2008; Kozhan and Tham, 2010). 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, e.g., first steadily increasingly during the 1970s and 1980s, 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 afterwards.[13] 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 the extent and time-series of financial market dislocations (and the frictions driving them) over our sample period.

2.1.3 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

[12] 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 of prices from Eq. (2) and/or from direct-to-indirect quote conversion (i.e., from $S_{t,A/B} = \left(S_{t,B/A}\right)^{-1}$). 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.

[13] We note here that DEM, FRF, and ITL exit our database only on the day the euro is introduced (January 1, 1999). Removing cross-rates relative to ITL and FRF from the full sample has little impact on TAP_m.

markets (especially in the U.S.) 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 pre-specified amount ("ratio") of a foreign company's publicly traded equity held on deposit at a U.S. depositary bank.[14] Depositary banks (e.g., Bank of New York, 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 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 (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 Eq. (3) is violated ($P_{i,t} \neq P^*_{i,t}$) is complex. E.g., 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, e.g., 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

[14] A minority of companies, mostly Canadian, cross-list their stock in the U.S. in the form of ordinary shares. Ordinary shares are identical certificates trading in both the U.S. and a foreign market (i.e., with a ratio of one; see Bekaert and Hodrick, 2009). In the U.S., "Canadian 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).

$P_{i,t}^{H}$). 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, risks, and barriers to trading in the literature may impede the successful exploitation of both types of ADR arbitrage. ADRs' fungibility, as captured by Eq. (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).

As the above discussion makes clear, measuring ADR parity violations has the potential to shed light on the extent and dynamics of a wide array of impediments 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 capture the systematic component of ADRP violations across the broadest spectrum of stocks (and currencies) over the longest feasible sample period. To that purpose, we obtain the complete sample of all foreign stocks cross-listed in the U.S. 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 ratios) for exchange-listed (on NYSE, AMEX, or NASDAQ; sponsored or unspon-

[15] For instance, Gagnon and Karolyi (2010) address non-synchronicity 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 http://www.adrbnymellon.com/dr_directory.jsp.

sored) 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 Eq. (3) and exchange rates from Pacific 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 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, $ADRP_m$ is generally declining over our sample period, hinting at a broad trend for lower barriers to (arbitrage) trading and greater world 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).

2.2 Index construction

The three textbook arbitrage parities described in Sections 2.1.1 to 2.1.3 yield 595 daily potential mispricings in the global stock, foreign exchange, and money markets. Each of them is only an imprecise estimate of the extent of dislocations in the market(s) in which it is observed (as well

[17] Sponsored ADRs are initiated by the foreign company of the underlying shares. Unsponsored ADRs are initiated by a depositary bank. Most developed ADRs 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), Brazil (23), South Africa (14), and India (10), among others.

[18] As for CIRP and TAP violations in Sections 2.1.1 and 2.1.2, 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.

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

[20] Consistently, Pasquariello (2008) finds evidence of greater ADRP violations for emerging markets stocks during recent financial crises.

as of the explicit and implicit impediments 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 systematic financial market dislocation risk more precisely.

We construct our novel index of dislocation risk in two 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 to assess the extent to which each realized individual absolute arbitrage parity violation was *historically large* on the day it occurred without introducing look-ahead bias, while making these violations comparable across and within different parities. Equivalently, each so-defined standardized arbitrage parity violation represents an *innovation* with respect to its historical mean (i.e., *expected*) mispricing. Their paritywide monthly means ($CIRP^z_m$, TAP^z_m, $ADRP^z_m$; see Panel B of Table 1 and Figures 1d to 1e) are frequently negative, often statistically significant, (less than perfectly) correlated, and subject to large intertemporal fluctuations.[22] Second, we compute a monthly index of financial market dislocation risk, MDI_m, as the equal-weighted, cross-parity average of these monthly means. This step allows to isolate the common, systematic component of the cross-section of innovations in (i.e., abnormal) absolute 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 3) is positive in correspondence with greater-than-normal marketwide mispricings, i.e., in the presence of historically large financial market dislocations.

[21] To that end, on any day t we exclude parity deviations with less than 22 past and current realizations.

[22] Monthly averaging smooths potentially spurious daily variability in these normalized arbitrage parity violations, e.g., due to price staleness or non-synchronicity.

2.3 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 systematic 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 3) displays several short-lived upward and downward spikes, as well as meaningful longer-lived, cycle-like dynamics over our sample period 1973-2009.[23] Many of these spikes and cycles occur in proximity of 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 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, and the quant meltdown in August 2007. Consistent with this chronology, most sizably positive realizations of our index (i.e., most abnormal mispricings) occur in the latter portion of our sample. The index is highest in October 2008, in the wake of Lehman's default and in the midst of the most significant economic crisis and financial freeze since the Great Depression.[24] It is plausible to conjecture that in those circumstances, impediments

[23] According to Cochrane (2001, p. 150), risk factors in linear asset pricing models "do not have to be totally unpredictable," as long as they are expressed in the "right units" since these models are often applied to excess returns without identifying the conditional mean of the discount factor (as in Sections 3.1 and 3.2). The market dislocation index MDI_m is not highly persistent (e.g., a first-order autocorrelation of 0.68) and measures innovations in relative mispricings with respect to their *historical* levels. Further, the lack of strong predictive evidence in Section 3.3 suggests our cross-sectional inference is unlikely to be contaminated by correlation between MDI_m and future excess returns. Alternatively, the time-series of month-to-month changes in the index, ΔMDI_m, measures 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 in the aftermath of Lehman Brothers' default. The correlation between MDI_m and ΔMDI_m is 0.40. The inference reported in the paper is robust to using ΔMDI_m instead of MDI_m. We describe some of these untabulated results in subsequent footnotes.

[24] 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 MDI_m on a dummy equal to one during the aforementioned crisis periods and zero otherwise yields a R^2 of less than 7%.

to trading and arbitrage may have become more severe, and asset mispricings larger and more widespread.

Further insight on the nature and properties of our index of standardized innovations in arbitrage parity violations comes from regressing its realizations on the change in several U.S. and international, economic and financial market variables, in Table 2.[25] Variable selection is driven by the observation (motivated by the aforementioned literature on limits to arbitrage) that mispricings are more likely during periods of U.S. and/or global economic and financial uncertainty, illiquidity, and overall financial distress.[26] 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, as measured by Moody's Baa-Aaa corporate bond spread; columns (3) and (4)), as well as in correspondence with higher world stock market volatility (columns (1) and (4)), lower U.S. systematic liquidity (as estimated by Pastor and Stambaugh, 2003; column (4)), and higher financial instability (e.g., lower balance sheet capacity of financial intermediaries, as measured by Adrian et al., 2012; column (4)). Yet, we find MDI_m to be (weakly) higher during more tranquil times as well (e.g., lower "TED" spread between LIBOR and Treasury Bill rates; columns (3) and (4)). Ceteris paribus, average abnormal arbitrage parity violations also weakly increase in correspondence with lower marketwide "risk appetite" (higher CBOE VIX index, columns (1) and (4); e.g., 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 downturns (and

[25] Regressions in changes help mitigate biases related to potential nonstationarity in the data. Regressing MDI_m on either raw or similarly normalized levels of these variables yields nearly identical inference.

[26] The regressors in Table 2 include monthly U.S. stock returns (from Kenneth French's website), 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 website), as well as monthly changes in Chauvet and Piger's (2008) historical U.S. recession probabilities (from Piger's website), VIX (monthly average of daily S&P500 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 et al., 2010), TED spread (average of three-month USD LIBOR minus constant maturity Treasury yields, from Datastream), default spread (average of Aaa minus Baa corporate bond yields, from Moody's), and innovations in Adrian et al.'s (2012) broker-dealer leverage (from Muir's website).

the accompanying illiquidity, as argued by Chordia et al., 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, in column (2); see Hu et al., 2010).[27]

Insight on MDI_m can also be drawn from regressing each of its components ($CIRP_m^z$, TAP_m^z, and $ADRP_m^z$) 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 a lesser one for CIRP and TAP deviations. For instance, $ADRP_m^z$ (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). While $CIRP_m^z$ displays some similar sensitivities (column (5)), TAP_m^z 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 2.1.2), 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)).[28]

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

[27] In untabulated regressions of MDI_m on each of the variables listed in Table 2 separately, we find its sensitivity to Pastor and Stambaugh (2003)'s innovations in U.S. stock market liquidity to be the most statistically significant (a slope coefficient of -0.393, with $t = -2.22$), but changes in VIX to have the greatest explanatory power (R^2 of 10.92%). We explore the impact of either measure on whether MDI_m is a price state variable in Sections 3.1.2 and 3.1.3.

[28] The adjusted R^2 (R_a^2) in column (4) of Table 2 drops to less than 9% (and to 4%, -2%, and 14% in columns (5) to (7)) when the most recent period of financial turmoil (2008-2009) is removed from the sample. 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) and 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 break-even inflation rates) in the regressions of Table 2. In unreported analysis excluding the sub-period 2008-2009 because of data availability, we also find MDI_m to weakly increase in correspondence with greater investor sentiment (as estimated in Baker and Wurgler, 2006) or greater worldwide intensity of capital controls (as estimated in Edison and Warnock, 2003).

3 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. As discussed above, MDI_m has several desirable properties. It is parsimonious and easy to compute; it relies on model-free assessment of asset mispricings; it is privy of look-ahead 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, the cross-section of currency portfolio returns, and future aggregate stock and currency portfolio returns.

3.1 Financial market dislocations and risk premiums: Stocks

3.1.1 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 et al., 1997). First, we run 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} using all portfolios:

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

We consider two samples of 26 U.S. and 50 international equity portfolios over the period 1973-2009. The U.S. sample includes the U.S. market (MKT) and 25 U.S. portfolios formed on size (market equity) and book-to-market (book equity to market equity), from French's website.[29] The international sample is unbalanced and includes the world market portfolio (WMKT), 23 developed, and 26 emerging country portfolios (listed in Table 4), from MSCI.[30] Tables 3 and 4 report estimated MDI betas from Eq. (4) for U.S. and international portfolios, respectively. Figures 4a and 4b display scatter plots of their annualized mean percentage excess returns versus these MDI betas. The largest, circular scatters refer to the U.S. and world market portfolios; scatters with dark (white) background refer to statistically (in)significant MDI betas, at the 10% level or less. Estimated MDI betas 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 — i.e., when arbitrage parity violations are (in aggregate) greater than their historical means ($MDI_m > 0$).[31] MDI betas are more negative for "riskier" portfolios: Portfolios of smaller U.S. stocks, U.S. stocks with higher book-to-market, and stocks of emerging countries.

Figures 4a and 4b suggest that stock portfolios with more negative MDI betas have higher average excess returns. Accordingly, estimates of Eq. (5), in Panel A of Table 5, indicate that the

[29] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. In unreported analysis, we find similar inference from studying either a larger (100) or a smaller (10) number of portfolios sorted on size and book-to-market.

[30] 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), Czech Republic, Egypt, Hungary, Morocco, and Russia (January 1995).

[31] For instance, the estimates of MDI betas in Tables 3 and 4 imply that excess returns of U.S. and international stock portfolios decline on average by 0.62% and 1.61% per month, respectively, from a one standard deviation shock to MDI_m (in Panel B of Table 1).

annualized price of financial market dislocation risk is negative ($\lambda_{MDI} < 0$) and statistically significant within both U.S. and international stock portfolio samples.[32] Dislocation risk premiums are economically significant, amounting to -2.1% and -0.5% per unit of MDI beta — i.e., 7.5% and 4.4% per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$) — for U.S. and international stock portfolios, respectively. The accompanying R^2 of 51% and 20% suggest that financial market dislocation risk can explain a meaningful portion of the cross-section of equity portfolio returns. These properties are generally robust across sample sub-periods, although absolute estimated λ_{MDI} and Eq. (5)'s cross-sectional explanatory power are greater in the first sub-period (1973-1993) for U.S. portfolios, and in the second sub-period (1994-2009) for country portfolios.[33]

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

3.1.2 Multivariate MDI beta estimation

Financial market dislocation risk may be subsumed by additional systematic risk factors. For instance, Figure 4 and Tables 3 and 4 show that both the U.S. and world market portfolios are highly sensitive to MDI_m. We investigate this possibility by employing the multivariate asset pricing model in Pastor and Stambaugh (2003). This model allows to assess the marginal contribution of MDI_m to the cross-section of equity portfolio returns while accounting for their sensitivities to other factors.

[32] Annualized risk premium estimates are computed multiplying monthly estimates by 12. Because of MDI_m's relatively large variance (e.g., see Panel B of Table 1), similar inference is drawn from applying the errors-in-variables correction described in Shanken (1992) to their conventional t-statistics (in Tables 5 and 10). The single-stage GMM estimation of $\beta_{i,MDI}$ and λ_{MDI} in Section 3.1.2 (and Tables 5 and 9) yields heteroskedasticity-robust inference as well (e.g., Cochrane, 2001).

[33] Those uneven sub-periods are chosen to correspond to the even sub-periods (1978-1993, 1994-2009) stemming from the analysis of the cross-section of U.S. stock returns in Section 3.2. Dislocation risk premiums are smaller (yet still economically and statistically significant) per average change-in-MDI (ΔMDI_m) beta, e.g., as high as 1.9% ($t = 1.72$) for U.S. portfolios and 2.6% ($t = 2.58$) for country portfolios over the full sample 1973-2009.

Specifically, we define a multivariate extension of Eq. (4):

$$R_m = \beta_0 + BF_m + \beta_{MDI} MDI_m + \varepsilon_m, \tag{6}$$

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. Assuming that the N portfolios are priced by the factor betas in Eq. (6) implies that

$$E(R_m) = B\lambda_F + \beta_{MDI}\lambda_{MDI}. \tag{7}$$

Since our index MDI_m is not the payoff of a trading strategy, in general $\lambda_{MDI} \neq E(MDI_m)$, while $\lambda_F = E(F_m)$ for traded factors F_m. Hence, substitution of Eq. (7) in Eq. (6), after taking expectations of both its sides, yields the restriction:

$$\beta_0 = \beta_{MDI}\left[\lambda_{MDI} - E(MDI_m)\right]. \tag{8}$$

We consider several factor specifications. The U.S. portfolios in our sample are already sorted on firm size and book-to-market. Thus, we characterize the vector F_m in Eq. (6) for these portfolios as including either the U.S. market alone (MKT_m) or in conjunction with two traded U.S. risk factors — the momentum factor, MOM_m (from French's website), and the liquidity factor of Pastor and Stambaugh (2003), PS_m (from Pastor's website). Further accounting for the popular size (SMB) and book-to-market (HML) traded factors of Fama and French (1993), also from French's website, yields qualitatively similar inference. In the next section we consider all of these factor models when examining the cross-section of individual U.S. stock returns. The World 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). Accordingly, we assume that, besides MDI_m, common sources of risk F_m for country-level portfolio returns include either the world market ($WMKT_m$) or the four global market ($GMKT_m$), size ($GSMB_m$), value ($GHML_m$), and momentum ($GMOM_m$) factors of Fama and French (2012), from French's website.[34]

We estimate the ensuing MDI risk premiums separately for the remaining 25 U.S. stock portfolios and the 49 country equity portfolios in our sample using the GMM procedure described in Pastor and Stambaugh (2003).[35] Panel B of Table 5 reports the corresponding estimates of annualized λ_{MDI}, their asymptotic t-statistics, as well as asymptotic chi-square J-tests for the over-identifying restriction in Eq. (8).[36] Full-period and sub-period GMM estimates of dislocation risk premiums for U.S. and eligible international stock portfolios are always negative and nearly always statistically significant, even after accounting for the effect of alternative marketwide risks. Accordingly, MDI risk premiums per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$), while unsurprisingly smaller and less often statistically significant than in Panel A of Table 5, remain economically large, e.g., ranging between 2.25% and 2.47% for U.S. portfolios (relative to CAPM) and as high as 4.17% for country portfolios (relative to the global four-factor model).[37]

[34] Returns on the global Fama-French portfolios, formed by sorting stocks of 23 developed countries, are available exclusively from November 1990 onward. It is worth noting that the aforementioned U.S. and global factor portfolios also tend to perform poorly during market dislocations: E.g., estimated $\beta_{i,MDI}$ is -3.12 ($t = -2.39$) for MKT (in Table 3), -0.61 ($t = -0.68$) for SMB, -2.69 ($t = -3.13$) for HML, -0.87 ($t = -0.67$) for MOM, -2.91 ($t = -2.89$) for PS, and -4.21 ($t = -3.47$) for WMKT (in Table 4) over 1973-2009; -7.55 ($t = -5.16$) for GMKT, -0.65 ($t = -0.82$) for GSMB, -1.21 ($t = -1.37$) for GHML, and -0.51 ($t = -0.33$) for GMOM over 1990-2009.

[35] To that purpose, let γ be the set of $2 + N(K+1)$ unknown parameters: λ_{MDI}, β_{MDI}, B, and $E(MDI_m)$. Next, define $f_m(\gamma) = \binom{h_m \otimes \varepsilon_m}{MDI_m - E(MDI_m)}$, where $h'_m = (1 \; F'_m \; MDI_m)$ and $\varepsilon_m = R_m - \beta_{MDI}[\lambda_{MDI} - E(MDI_m)] - BF_m - \beta_{MDI} MDI_m$. Then, $\widehat{\gamma}_{GMM} = \arg\min g(\gamma)' W g(\gamma)$, where $g(\gamma) = (1/M)\sum_{m=1}^{M} f_m(\gamma)$, W is the inverse of $(1/M)\sum_{m=1}^{M} f_m(\widehat{\gamma}) f_m(\widehat{\gamma})'$, and $\widehat{\gamma} = \arg\min g(\gamma)' g(\gamma)$.

[36] In many (but not all) cases, this restriction cannot be rejected at any conventional significance level. Because of data availability, Eqs. (6) to (8) can be jointly estimated via GMM only for 18 developed country portfolios (excluding Finland, Greece, Ireland, New Zealand, and Portugal) over 1973-2009 and 1973-1993, and for 44 country portfolios (excluding Czech Republic, Egypt, Hungary, Morocco, and Russia) over 1994-2009. For similar reasons, we estimate MDI risk premiums relative to the international four-factor model ($GMKT_m$, $GSMB_m$, $GHML_m$, $GMOM_m$) exclusively over 1990-2009 for 35 of those 44 country portfolios (further excluding China, Colombia, India, Israel, Pakistan, Peru, Poland, South Africa, and Sri Lanka).

[37] Estimates of $\lambda_{MDI}\overline{\beta_{i,MDI}}$ for U.S. portfolios relative to conventional three-factor (market, size, and book-to-market), four-factor (i.e., plus momentum), and five-factor (i.e., plus PS) models are as follows: 0.61% ($t = 2.59$), 0.39% ($t = 1.83$), and -0.06% ($t = -0.30$) over 1973-2009; 0.48% ($t = 1.92$), 0.62% ($t = 2.24$), and 0.68% ($t = 2.37$) over 1973-1993; 1.75% ($t = 3.32$), 0.64% ($t = 1.67$), and -0.29% ($t = -0.97$) over 1994-2009. Notably, the corresponding estimated MDI betas relative to three-factor and four-factor models are often positive. We discuss this feature of U.S. stocks' sensitivity to dislocation risk in Section 3.1.3.

Overall, U.S. and international stock portfolios' sensitivities to financial market dislocations appear to explain a non-trivial portion of these portfolios' risk, one that is not captured by fluctuations in local and global factors and for which investors require meaningful compensation.

3.1.3 Portfolio construction by financial market dislocation betas

The evidence in Tables 3 to 5 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, i.e., to their MDI betas. We follow a portfolio-based approach similar to the one in Pastor and Stambaugh (2003). At the end of every year of 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, post-formation 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.[38] 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 coefficient

[38] As 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 U.S., and American Depositary Receipts (ADRs). The latter is important since 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.

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

$$\begin{aligned} R_{j,m} &= \beta_{j,0} + \beta_{j,M} MKT_m + \beta_{j,S} SMB_m + \beta_{j,B} HML_m \\ &\quad + \beta_{j,M} MOM_m + \beta_{j,L} PS_m + \beta_{j,MDI} MDI_m + \eta_{j,m}, \end{aligned} \tag{9}$$

where MKT_m, SMB_m, and HML_m are the market, size, and book-to-market traded factors of Fama and French (1993); MOM_m is the traded momentum factor; and PS_m is the traded liquidity factor of Pastor and Stambaugh (2003). Our results are stronger when excluding from Eq. (9) either MOM_m alone or both MOM_m and PS_m (as in Pastor and Stambaugh, 2003). We then sort all stocks by their pre-ranking, *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.[39] 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.[40]

Panel A of Table 6 reports post-ranking MDI betas from running Eq. (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) pre-ranking MDI betas (decile 1) and short stocks with the highest (i.e., most positive) pre-ranking MDI betas (decile 10). Focus on this spread portfolio is motivated by the evidence in the previous section that stock portfolios with the greatest negative exposure to financial market dislocation risk experience the highest mean excess returns. Panel B of Table 6 reports additional features of these portfolios: Their average market capitalization

[39] 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.

[40] Alternatively, we sort stocks by *predicted* MDI betas from a linear model including such stock characteristics as their cross-sectionally demeaned historical MDI betas, past six-month cumulative returns and return standard deviation, natural log of lagged stock price, and number of shares outstanding. Historical MDI beta, past returns, and return volatility are the most significant predictors over our sample period; yet, sign and magnitude of all predictor coefficients display non-trivial intertemporal dynamics. The inference based on portfolios sorted on these predicted betas is qualitatively comparable to the one based on historical MDI betas.

and sensitivities to the standard market, size, and book-to-market factors, as well as to the traded momentum and liquidity factors. Lower (i.e., more negative) historical MDI beta stocks are generally larger; their portfolios weakly tilt toward value stocks (positive HML betas) and past losers (negative MOM betas), but are insensitive to liquidity risk (small, insignificant PS betas).[41] Interestingly, post-ranking MDI betas are small or weakly decline across deciles, and the spread portfolio's MDI beta is positive and significant only over the sub-period 1994-2009.[42] Ceteris paribus, 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 (positive yet small, insignificant post-ranking MDI betas when $MDI_m \leq 0$). However, stocks doing relatively well during past financial market dislocations (large and positive MDI betas when $MDI_m > 0$) may preserve or add to those gains afterwards (small or negative and significant post-ranking 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) pre-ranking 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 7 reports post-ranking annualized raw returns and alphas for each pre-ranking MDI beta portfolio and the 1-10 spread with respect to four conventional traded factor specifications: CAPM (the market factor: $R_{M,m}$), 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, except in the earlier,

[41] In unreported analysis, similar inference ensues from including the S&P100 VIX mimicking factor of Ang et al. (2006). Monthly returns of low MDI beta portfolios (and the 1-10 spread) tend to be either statistically unrelated or negatively related to this factor. We thank Deniz Anginer for the VIX factor data.

[42] Consistently, as noted in footnote 37, (untabulated) sample-wide estimates of MDI betas of (size and book-to-market sorted) U.S. stock portfolios, after controlling for their exposure to the conventional three or four traded factors, are also positive.

more tranquil sub-period (1978-1993). All four spread portfolio alphas are positive over the full sample (1978-2009), and especially large and statistically significant in the later sub-period (1994-2009) — when large dislocations (i.e., sizably positive realizations of MDI_m) occur most often (see Figure 2). For instance, five-factor alpha for the 1-10 spread portfolio is 5.29% ($t = 2.34$) over 1978-2009, 1.08% ($t = 0.35$) over 1978-1993 (during which most $MDI_m \leq 0$), and 9.26% ($t = 2.76$) over 1994-2009 (in correspondence with the most well-known episodes of financial turmoil).[43] Equally-weighted decile portfolios have similar characteristics. E.g., Table 8 shows that the equally-weighted 1-10 spread portfolio displays a positive but insignificant post-ranking MDI beta (0.87) and positive and significant CAPM, Fama-French, four-factor, and five-factor alphas (5.36%, 4.41%, 5.66%, and 3.91%, respectively) over 1994-2009.[44]

Further insight on the sign and significance of the financial market dislocation risk premium comes from its direct estimation using all ten MDI beta decile portfolios, via the multivariate GMM procedure described in Section 3.1.2. Table 9 reports estimates of λ_{MDI} and $\beta_{i,MDI}$ from Eq. (7) for value-weighted (Panel A) and equal-weighted (Panel B) portfolios after accounting for priced sensitivities to the three ($F'_m = (MKT_m \;\; SMB_m \;\; HML_m)$), four ($F'_m = (MKT_m \;\; SMB_m \;\; HML_m \;\; MOM_m)$), or five ($F'_m = (MKT_m \;\; SMB_m \;\; HML_m \;\; MOM_m \;\; PS_m)$) aforementioned traded factors in Eq. (6). Consistent with the sign and declining magnitude of the value-weighted decile portfolios' post-ranking alphas and MDI betas in Tables 6 and 7, both

[43] 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% ($t = 2.30$) over 1986-2009, 0.31% ($t = 0.08$) over 1986-1993, and 9.02% ($t = 2.53$) over 1994-2009. Even stronger inference can be drawn from forming MDI beta decile portfolios relative to just the three Fama-French factors or the Fama-French factors plus the liquidity factor of Pastor and Stambaugh (2003) in Eq. (9). For instance, the former imply five-factor alphas for the 1-10 spread portfolio of 6.72% ($t = 2.68$) over 1978-2009, 2.31% ($t = 0.75$) over 1978-1993, and 11.07% ($t = 2.82$) over 1994-2009; the latter's post-ranking spread alphas are 7.31% ($t = 2.88$) over 1978-2009, 2.45% ($t = 0.80$) over 1978-1993, and 12.23% ($t = 3.00$) over 1994-2009. Sorting stocks into decile portfolios based on their pre-ranking change-in-MDI (ΔMDI_m) betas yields smaller (but still non-trivial) 1-10 spread alphas: E.g., 2.88 ($t = 1.43$), 3.75 ($t = 1.86$), 3.76 ($t = 1.82$), 3.05 ($t = 1.47$), and 5.21 ($t = 2.01$) relative to the CAPM, three, four, five, and six-factor models, respectively, over 1978-2009.

[44] Post-ranking MDI betas are more often statistically significant but less disperse for equally-weighted decile portfolios, yielding lower spread alphas and MDI betas. However, in unreported analysis we also find that the null hypothesis that all decile portfolio alphas are jointly zero is nearly always rejected by the F statistic of Gibbons et al. (1989) for equally-weighted returns, but neither with CAPM alphas nor in the earlier subperiod (1978-1993) for value-weighted returns.

estimated risk premiums and spread portfolio's MDI betas ($\beta_{1,MDI} - \beta_{10,MDI}$) in Panel A of Table 9 are nearly always positive and economically and statistically significant.[45] For example, annualized MDI risk premiums per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$) are 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 sub-period (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 — e.g., ranging between 6.85% ($t = 2.89$) per five-factor MDI beta of 2.84 ($t = 3.31$) and 7.80% ($t = 2.87$) per three-factor MDI beta of 4.23 ($t = 3.72$) over 1994-2009 — and broadly consistent with the estimates reported in Table 7. Estimated dislocation risk premiums for equally-weighted portfolios are comparably significant — e.g., amounting to up to 2.40% (3.16%) per average full-period (later-period) MDI beta.

Overall, the evidence in Tables 6 to 9 provides additional support to the notion that not only across U.S. or international stock portfolios but also within U.S. stocks, abnormal mispricings are undesirable and MDI betas may be priced such that greater exposure to financial market dislocation risk is accompanied by higher expected returns.

3.2 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, described in Section 2) may stem from foreign exchange markets. Thus, these markets are a potentially important source of financial 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 et al. (2011) from the perspective of a U.S. investor. Lustig et al. (2011) compute monthly excess

[45] Notably, according to Panel A of Table 9 the over-identifying restriction in Eq. (8) is never rejected by the asymptotic chi-square J-tests at standard significance levels.

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. These 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, while the last ($i = 6$) contains currencies with the highest interest rates.[46] These portfolios have appealing properties. Currency speculation via forward contracts is easy to implement and yields Sharpe ratios comparable to those offered by international equity markets (e.g., see Lustig et al., 2011, 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 et al. (2011) also find that both the *slope* factor HML_{FX} and the average *level* of foreign exchange excess returns, RX — i.e., 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 3.1.1 (Eqs. (4) and (5)) in Table 10. As for U.S. and international equity markets, most estimated MDI betas ($\beta_{i,MDI}$ in Eq. (4)) for currency excess returns are large, negative, and often statistically significant.[47] Portfolios made of currencies carrying higher interest rates tend to exhibit greater sensitivity to dislocation risk, as do both the basket currency (RX) and the carry trade (HML_{FX}) portfolios, especially in the latter sub-period (1994-2009).[48] 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

[46] This data is available on Verdelhan's website at http://web.mit.edu/adrienv/www/Data.html. We obtain similar results within a sub-sample made exclusively of developed countries.

[47] For example, these estimates imply that excess returns of the currency portfolios in Table 10 decline on average by 0.27% per month from a one standard deviation shock to MDI_m.

[48] Consistently, Brunnermeier et al. (2008), Hu et al. (2010), Lustig et al. (2011), and Menkhoff et al. (2012) 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.

relative mispricings.

Investors in foreign currencies require a meaningful compensation for exposure to such risk. Figure 4c shows that — as for U.S. and international stock portfolios in Figures 4a and 4b and Table 5 — currency portfolios' average excess returns are inversely related to their MDI betas. Thus, Eq. (5) yields negative estimates of the annualized price of MDI risk: $\lambda_{MDI} < 0$ in Table 10. 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 ($t = 4.49$), implying a dislocation premium of 2.30% per average MDI beta (and 5.28% for the carry trade portfolio). Dislocation premiums rise to nearly 4% (more than 7%) over 1994-2009. In addition, MDI betas in Eq. (5) can explain up to 80% of the cross-sectional variation in currency portfolio returns.[49]

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

3.3 Predicting asset returns

In this section we investigate whether financial market dislocations can predict future stock and currency returns. As discussed earlier, positive innovations in the extent of arbitrage parity violations may stem from more severe, abnormal impediments to speculators' ability to trade. Hence, they may contain information about current and future stressful conditions in financial markets ultimately leading to lower future asset prices, at least in the short term. Yet, evidence of positive dislocation risk premiums in Tables 5 and 10 suggests that abnormally high current mispricings may imply higher future asset prices in the long term.

We test the ability of our index MDI_m to predict excess returns of U.S. and international stock

[49] Dislocation risk premiums per unit change-in-MDI (ΔMDI_m) beta are also large, e.g., implying a compensation of 1.85% ($t = 4.27$) per average $\beta_{i,\Delta MDI}$ and 6.54% for HML_{FX} over 1994-2009 (with $R^2 = 84\%$).

portfolios and currency portfolios over different horizons by running the following regressions,

$$R_{i,m,m+h} = \delta^h_{i,0} + \delta^h_{i,1} R_{i,m-h,m} + \delta^h_{i,MDI} MDI_m + e_{m,m+h}, \tag{10}$$

where $R_{i,m,m+h}$ is portfolio i's cumulative excess return over the next h months and $R_{i,m-h,m}$ controls for the previous horizon's excess return, for each of the 26 U.S. and 50 country stock portfolios described in Section 3.1.1, and each of the 8 currency portfolios described in Section 3.2. Table 11 reports summary statistics for the estimates of the coefficients of interest: $\delta^{h=1}_{i,MDI}$ for one-month-ahead (in Panel A) and $\delta^{h=6}_{i,MDI}$ for six-month-ahead (in Panel B) cumulative stock returns, multiplied by the in-sample standard deviation of MDI_m to ease their economic interpretation. Individual such estimates for currency portfolios are in Panels A ($h = 1$) and B ($h = 6$) of Table 12.[50]

As conjectured above, estimated near-future predictive coefficients $\delta^{h=1}_{i,MDI}$ are nearly always negative across stock and currency portfolios and over time, but not as often statistically significant. For instance, Panel A of Table 11 shows this to be the case for only 3 U.S. portfolios over the full sample period 1973-2009. Interestingly, those are portfolios made of firms with high book-to-market. This is consistent with our finding in Sections 3.1.1 and 3.1.3 (and Tables 3 and 6) that U.S. value firms' stock returns display the greatest pre- and post-ranking sensitivity to dislocation risk. Estimates of $\delta^{h=1}_{i,MDI}$ for currency portfolio returns (in Panel A of Table 12) are also mostly negative, and statistically significant only for relatively high and low interest currencies.

Current financial market dislocations have only marginally greater predictive power for near-future returns of international stock portfolios. Panel A of Table 11 shows that a one standard deviation increase in aggregate abnormal asset mispricings statistically significantly predicts an

[50] These estimates are unlikely to be affected by the finite-sample biases documented in Stambaugh (1999), since our measure of average innovations in arbitrage parity violations MDI_m is neither very persistent (see footnote 23) nor made of scaled price variables.

average of 1.10% lower excess return next month for 5 of the country stock portfolios in our sample (with a corresponding mean adjusted R^2 [R_a^2] of 4%) between 1973 and 2009. This short list includes both developed (Finland, Ireland) and emerging markets (Jordan, Morocco, Poland) but neither the U.S. nor the World market. This evidence is robust across the two sub-periods.[51] For instance, positive innovations in aggregate arbitrage parity violations over 1973-1993 — while often smaller than later in the sample — were followed by an average of -0.25% lower monthly excess returns (when significant, with a mean R_a^2 of 9%), and as much as -3.71% in China.

MDI's predictive coefficients for six-month-ahead holding-period returns ($\delta_{i,MDI}^{h=6}$) are more often positive and significant, consistent with the cross-sectional evidence in Sections 3.1. and 3.2. For instance, estimated $\delta_{i,MDI}^{h=6}$ in Panel B of Table 11 imply that a one standard deviation increase in abnormal arbitrage parity violations during the later, more turbulent sub-period 1994-2009 — when estimated dislocation risk premiums in Tables 5 to 9 are the largest — is followed by an average of 3.19% (5.10%) higher excess U.S. (international) stock returns over the next six months when statistically significant, and by as much as 4.30% (8.69%) higher excess returns for small growth firms (Indonesia). Similarly, estimates of $\delta_{i,MDI}^{h=6}$ for currency portfolios over 1994-2009 are nearly always positive, albeit never statistically significant.

4 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 six hundred 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,

[51] Because of data availability, Eq. (10) cannot be estimated for Czech Republic, Egypt, Hungary, Morocco, and Russia over the sub-period 1973-1993.

e.g., 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, easy to compute macroprudential policy tool to oversee the integrity of financial markets and detect systemic risks to their orderly functioning.

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Table 1. Arbitrage parity violations: Summary statistics

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 2.1.1 ($CIRP_m$ and $CIRP_m^z$, respectively), of the Triangular Arbitrage Parity described in Section 2.1.2 (TAP_m and TAP_m^z), of the ADR Parity described in Section 2.1.3 ($ADRP_m$ and $ADRP_m^z$), as well as for the ensuing Market Dislocation Index described in Section 2.2 (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.

								Correlation matrix			
Parity	N_p	N	Mean	Median	Stdev	Min	Max	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

Table 2. MDI: Time-series regression analysis

This table reports OLS coefficients from time-series regressions of the financial market dislocation index described in Section 2.2, MDI_m (columns (1) to (4)) and its components ($CIRP^z_m$, column (5); TAP^z_m column (6); $ADRP^z_m$ column (7)). Regressors include monthly U.S. stock returns (from French's website), official NBER recession dummy, world market returns (from MSCI), innovations in liquidity (from Pastor and Stambaugh, 2003), innovations in broker-dealer leverage (from Adrian et al., 2012), as well as monthly changes in U.S. recession probability (from Chauvet and Piger, 2008), 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^2_a is the adjusted R^2. Newey-West t-statistics are in parentheses. A "*", "**", or "***" indicates significance at the 10%, 5%, or 1% level, respectively.

	MDI_m				$CIRP^z_m$	TAP^z_m	$ADRP^z_m$
	(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 - T-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^2_a	31.87%	0.75%	15.81%	42.47%	37.96%	-2.27%	38.14%

Table 3. MDI betas: U.S. stock portfolios

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 26 U.S. stock portfolios i on MDI_m, the financial market dislocation index described in Section 2.2 (Eq. (4)), over the full sample period (January 1973 to December 2009, 444 observations). The sample includes the U.S. market (MKT_m) and 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 website. t-statistics are in parentheses. A "*", "**", or "***" indicates significance at the 10%, 5%, or 1% level, respectively.

U.S. market	25 U.S. portfolios					
$\beta_{MKT,MDI}$	$\beta_{i,MDI}$	Low B/M	2	3	4	High B/M
-3.12**	Small M	-3.05	-3.09	-3.92**	-3.81**	-6.37***
(-2.39)		(-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)

Table 4. MDI betas: International stock portfolios

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 50 international stock portfolios i on MDI_m, the financial market dislocation index described in Section 2.2 (Eq. (4)). The sample includes the world market ($WMKT_m$), 23 developed, and 26 emerging country portfolios, from MSCI. World and developed country portfolio returns are available from January 1973 to December 2009 (444 observations), with the exception of Finland (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, and Sri Lanka (January 1993, 204 observations), Czech Republic, Egypt, Hungary, Morocco, and Russia (January 1995, 180 observations). t-statistics are in parentheses. A "*", "**", or "***" indicates significance at the 10%, 5%, or 1% level, respectively.

World market	Developed countries				Emerging countries			
$\beta_{WMKT,MDI}$		$\beta_{i,MDI}$		$\beta_{i,MDI}$		$\beta_{i,MDI}$		$\beta_{i,MDI}$
-4.21***	Australia	-6.38***	Netherlands	-6.21***	Argentina	-12.74**	Mexico	-7.81**
(-3.47)		(-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)

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

This table reports estimates of annualized percentage MDI risk premiums (λ_{MDI}, multiplied by 12) for univariate (Panel A) and multivariate (Panel B) MDI betas ($\beta_{i,MDI}$) of U.S. and international country portfolios. The U.S. portfolios include the U.S. market and the intersections of five U.S. stock portfolios formed on size and five portfolios formed on book-to-market (from French's website). The international portfolios include the world market, 23 developed, and 26 emerging country portfolios (from MSCI). Panel A reports OLS estimates of λ_0 and λ_{MDI} from regressing portfolio-level mean excess percentage monthly returns $R_{i,m}$ on previously estimated univariate MDI betas $\beta_{i,MDI}$ (Eqs. (4) and (5), in Section 3.1.1), as well as the risk premium per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$), over the full sample 1973-2009 and two sub-periods (1973-1993, 1994-2009). Our unbalanced MSCI sample limits the joint estimation of Eqs. (6) to (8) via GMM 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. t-statistics are in parentheses. Panel B reports GMM estimates of λ_{MDI} and $\lambda_{MDI}\overline{\beta_{i,MDI}}$ (Eqs. (6) to (8), in Section 3.1.2) when accounting for excess returns' sensitivity to either the U.S. (World) market alone or three (four) U.S. (global) factors — U.S. market (MKT_m), momentum (MOM_m), from French's website, and liquidity (PS_m), from Pastor's website (global market [$GMKT_m$], size [$GSMB_m$], book-to-market [$GHML_m$], and momentum [$GMOM_m$], also from French's website). Global factors are available only from November 1990 onward; over this sub-period (°), 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). Asymptotic t-statistics are in parentheses. J-test is the asymptotic chi-square statistic for the over-identifying restriction in Eq. (8); the corresponding p-values are below. A "*", "**", or "***" indicates significance at the 10%, 5%, or 1% level, respectively.

	Panel A: Univariate MDI betas & OLS				Panel B: Multivariate MDI betas & GMM					
	λ_0	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	R^2	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	J-test	λ_{MDI}	$\lambda_{MDI}\overline{\beta_{i,MDI}}$	J-test
	U.S. plus 25 U.S. portfolios				25 U.S. portfolios, CAPM			25 U.S. portfolios, 3-factor		
1973-2009	0.32	-2.07***	7.49***	51%	-4.54***	2.25**	26.98	-1.38***	0.68	85.03***
	(0.21)	(-5.03)	(4.61)		(-5.00)	(2.52)	0.31	(-3.81)	(1.25)	0.00
1973-1993	12.68***	-2.39***	–4.68***	65%	-5.66***	2.31**	25.19	-1.33***	0.65	85.77***
	(15.75)	(-6.65)	(-3.75)		(-3.46)	(2.14)	0.40	(-3.65)	(0.74)	0.00
1994-2009	1.89	-0.73	5.66**	9%	-4.17***	2.47*	23.21	-0.90**	0.45	70.10***
	(0.52)	(-1.57)	(2.03)		(-6.32)	(1.75)	0.51	(-2.05)	(0.86)	0.00
	World plus 49 country portfolios				49 country portfolios, WCAPM			49 country portfolios, 4-factor°		
1973-2009	-2.38*	-0.46***	4.36***	20%	-0.05	0.09	7.67	n.a.	n.a.	n.a.
	(-1.74)	(-3.50)	(3.45)		(-0.12)	(0.13)	0.97	n.a.	n.a.	n.a.
1973-1993	14.58***	-0.08	-0.26	1%	-1.42*	0.77	5.89	n.a.	n.a.	n.a.
	(2.95)	(-0.47)	(-0.40)		(-1.90)	(0.85)	0.90	n.a.	n.a.	n.a.
1994-2009	-4.52**	-0.51***	5.91***	14%	-0.20	0.47	46.10	-1.67***	4.17**	120.16***
	(-2.01)	(-2.76)	(2.74)		(-0.61)	(0.62)	0.35	(-4.70)	(2.27)	0.00

Table 6. Value-weighted portfolios of U.S. stocks sorted on historical MDI betas

This table reports post-ranking 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 sub-periods (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 Eq. (9), in Section 3.1.3) from a multivariate regression of their percentage monthly excess returns on our financial market dislocation index MDI_m (described in Section 2.2), the three traded Fama-French factors (U.S. market [MKT_m], size [SMB_m], and book-to-market [HML_m], from French's website), the traded momentum factor (MOM_m, also from French's website), and the traded liquidity factor of Pastor and Stambaugh (2003) (PS_m, from Pastor's website). The resulting value-weighted decile portfolio returns for the next 12 months are stacked across years to generate post-ranking return series. Panel A reports their estimated post-ranking 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 post-ranking factor betas (B of Eq. (6), in Section 3.1.2). t-statistics are in parentheses. A "*", "**", or "***" indicates significance at the 10%, 5%, or 1% level, respectively.

Pre-ranking	1	2	3	4	5	6	7	8	9	10	1-10
	Panel A: Post-ranking 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)
SML 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)

Table 7. Alphas of value-weighted portfolios of U.S. stocks sorted on historical MDI betas

This table reports annualized raw percentage excess returns as well as intercepts (percentage alphas, multiplied by 12) from the regression of monthly excess post-ranking returns of twelve-month value-weighted portfolios (constructed by sorting U.S. stocks by their pre-ranking, 60-month historical MDI betas; see Section 3.1.3) 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. A "*", "**", or "***" indicates significance at the 10%, 5%, or 1% level, respectively.

Pre-ranking	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)

Table 8. MDI betas and alphas of equal-weighted portfolios of U.S. stocks sorted on historical MDI betas

This table reports annualized intercepts (percentage alphas, multiplied by 12) from the regression of monthly excess post-ranking returns of twelve-month equal-weighted portfolios (constructed by sorting U.S. stocks by their pre-ranking, 60-month historical MDI betas; see Section 3.1.3) 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]), as well as their post-ranking, 5-factor MDI betas. t-statistics are in parentheses. A "*", "**", or "***" indicates significance at the 10%, 5%, or 1% level, respectively.

Pre-ranking	1	2	3	4	5	6	7	8	9	10	1-10
						1978-2009					
Post-ranking MDI beta	1.64***	1.22***	1.32***	0.92**	1.45***	1.15***	1.88***	2.10***	2.06***	0.91**	0.73
	(3.09)	(2.66)	(2.98)	(2.19)	(3.36)	(2.91)	(4.10)	(4.52)	(4.10)	(2.36)	(0.86)
CAPM alpha	4.35***	4.13***	4.50***	4.30***	3.46***	3.84***	3.55***	4.36***	2.34*	2.24	2.11
	(2.60)	(3.20)	(3.75)	(3.97)	(3.15)	(3.69)	(3.16)	(3.62)	(1.80)	(1.44)	(1.29)
3-factor alpha	1.84	1.89*	1.94**	2.00**	1.09	1.52*	1.26	1.99**	0.00	0.64	1.20
	(1.36)	(1.74)	(2.02)	(2.27)	(1.22)	(1.85)	(1.35)	(2.02)	(0.00)	(0.56)	(0.74)
4-factor alpha	4.24***	3.61***	3.14***	2.87***	2.01**	2.14***	1.68*	2.46**	0.38	1.69	2.55
	(3.44)	(3.56)	(3.36)	(3.29)	(2.28)	(2.60)	(1.78)	(2.47)	(0.36)	(1.49)	(1.57)
5-factor alpha	4.31***	3.44***	2.99***	2.69***	1.90**	2.11**	1.83*	2.82***	0.63	2.39**	1.92
	(3.45)	(3.34)	(3.16)	(3.04)	(2.12)	(2.52)	(1.90)	(2.81)	(0.59)	(2.11)	(1.18)
						1978-1993					
Post-ranking MDI beta	-1.25	-0.57	-0.14	0.20	-0.35	-0.56	-0.27	0.05	0.75	0.70	-1.95
	(-1.09)	(-0.76)	(-0.22)	(0.35)	(-0.54)	(-0.85)	(-0.37)	(0.06)	(0.94)	(0.77)	(-1.23)
CAPM alpha	1.80	1.45	3.74***	3.15***	2.11**	2.71**	1.79	3.32***	1.25	3.03	-1.23
	(0.87)	(1.09)	(3.41)	(3.24)	(2.06)	(2.34)	(1.48)	(2.64)	(0.89)	(1.64)	(-0.56)
3-factor alpha	0.18	0.35	2.46***	2.04**	0.65	1.09	0.29	1.81*	0.14	2.12	-1.94
	(0.10)	(0.29)	(2.66)	(2.37)	(0.71)	(1.06)	(0.27)	(1.66)	(0.12)	(1.63)	(-0.85)
4-factor alpha	2.51	2.29**	3.48***	3.10***	1.30	2.81***	1.85*	3.51***	1.13	2.71**	-0.19
	(1.48)	(2.06)	(3.78)	(3.65)	(1.39)	(2.89)	(1.75)	(3.37)	(0.97)	(2.00)	(-0.08)
5-factor alpha	3.01*	2.62**	3.63***	3.02***	1.26	2.68***	1.71	3.50***	0.98	3.02**	-0.01
	(1.79)	(2.37)	(3.92)	(3.53)	(1.34)	(2.74)	(1.60)	(3.33)	(0.84)	(2.24)	(-0.00)
						1994-2009					
Post-ranking MDI beta	2.76***	2.14***	2.01***	1.22**	1.97***	1.77***	2.49***	2.55***	2.37***	0.98	1.78*
	(3.83)	(3.18)	(3.22)	(2.05)	(3.45)	(3.48)	(4.39)	(4.13)	(3.57)	(1.18)	(1.75)
CAPM alpha	6.81***	6.71***	5.17**	5.32***	4.64**	4.80***	5.04***	5.10***	3.16	1.45	5.36**
	(2.60)	(3.06)	(2.43)	(2.78)	(2.42)	(2.83)	(2.79)	(2.61)	(1.49)	(0.57)	(2.25)
3-factor alpha	4.10**	4.16**	2.29	2.71*	2.08	2.34**	2.53**	2.46*	0.43	-0.31	4.41*
	(2.05)	(2.43)	(1.49)	(1.97)	(1.49)	(2.06)	(1.99)	(1.79)	(0.29)	(-0.17)	(1.90)
4-factor alpha	6.54***	5.82***	3.62**	3.65***	3.28**	2.83**	2.97**	2.99**	0.98	0.88	5.66**
	(4.00)	(3.80)	(2.56)	(2.77)	(2.56)	(2.51)	(2.34)	(2.18)	(0.67)	(0.49)	(2.49)
5-factor alpha	5.55***	4.66***	2.63*	2.85**	2.55**	2.41**	2.77**	3.02**	0.98	1.64	3.91*
	(3.41)	(3.11)	(1.89)	(2.18)	(1.99)	(2.12)	(2.14)	(2.16)	(0.65)	(0.91)	(1.76)

Table 9. MDI risk premiums: U.S. stocks

This table reports estimates of annualized percentage MDI risk premiums (λ_{MDI}, multiplied by 12) for multivariate MDI betas ($\beta_{i,MDI}$) of value-weighted (Panel A) and equal-weighted (Panel B) portfolios constructed by sorting U.S. stocks by their pre-ranking, 60-month historical MDI betas (from the lowest [decile 1] to the highest [decile 10], see Section 3.1.3). Specifically, the table reports GMM estimates of λ_{MDI} when accounting for the sensitivity of these portfolios' excess returns to the three traded Fama-French factors (U.S. market [MKT_m], size [SMB_m], and book-to-market [HML_m]), four traded factors (Fama-French factors plus momentum [MOM_m]), or five traded factors (Fama-French factors plus momentum and liquidity [PS_m]) in Eqs. (6) to (8) (in Section 3.1.2), over the full sample 1978-2009 and two sub-periods (1978-1993, 1994-2009). We also report estimates of risk premiums per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$) and for the 1-10 spread portfolio (going long decile 1 stocks and short decile 10 stocks, $\lambda_{MDI}\left(\beta_{1,MDI}-\beta_{10,MDI}\right)$), as well as the MDI beta for the latter ($\beta_{1,MDI}-\beta_{10,MDI}$). Asymptotic t-statistics are in parentheses. J-test is the asymptotic chi-square statistic for the over-identifying restriction in Eq. (8); the corresponding p-values are below. A "*", "**", or "***" indicates significance at the 10%, 5%, or 1% level, respectively.

	1978-2009			1978-1993			1994-2009		
	3-factor	4-factor	5-factor	3-factor	4-factor	5-factor	3-factor	4-factor	5-factor
Panel A: Value-weighted portfolios									
λ_{MDI}	1.27***	1.64***	1.85***	-1.50**	-1.30**	1.43	1.84***	2.62***	2.41***
	(2.72)	(2.71)	(2.77)	(-2.21)	(-1.98)	(1.40)	(3.23)	(3.08)	(2.95)
$\lambda_{MDI}\overline{\beta_{i,MDI}}$	0.48**	0.57**	0.60**	0.39*	0.38	0.21	0.81**	0.82**	0.80**
	(2.37)	(2.44)	(2.53)	(1.74)	(1.56)	(1.11)	(2.28)	(2.06)	(2.08)
$\beta_{1,MDI}-\beta_{10,MDI}$	2.09**	1.85**	1.87**	0.03	-1.12	1.53	4.23***	2.93***	2.84***
	(2.36)	(2.46)	(2.40)	(0.02)	(-0.67)	(1.14)	(3.72)	(3.74)	(3.31)
$\lambda_{MDI}\left(\beta_{1,MDI}-\beta_{10,MDI}\right)$	2.66*	3.04**	3.47**	-0.04	1.46	2.18	7.80***	7.69***	6.85***
	(1.93)	(2.11)	(2.25)	(-0.02)	(0.67)	(1.10)	(2.87)	(3.09)	(2.89)
J-test	5.47	7.27	7.13	3.02	2.54	14.50	5.69	6.07	5.28
	0.79	0.61	0.62	0.96	0.98	0.11	0.77	0.73	0.81
Panel B: Equal-weighted portfolios									
λ_{MDI}	1.17**	2.44***	2.95***	9.37	1.50	3.35**	0.81**	2.40***	1.60***
	(2.55)	(3.15)	(2.73)	(0.61)	(0.46)	(2.29)	(2.10)	(2.78)	(2.86)
$\lambda_{MDI}\overline{\beta_{i,MDI}}$	1.65**	2.40***	2.27***	1.30	-0.06	2.50***	1.92*	3.16***	2.79***
	(2.55)	(3.76)	(3.43)	(1.57)	(-0.14)	(4.26)	(1.87)	(3.24)	(2.83)
$\beta_{1,MDI}-\beta_{10,MDI}$	1.05	0.93	0.42	-0.18	-0.03	0.31	2.05	1.80**	1.62*
	(1.24)	(1.56)	(0.88)	(-0.50)	(-0.03)	(0.57)	(1.62)	(2.23)	(1.79)
$\lambda_{MDI}\left(\beta_{1,MDI}-\beta_{10,MDI}\right)$	1.23	2.26	1.24	-1.67	-0.05	1.02	1.65	4.33**	2.59*
	(1.15)	(1.56)	(0.89)	(-0.87)	(-0.03)	(0.59)	(1.25)	(2.09)	(1.70)
J-test	10.21	11.14	11.71	2.94	26.03***	14.42	11.67	12.24	9.93
	0.33	0.27	0.23	0.97	0.00	0.11	0.23	0.20	0.36

Table 10. MDI betas and risk premiums: Currency portfolios

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 8 currency portfolios i in Lustig et al. (2011) on MDI_m, the financial market dislocation index described in Section 2.2 (Eq. (4) in Section 3.1.1), over the full sample period November 1983-December 2009 (314 observations) and two sub-periods (1983-1993, 1994-2009). The sample includes six currency portfolios formed on interest rates, from low (1) to high (6), 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 website. 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 returns $\overline{R_{i,m}}$ on those previously estimated univariate MDI betas $\beta_{i,MDI}$ (Eq. (5), in Section 3.1.1), as well as the risk premium per average MDI beta ($\lambda_{MDI}\overline{\beta_{i,MDI}}$). t-statistics are in parentheses. A "*", "**", or "***" indicates significance at the 10%, 5%, or 1% level, respectively.

	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)	(-0.77)	(-4.49)	(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)	(2.99)	(-1.23)	(-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)	(-2.25)	(-4.88)	(4.34)	

Table 11. MDI and stock return predictability

This table reports summary statistics for the estimated coefficients of OLS regressions of one-month-ahead percentage excess returns ($R_{i,m,m+1}$, Panel A) or six-month-ahead cumulative percentage excess returns ($R_{i,m,m+6}$, Panel B) of each of 26 U.S. stock portfolios i formed on size and book-to-market (or each of 50 international stock portfolios i) on their previous month's excess returns ($R_{i,m,m}$) or their previous six-month cumulative excess returns ($R_{i,m-6,m}$), respectively, and previous month's realization of the financial market dislocation index described in Section 2.2 (MDI_m). Specifically, we compute and report summary statistics for the aforementioned regressions' coefficients for MDI_m ($\delta^{h=1}_{i,MDI}$ and $\delta^{h=6}_{i,MDI}$ of Eq. (10), estimated over the longest span of available data within the full sample 1973-2009 and two sub-periods [1973-1993, 1994-2009]), multiplied by the corresponding in-sample standard deviation of MDI_m (i.e., $\delta^{h}_{i,MDI}\sigma_{MDI}$), as well as for their Newey-West t-statistics (in square brackets). Because of data availability, $\delta^{h}_{i,MDI}$ cannot be estimated for Czech Republic, Egypt, Hungary, Morocco, and Russia over 1973-1993. N^* is the number of portfolios for which $\delta^{h}_{i,MDI}$ is significant at the 10% level or less; $\overline{\delta^*_i\sigma}$ is the corresponding average $\delta^{h}_{i,MDI}\sigma_{MDI}$ (with average t-statistics in square brackets); $\overline{R^{2*}_a}$ is the corresponding average adjusted R^2. For the minimum and maximum $\delta^{h}_{i,MDI}\sigma_{MDI}$, actual t-statistics are in parentheses.

	Panel A: One-month-ahead excess returns								Panel B: Six-month-ahead cumulative excess returns							
	Estimated $\delta^{h=1}_{i,MDI}$ times σ_{MDI}								Estimated $\delta^{h=6}_{i,MDI}$ times σ_{MDI}							
	Mean	Median	Stdev	Min	Max	N^*	$\overline{\delta^*_i\sigma}$	$\overline{R^{2*}_a}$	Mean	Median	Stdev	Min	Max	N^*	$\overline{\delta^*_i\sigma}$	$\overline{R^{2*}_a}$
	U.S. plus 25 U.S. portfolios								U.S. plus 25 U.S. portfolios							
1973-2009	-0.39	-0.37	0.15	-0.71	-0.11	3	-0.67	4.17%	1.25	1.18	0.54	0.33	2.55	2	2.36	1.57%
	[-1.15]	[-1.16]	[0.39]	(-1.74)	(-0.36)		[-1.81]		[1.08]	[1.08]	[0.42]	(0.30)	(1.80)		[1.77]	
1973-1993	-0.27	-0.25	0.23	-0.76	0.18	0	n.a.	n.a.	0.96	1.02	0.43	-0.28	1.57	0	n.a.	n.a.
	[-0.59]	[-0.65]	[0.48]	(-1.43)	(0.56)		[n.a.]		[0.60]	[0.63]	[0.28]	(-0.18)	(1.02)		[n.a.]	
1994-2009	-0.49	-0.47	0.22	-1.00	-0.13	1	-0.95	5.90%	1.78	1.67	1.06	0.26	4.30	5	3.19	2.69%
	[-0.96]	[-0.98]	[0.42]	(-1.41)	(-0.19)		[-2.07]		[1.06]	[1.08]	[0.60]	(0.11)	(1.88)		[1.91]	
	World plus 49 country portfolios								World plus 49 country portfolios							
1973-2009	-0.46	-0.44	0.57	-1.85	0.41	5	-1.10	4.09%	1.29	1.49	2.11	-3.59	6.85	9	3.60	2.74%
	[-0.80]	[-0.92]	[0.97]	(-1.94)	(0.56)		[-2.01]		[0.74]	[0.92]	[0.99]	(-1.12)	(2.33)		[2.00]	
1973-1993	-0.24	-0.41	2.30	-3.71	4.34	7	-0.25	8.84%	-1.64	-0.10	5.03	-18.23	9.87	8	-5.29	13.44%
	[-0.20]	[-0.59]	[1.48]	(-1.68)	(6.45)		[-0.05]		[-0.39]	[-0.09]	[1.52]	(-4.32)	(1.82)		[-1.87]	
1994-2009	-0.46	-0.57	0.60	-1.72	0.51	2	-0.85	6.14%	1.98	1.66	2.46	-3.59	8.69	11	5.10	3.38%
	[-0.70]	[-0.84]	[0.99]	(-1.65)	(1.00)		[-2.14]		[0.90]	[0.99]	[1.00]	(-1.12)	(2.58)		[2.22]	

Table 12. MDI and currency return predictability

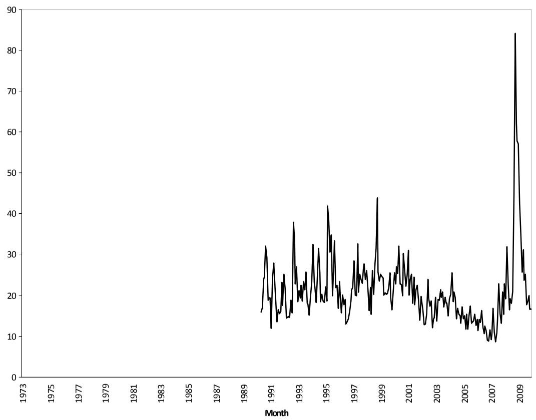
This table reports the estimated predictive coefficients of OLS regressions of one-month-ahead percentage excess returns ($R_{i,m,m+1}$, Panel A) or six-month-ahead cumulative percentage excess returns ($R_{i,m,m+6}$, Panel B) of each of the 8 currency portfolios i described in Section 3.2 (six currency portfolios formed on interest rates, from low [1] to high [6], 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) on their previous month's excess returns ($R_{i,m,m}$) or their previous six-month cumulative excess returns ($R_{i,m-6,m}$), respectively, and previous month's realization of the financial market dislocation index described in Section 2.2 (MDI_m). Specifically, we report the aforementioned regressions' coefficients for MDI_m ($\delta^{h=1}_{i,MDI}$ and $\delta^{h=6}_{i,MDI}$ of Eq. (10), estimated over the full sample 1983-2009 and two sub-periods [1983-1993, 1994-2009]), multiplied by the corresponding in-sample standard deviation of MDI_m (i.e., $\delta^{h}_{i,MDI}\sigma_{MDI}$), as well as their Newey-West t-statistics (in parentheses). R^2_a is the corresponding adjusted R^2. A "*", "**", or "***" indicates significance at the 10%, 5%, or 1% level, respectively.

	1	2	3	4	5	6	RX	HML_{FX}
	Panel A: One-month-ahead excess returns							
	Estimated $\delta^{h=1}_{i,MDI}$ times σ_{MDI}							
1983-2009	-0.05	-0.18*	-0.08	-0.09	-0.19	-0.02	-0.11	0.04
	(-0.29)	(-1.67)	(-0.60)	(-0.69)	(-1.41)	(-0.09)	(-0.84)	(0.25)
R^2_a	-0.59%	0.69%	-0.50%	1.36%	2.81%	1.85%	0.70%	1.63%
1983-1993	0.03	-0.002	0.26	0.18	0.16	0.39	0.17	0.38*
	(0.12)	(-0.01)	(1.25)	(0.78)	(0.66)	(1.48)	(0.83)	(1.74)
R^2_a	-1.22%	-1.68%	-0.66%	-0.66%	-0.61%	1.74%	-1.11%	1.28%
1994-2009	-0.10	-0.24*	-0.20	-0.17	-0.28*	-0.15	-0.19	-0.03
	(-0.39)	(-1.81)	(-1.14)	(-0.99)	(-1.75)	(-0.60)	(-1.10)	(-0.16)
R^2_a	-0.34%	3.09%	0.08%	4.54%	7.79%	2.43%	3.54%	2.30%
	Panel B: Six-month-ahead cumulative excess returns							
	Estimated $\delta^{h=6}_{i,MDI}$ times σ_{MDI}							
1983-2009	-0.002	0.05	0.49	0.10	0.54	0.80	0.44	2.69
	(-0.00)	(0.12)	(1.30)	(0.26)	(-1.04)	(1.54)	(0.97)	(0.90)
R^2_a	1.98%	-0.02%	1.00%	0.97%	-0.08%	1.01%	0.95%	0.07%
1983-1993	-0.83	0.18	1.38*	0.19	0.53	1.55*	0.44	2.69***
	(-1.07)	(0.25)	(1.77)	(0.25)	(0.78)	(1.91)	(0.67)	(3.94)
R^2_a	5.59%	-1.50%	2.30%	-1.79%	-1.33%	1.70%	-0.78%	11.23%
1994-2009	0.11	-0.15	0.36	0.26	0.32	0.78	0.35	-0.02
	(0.22)	(-0.33)	(0.76)	(0.54)	(0.56)	(1.24)	(0.76)	(-0.02)
R^2_a	-0.94%	-0.47%	1.38%	5.46%	-0.46%	1.00%	0.93%	-0.42%

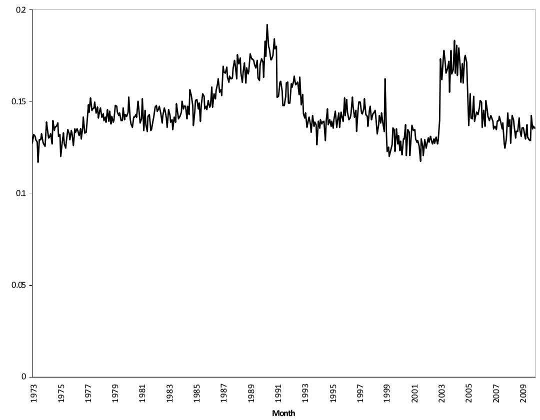
Figure 1. Arbitrage parity violations

This figure plots monthly averages of daily equal-weighted means of observed (in basis points, i.e., multiplied by 10,000) and standardized absolute log violations across 63 permutations of the Covered Interest Rate Parity described in Section 2.1.1 ($CIRP_m$, Figure 1a, 236 months m; $CIRP_m^z$, Figure 1d, 235 months), across 122 permutations of the Triangular Arbitrage Parity described in Section 2.1.2 (TAP_m, Figure 1b, 444 months; TAP_m^z, Figure 1e, 444 months), and across 410 permutations of the ADR Parity described in Section 2.1.3 ($ADRP_m$, Figure 1c, 441 months; $ADRP_m^z$, Figure 1f, 441 months), between January 1973 and December 2009.

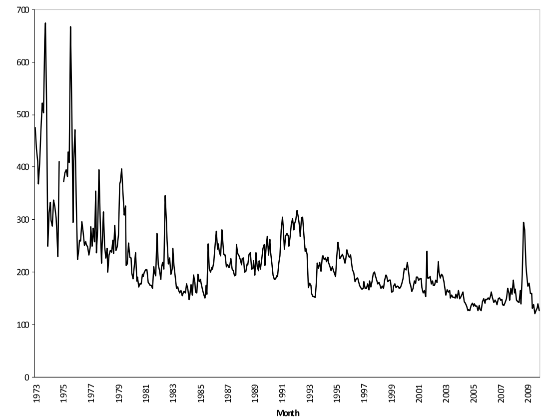
a) CIRP arbitrage ($CIRP_m$, in bps)



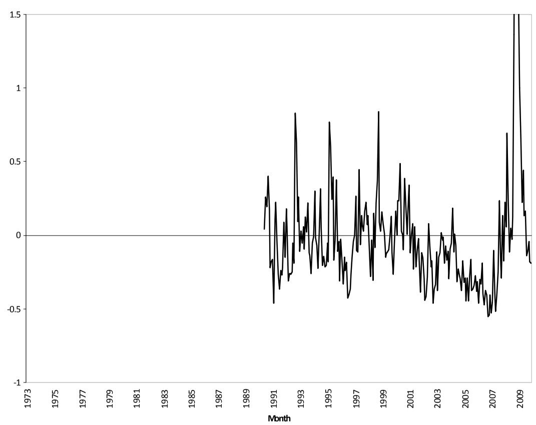
b) TAP arbitrage (TAP_m, in bps)



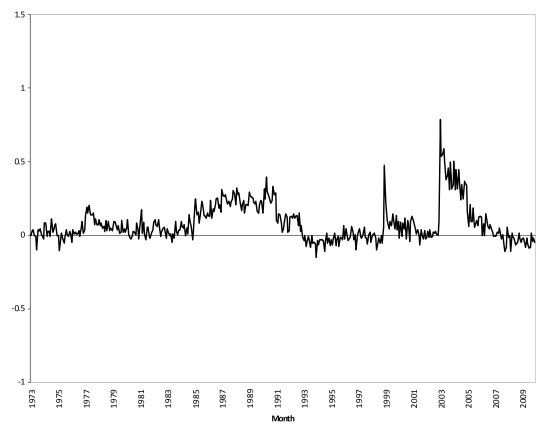
c) ADR arbitrage ($ADRP_m$, in bps)



d) Normalized CIRP arbitrage ($CIRP_m^z$)



e) Normalized TAP arbitrage (TAP_m^z)



f) Normalized ADR arbitrage ($ADRP_m^z$)

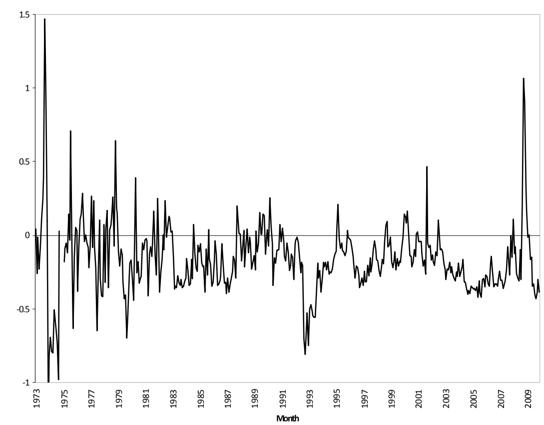


Figure 2. The market dislocation index

This figure plots the Market Dislocation Index described in Section 2.2 (MDI_m). 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 2.1.1 ($CIRP^z_{i,m}$), 122 permutations of the Triangular Arbitrage Parity described in Section 2.1.2 ($TAP^z_{i,m}$), and 410 permutations of the ADR Parity described in Section 2.1.3 ($ADRP^z_{i,m}$), 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.

Market dislocation index (MDI_m)

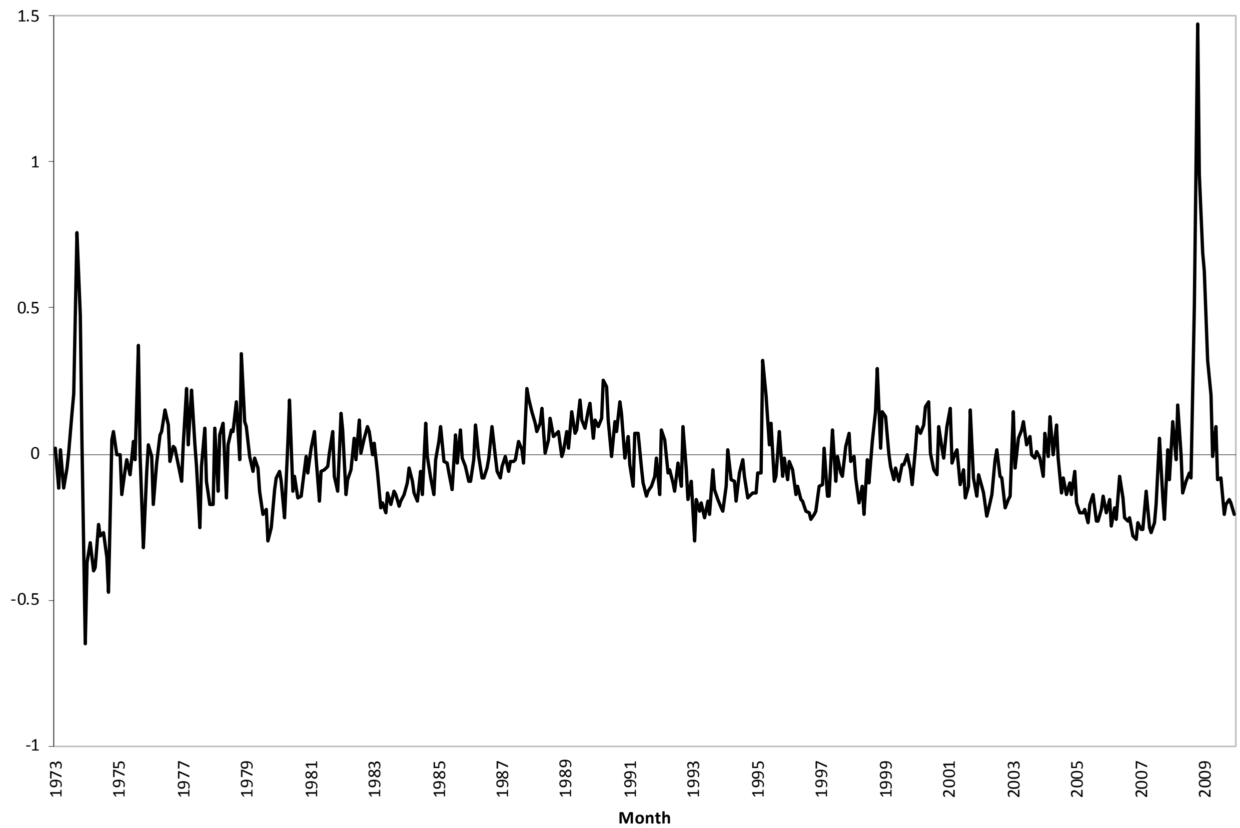
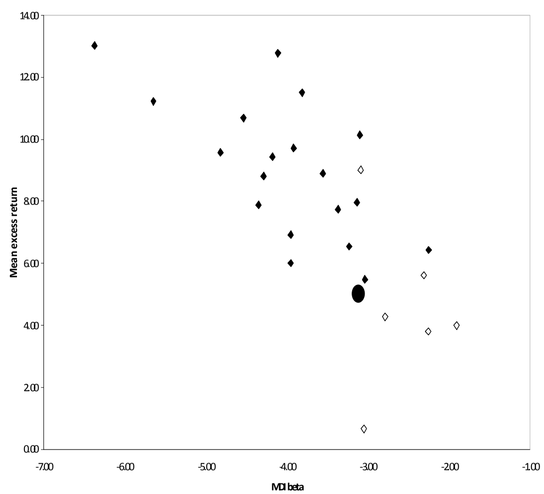


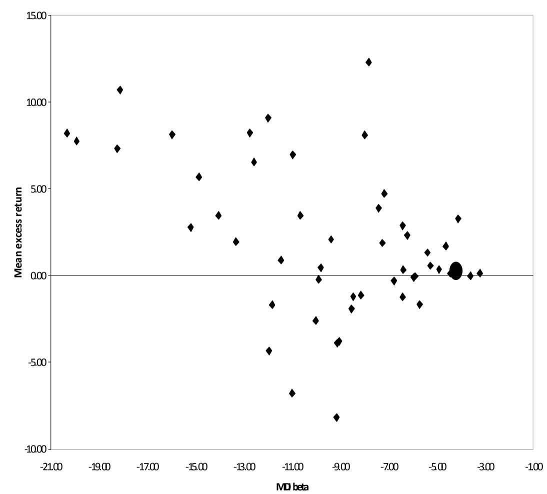
Figure 3. MDI betas and stock and currency portfolios' excess returns

This figure presents 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 Eq. (4). Figure 3a is based on 26 U.S. stock portfolios: The U.S. market (MKT, the largest, circular scatter) and 25 portfolios at the intersection of five portfolios formed on size (market equity) and five portfolios formed on book-to-market (book equity divided by market equity), from French's website. MDI betas and mean excess returns are estimated for each U.S. portfolio over the full sample 1973-2009. Figure 3b is based on 50 international stock portfolios: The world market ($WMKT$, the largest, circular scatter), 23 developed, and 26 emerging market portfolios, from MSCI. MDI betas and mean excess returns are estimated for each country over the longest span of available data within the full sample 1973-2009. Figure 3c is based on 8 currency portfolios: Six portfolios formed on interest rates, 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}, the largest, circular scatter). MDI betas and mean excess 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.

a) MDI betas and U.S. stock returns



b) MDI betas and country stock returns



c) MDI betas and currency returns