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Abstract: We extend the standard price discovery analysis to estimate the information share of dual-class shares across domestic and foreign markets. By examining both common and preferred shares, we aim to extract information not only about the fundamental value of the firm, but also about the dual-class premium. In particular, our interest lies on the price discovery mechanism regulating the prices of common and preferred shares in the BM&FBovespa as well as the prices of their ADR counterparts in the NYSE and in the Arca platform. However, in the presence of contemporaneous correlation between the innovations, the standard information share measure depends heavily on the ordering we attribute to prices in the system. To remain agnostic about which are the leading share class and market, one could for instance compute some weighted average information share across all possible orderings. This is extremely inconvenient given that we are dealing with 2 share prices in Brazil, 4 share prices in the US, plus the exchange rate (and hence over 5,000 permutations!). We thus develop a novel methodology to carry out price discovery analyses that does not impose any ex-ante assumption about which share class or trading platform conveys more information about shocks in the fundamental price. As such, our procedure yields a single measure of information share, which is invariant to the ordering of the variables in the system. Simulations of a simple market microstructure model show that our information share estimator works pretty well in practice. We then employ transactions data to study price discovery in two dual-class Brazilian stocks and their ADRs. We uncover two interesting findings. First, the foreign market is at least as informative as the home market. Second, shocks in the dual-class premium entail a permanent effect in normal times, but transitory in periods of financial distress. We argue that the latter is consistent with the expropriation of preferred shareholders as a class.

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1 Introduction

Price discovery has recently become a hot topic mainly for two reasons. First, the increasing availability of high-frequency data allows studying how efficiently and timely each market reacts to news in a much more precise manner. Second, quantitative trading strategies that rely on price discovery analyses (e.g., pair trading) are nowadays responsible for a substantial amount of assets under management. This paper extends the standard price discovery methodology to deal with dual-class assets traded on multiple markets. The idea is to exploit every piece of information we have about the fundamental value of a firm by looking at the prices of both common and preferred shares across different trading platforms. As a by-product, by looking at the difference between the prices of the common and preferred shares, we may also shed some light on the behavior of the dual-class premium.

The main technical difficulty is to contrive a unique price discovery measure that does not assume *a priori* which share class and/or market lead the impounding of new information. For the standard information share (IS) measure of price discovery (Hasbrouck, 1995), which gauges the fraction of the variance of the fundamental price innovation due to the the variance of a given asset/market price innovation, one normally imposes a triangular structure from the most informative to least informative market price in order to handle contemporaneous correlation. The information share of the price of a given share class at a given trading platform will thus depend on the specific ordering we employ. This is definitely a problem if one wishes to keep agnostic about lead-lag patterns.

There are two standard solutions for the nonuniqueness of the IS measure in the literature. The first is to increase the sampling frequency at which we record prices hoping for less contemporaneous correlation between the price innovations. The idea is that one-way causality at the high frequency could well dissolve into contemporaneous correlation at the low frequency. However, there is unfortunately no guarantee that this will work in practice, especially for dual-class shares. The second is to consider the average IS across different orderings of market prices. This is a simple and, most likely, effective solution if there are only a few market prices. However, as the number of assets/markets increase, one would have to average over thousands of information shares as there are a factorial number of possible orderings. For instance, a system consisting of 7 market prices as in Section 4 would lead to the unreasonable amount of $7! = 5,040$ distinct orderings. Additionally, the ordering becomes more crucial to determine importance as the number of markets/assets increase. In this situation, one could be taken averages of such different values that interpretation becomes unclear.

To avoid such problems, we derive a variant of the IS measure that rests on the spectral decomposition of the covariance matrix of the price innovations. The latter decomposition is unique and order invariant. As a result, our measure of information share is completely agnostic about which market price reacts first to new information. This is especially important for the case of dual-class shares because we have no reason to believe that one share class (or market) is relatively more informative than the others. In addition, Monte Carlo simulations show that the spectral-based IS measure works pretty well in finite samples as opposed to the standard measure in the presence of contemporaneous correlation.

(Lien and Shrestha, 2009) also propose an order-invariant IS measure. The idea of avoiding the above mentioned is somehow similar to ours, though much more complicated for it involves a decomposition of the correlation matrix rather than of the covariance matrix. It is not clear what is the economic intuition behind their more complicated method, moreover it does not yields better performance results. We perform a Monte Carlo exercise, where we show that our proposed measure outperforms theirs in every setting studied. (Grammig and Peter, 2012) achieve unique identification for the IS measure by imposing tail dependence restrictions. Their identification strategy is very ingenious, relying on the distinctive market microstructures of each trading platform. However, it requires the econometrician to take a stand on how the shocks disseminate across markets. In contrast, our spectral-based procedure is completely agnostic, keeping the reduced-form philosophy of the original IS measure. Hence, the first contribution of this paper is methodological.

Our contribution is not only methodological, though. We also empirically investigate price discovery in dual-class shares trading both at the Sao Paulo Stock Exchange (BM&FBovespa) and at the New York Stock Exchange (NYSE) through the American Depositary Receipt (ADR) program. This means investigating price discovery using a much richer data set than previous studies. It is richer because it takes advantage of the fact that, dual-class premium aside, both common and preferred stock prices depend on the latent efficient/fundamental stock price. The focus on Brazilian stocks and their ADRs is convenient for a number of reasons. First, the BM&FBovespa is the leading exchange in Latin America and among the 10 largest stock exchanges in the world. Second, the trading hours at the BM&FBovespa track to a large extent the trading hours at the NYSE, amounting to an overlapping of 6.5 hours from mid-February to mid-November and of 5.5 hours in the remaining 3 months of the year. This comes as a huge advantage relative to most studies in price discovery, which end up with only 2 to 3 hours of intersection for using European stocks and their ADR counterparts. Third, preferred shares are historically very liquid in the BM&FBovespa because Brazilian firms could issue two preferred shares for each common share before 2001 (now it is a one-to-one ratio). The number of common shares over the number of preferred shares is indeed about 0.75 for Petrobras and 0.65 for Vale. Fourth, quality transactions data from the BM&FBovespa are available from December 2007 to November 2009, allowing us to examine how price discovery works over different market cycles.

We restrict attention to the two most liquid stocks in Brazil, namely, Petrobras and Vale, whose common and preferred shares also trade as ADRs at the NYSE. Note that, for Petrobras, we also able to employ ADR trades and quotes from Arca (previously known as Archipelago Exchange or ArcaEx), NYSE's Chicago-based electronic platform. The latter is the second largest electronic communication network in the world, accounting for roughly 10% of NYSE-listed securities traded and 20% of Nasdaq-listed securities traded. This amounts to a system of 7 variables: common and preferred share prices in the BM&FBovespa, Arca and NYSE, plus the exchange rate. We include the latter so as to gauge how stock prices adjust to exchange-rate shocks. To validate our results we also implement the proposed methodology to other Brazilian stocks cross listed in the US.

Our price discovery analysis yields some interesting findings. First, the US market is at least as informative as the home market for both Petrobras and Vale. This is not so surprising given that these Brazilian behemoths are commodity exporters and hence more sensitive to international (rather than local) market conditions. Second, we evince that Petrobras' common shares are more informative than preferreds in the US and vice-versa in Brazil. This seems to derive from liquidity issues given that the trade intensity is higher exactly for these class-market combinations. In contrast, common and preferred shares have a similar role in Vale's price discovery process. This illustrates the fact that Vale's common shares may actually entail control power, as opposed to the case of the state-owned Petrobras. Third, we find that the exchange rate seems to react to changes in the efficient prices of Petrobras and Vale (possibly due to the omission of commodity indices in the analysis). Fourth, shocks in the dual-class premium entail a permanent impact in normal times, whereas their effects are transitory during the financial crisis. We argue that the latter is consistent with a dual-class premium as a function of private benefits that shareholders may obtain for holding voting rights (see (Zingales, 1994) 1994, (Zingales, 1995)). As there are fewer opportunities to extract private benefits, investors cease to price the dual-class premium as an asset in periods of financial distress. Up to our knowledge, this is the first paper to provide evidence that the price discovery mechanism may change across market cycles.

The remainder of this paper is as follows. Section 2 develops the spectral-based information share measure that is more suitable to study price discovery in large price systems. Section 3 first discusses the institutional background at the BM&FBovespa and then describes how we handle the high-frequency data. Section 4 documents the empirical price discovery analyses for Petrobras and Vale and some external validation tests using other dual-listed Brazilian stocks. Section 5 offers some concluding remarks. We relegate to the Appendix a Monte Carlo study of the performance of the spectral-based IS measure relative to the extant IS measures in the literature.

2 Information share in a large price system

To allow for common and preferred shares in both domestic and foreign markets, we first extend the three-variable model proposed by (Grammig, Melvin, and Schlag, 2005) and then modify (Hasbrouck, 1995) IS methodology so as to ensure uniqueness of the price discovery measure. The setup is such that every stock price in the system shares a common component given by the fundamental value of the firm (i.e., the present value of the firm's expected cash flow). This means that these prices cointegrate in that they should not diverge too much from each other because they must track somehow the implicit efficient price. However, the latter is not the only common factor driving the system dynamics. To make stock prices in the foreign market comparable to stock prices in the domestic market, one must include the exchange rate in the system as in (Grammig, Melvin, and Schlag, 2005). This results in another common factor, which relates to the efficient exchange rate. Note that the latter may differ from the observed exchange rate due to transitory market microstructure effects.

In our setup, the dual-class premium stands for another potential common factor. In that case, the gap between common and preferred share prices gauges the dual-class premium, up to transient effects (e.g., liquidity issues). In principle, the dual-class premium stands for the price of voting rights (see (Zingales, 1994) and (Zingales, 1995)). It thus relates to the fundamental value of the firm through at least three channels (Scherrer, 2014). First, it depends on whether the investor is able to extract private benefits from holding voting rights. Such opportunities are more likely in boom periods, when the value of the firm is higher. Second, it also reflects the expected takeover premium paid to shareholders outside the control block. This implies a premium that increases with voting power, but decreases with ownership, size and trading liquidity (Smith and Amoako-Adu, 1995). Finally, the third channel is through a principal-agent problem. Stronger voting rights induce better monitoring of the board of directors. As such, positive shocks to the dual-class premium may reduce principal-agent concerns, increasing the value of the firm.

Regardless of the number of common factors governing the price dynamics, it remains the fact that common and preferred share prices must not drift apart, otherwise arbitrage opportunities would persist. There are several ways to represent such a cointegrated system. For instance, the vector error correction model (VECM) posits that

$$\Delta y_t = \xi_0\, y_{t-1} + \xi_1\, \Delta y_{t-1} + \xi_2\, \Delta y_{t-2} + \ldots + \xi_p\, \Delta y_{t-p} + \zeta + \epsilon_t,$$

where $\xi_0 = \alpha\beta'$, α is the error correction term, β is the cointegrating vector, and y_t is a vector of prices for both share classes and markets (including the exchange rate). We further assume that ϵ_t is a zero-mean white noise with a covariance matrix given by Ω and that ζ is such that cumulative price changes feature no deterministic time trends.

Albeit the VECM representation is amenable to estimation as well as to economic interpretation, it is not unique. There are actually infinitely many error-correction representations, though they all lead to the same vector moving average (VMA) representation:

$$\Delta y_t = \epsilon_t + \psi_1\, \epsilon_{t-1} + \psi_2\, \epsilon_{t-2} + \ldots = \Psi(L)\, \epsilon_t.$$

(Hasbrouck, 1995) thus propose to recover the VMA coefficients from the VECM estimates and then apply a Beveridge-Nelson random-walk decomposition. This results in $\psi\, \epsilon_t$ as the vector of common factor innovations, with ψ denoting a nonsquare matrix that discards any repeated row of the moving-average impact matrix $\Psi(1)$. The covariance matrix of the innovation vector then is $\psi\Omega\psi'$. If the latter is diagonal, (Hasbrouck, 1995) defines the information shares as the relative contributions of each share class/market to the total variation of the innovation in the permanent common factor.

However, the covariance matrix Ω of the reduced-form errors is no longer diagonal in the presence of contemporaneous correlation between markets, invalidating the above procedure.

To circumvent this, (Hasbrouck, 1995) proposes the use of a Cholesky decomposition of Ω. This amounts to assuming a lower-triangular structure in the system, with market prices sorted from least to most endogenous. As a result, the IS measure is not unique, varying with the ordering of the prices. This is particularly inconvenient in the context of dual-class shares in multiple markets. The number of possible permutations increases at a factorial rate with the system dimension. A stock with both common and preferred shares trading at the domestic and foreign markets would compose a system with (at least) 5 price series, implying over 1,000 different orderings. This is likely to entail a large gap between the minimum and maximum information shares, impairing any sort of meaningful price discovery analysis. (Huang, 2002), (Hupperets and Menkveld, 2002), (Kim, 2010b) ((Kim, 2010a),b), and (Grammig and Peter, 2012) indeed report sizeable differences even for systems of only two/three market prices.

To derive an order-invariant IS measure, we employ a spectral decomposition of Ω. The resulting IS measure is the ratio of $[\psi\, S]_{ij}^2$ to $[\psi\Omega\psi']_{ii}$, where $S = \Omega^{1/2} = V\Lambda^{1/2}V'$, with Λ and V respectively denoting the diagonal matrix with the eigenvalues along the principal diagonal and the matrix with the corresponding eigenvalues in the columns. In stark contrast with the Cholesky factorization, the spectral decomposition is completely agnostic about lead-lag patterns, imposing no assumption about which share class or market is more informative. This makes our framework particularly suitable to identify which markets are dominant in setting the price (Garbade and Silber, 1983).

Our spectral-based IS measure of contribution to the price discovery is very similar in spirit to (Lien and Shrestha, 2009). In particular, they suggest an alternative IS measure that rests on the spectral decomposition of the correlation matrix (rather than of the covariance matrix). This brings about unnecessary complications because one must back out the implicit decomposition of the covariance matrix from the spectral factorization of the correlation matrix to compute the information share. Monte Carlo simulations in the Appendix indeed show that it pays off to take a more direct approach based on the eigendecomposition of the covariance matrix.

3 Data description

The BM&FBovespa is the only stock exchange in Brazil and the leading exchange in Latin America. It results from a merge between the Bolsa de Valores de São Paulo (Bovespa) and the Brazilian Mercantile & Futures Exchange (BM&F) in 2008. It is a fully electronic exchange since 2005, operating under supervision of the CVM (Brazilian Securities Exchange Commission). The BM&FBovespa proportionates a central clearing for equity, commodity, derivatives, and foreign exchange markets as well as a trading platform for exchange-traded funds. With a trade value of almost USD 1 trillion and a market capitalization of USD 1.3 trillion in 2011, the BM&FBovespa is among the 10 largest stock exchanges in the world.

We focus on the two most liquid stocks in the BM&FBovespa, namely, Petrobras and Vale. They are both constituents of the IBOVESPA, the main benchmark indicator of the Brazilian capital markets. Petrobras is a publicly-traded integrated oil and gas multinational, whose main stockholder is the Brazilian government with over 55% of the common shares. It is the fifth largest energy company in the world, with presence in 28 countries. It focuses on exploration and production of oil and gas in offshore fields, though it also operates in many other segments of the energy sector, e.g., include petrochemicals and biofuel. As for Vale, it is a former state mining giant, which has been private since 1997. It is currently the second biggest metals-and-mining company in the world, with the largest production of iron ore and pellets. As a result from Vale's recent diversification strategy, the participation of non-ferrous metals (notably, nickel, copper, and kaolin) on total revenues has recently increased in a substantial manner.

Petrobras and Vale issue both common and preferred shares at the BM&FBovespa. In addition, they are also present at the NYSE through the ADR program at the highest level a foreign company may sponsor (i.e., level 3, allowing for listing and public offering). Petrobras and Vale are the most active ADRs in the NYSE, both by trading value and volume. The ADRs respond for about 30% of the Petrobras outstanding shares (26% for commons and 34% for preferreds), whereas these figures for Vale are about 25% for common shares and 40% for preferred shares. Our data set includes the prices of both common and preferred shares of Petrobras and Vale in Brazil as well as their ADR prices in the US from January 2008 to November 2009. This gives way to a system of 5 market prices for Vale: exchange rate, common and preferred share prices in Brazil and in US. For Petrobras, we are also able to distinguish trades at the NYSE from transaction at the NYSE Arca,[2] leading to a system of 7 market prices.

The trading hours at the BM&FBovespa follow to a large extent the trading hours at the NYSE. This results in 6.5 hours of overlapping from mid-February to mid-November and in 5.5 hours of overlapping from mid-November to mid-February. This is in stark contrast with price discovery analyses that employ European stocks and their ADR counterparts: Due to time difference, the intersection is of only 2 to 3 trading hours. Figure 1 shows the time intersection between the Brazilian and US markets during the year in Brazilian time.

3.1 Data handling and aggregation

Given that the goal is to check how timely markets react to news incorporating them into prices, it is paramount to work with intraday data. Sampling data at a lower frequency could well blur all sorts of lead-lag patterns between different assets and/or trading platforms. Suppose for instance that we employ daily data and trading platform B is less liquid than trading platform A. In the presence of new information, prices in A would react on average more quickly than prices in B, but they would both converge to the same fundamental value in the long run (i.e., as soon as enough transactions hit both trading platforms). As a matter of fact, it is very likely that this convergence will take place before market close at least for

[2] The NYSE Arca exchange in Chicago is the second largest electronic communication network in terms of shares traded. It results from a reverse marge on February 27, 2006 between the NYSE Group and Archipelago Holdings.

actively traded assets. The use of daily data would completely miss price B lagging a few seconds or minutes behind price A due to the proximity of the closing prices.

On the other hand, employing tick data raises a number of data handling issues. To control for reporting errors and delays as well as, to some extent, for microstructure effects (e.g., bid-ask bounce), we first purge the data from observations that seem implausible not only given the usual market conditions, but also given the market activity at the time. In particular, as in (Brownlees and Gallo, 2006), we exclude any price that does not satisfy $|p_i - \bar{p}_i(k, \delta)| < 3s_i(k) + \gamma$, where $\bar{p}_i(k, \delta)$ and $s_i(k)$ are respectively the δ-trimmed sample mean and the sample standard deviation of a neighborhood of k observations around i, and γ is a granularity parameter to avoid zero variances from a sequence of k equal prices. We restrict attention to neighborhoods within the same trading day. For instance, the first k prices of the day compose the neighborhood of the first observation, whereas the last k prices of the day form the neighborhood of the last observation. However, in general, neighborhoods are given by the first preceding $k/2$ prices and the following $k/2$ prices.

The above discriminant aims to validate observations on the basis of how much they deviate from what we expect given a neighborhood of valid observations. This means one should chose the filter parameters very carefully. The trimming parameter δ should obviously increase with the frequency of outliers, whereas k should increase with trading intensity. It turns out that the filter is much more sensitive to changes in γ than in the other parameters and so we set the granularity to the minimum price variation of 0.01. We fix δ at 10% and specify k according to the number of trades, ranging from 20 to 60 observations. As a robustness check, we construct alternative data sets by varying the values of (k, γ, δ). Table 1 reports the initial number of observations and the number of outliers we discard for each price series as well as the resulting sample sizes after the filtering.

The next step is to deal with the nonsynchronicity of tick data. Table 1 documents that common shares have much more ticks, and so more liquidity, than preferred shares in the US, especially for the electronic Arca platform. In contrast, preferred shares are much more actively traded than common shares at the BM&FBovespa. The reason for this combination of common shares high concentration and preferred shares high circulation in Brazil is mainly historical. First, the Brazilian government revoked in 1997 the article of the Brazilian Corporate Act that granted tag-along rights to common shareholders in order to promote the privatization program. As a consequence, common shares became much less appealing, with liquidity further migrating towards preferred shares. Second, Brazilian firms could issue two preferred shares for each common share until 2001, enabling shareholders to increase their capital leverage without diluting power. Although the ratio is now one to one for new issues, the overall ratio still causes imbalances between political and economic power, increasing the possibility of wealth expropriation.

Although it is possible to examine price discovery in tick time (Frijns and Schotman, 2009), we take the traditional route by aggregating data into regular intervals of time (we use replaceall as in (Harris, McInish, and Wood, 2002)). This allows using the standard VECM/VMA machinery that permeates (Hasbrouck, 1995) information share framework. As for the sampling frequency, the literature documents a trade-off between market microstructure noise and contemporaneous correlation between markets. As the data frequency increases, microstructure effects become more apparent, whereas the contemporaneous correlation presumably declines. As the spectral-based IS measure is robust to contemporaneous correlation, we give more weight to alleviating market microstructure effects as what concerns the choice of the sampling frequency. In particular, we sample prices at intervals of 30 and 60 seconds by capturing the most recent trade on each market.

Table 2 shows the number of observations before and after the aggregation procedure. As expected, liquidity is a chief concern for common shares in Brazil (namely, Petr3 and Vale3) due to their low circulation. The low trade intensity leads to many missing observations due to the absence of trades even at the 30-second frequency. This could lead to spurious serial correlation and hence we employ the Newey-West covariance matrix estimator in the analysis. As a robustness check, we estimate the covariance matrix using different lag structures (including no lags) as well as consider 60-second intervals in order to reduce the fraction of zero returns. The results are qualitatively very similar and hence we omit them to conserve on space. Needless to say, they are available from the authors upon request.

It is interesting to notice that there are less intervals with zero returns in the US market than at the home market. The latter seems sufficiently liquid only for preferred shares, whereas the proportion of zero returns are much more reasonable for the NYSE. We show in the next section that these liquidity concerns indeed matter, playing a major role in the price discovery analysis.

4 Which share class leads, and in which market?

We expect the dynamics of share and ADR prices to feature no more than three common factors. The first corresponds to the efficient exchange rate in view that the system must include the BRL/USD exchange rate to make ADR prices in US dollars comparable to share prices at the BM&FBovespa. The second refers to the fundamental values of Petrobras and Vale given by the present value of their expected cash flow. Note that CVM normally requires preferred shares to pay 10% more of preferential dividends relative to common shares (as calculated from a *minimum* dividend payment of 25% of the adjusted net income). However, both Petrobras and Vale distribute systematically more dividends than the minimum payment that CVM requires. As such, their common and preferred shares end up receiving the same amount of dividends and hence the same present value of expected cash flow.

The dual-class premium may stand as a third stochastic trend in the system. Note that the Brazilian government detains the vast majority of Petrobras voting shares and hence it makes no sense to speak about takeover premium. As the private benefits story, it seems to fit the bill for both Petrobras and Vale. The Brazilian government has been imposing a gasoline price cap on Petrobras since 2006 to help control inflation (see, e.g., The Economist, "The perils of Petrobras: How Graça Foster plans to get Brazil's oil giant back on track", November 17, 2012). Surprisingly, the same arguments also apply to Vale. Although it has been privatized in 1997, the Brazilian government indirectly detains the majority of the voting rights through a consortium of state pension funds. This not only makes takeovers very unlikely, but also raises the issue that the government may exert sway on Vale against the interest of the minority shareholders. For instance, the former CEO of Vale, Roger Agnelli, was ousted in 2011 by the state pension funds because he did not invest enough at home, particularly in low-margin industries such as steel and shipbuilding (see, e.g., The Economist, "Vale dumps its boss: Roger and out", April 1st, 2011).

Given their generous dividend policy, one would expect preferred shares to be more appealing to investors than common shares, therefore commanding a premium, in the absence of takeover risk. That is not the case, though. Their common share prices are superior to their preferred prices in Brazil and in the US. Further, liquidity premium does not suffice to justify the dual-class premium, otherwise the sign of the latter in Brazil would differ from the sign in the US. Indeed, preferred shares are much more actively traded at the BM&FBovespa than common shares for both Petrobras and Vale, whereas the opposite is true for their ADR counterparts. The fact that the difference between the common and preferred share prices is positive regardless of the trading platform perhaps indicates that the foreign market leads the process of impounding information for Petrobras and Vale. We thus conjecture that their common ADRs should play a major role in the price discovery mechanism.

In what follows, we first describe the results for Petrobras and then discuss the findings for Vale. Note that the main difference between the two analyses is that we only observe prices at the NYSE Arca for Petrobras. The price system for Vale thus consists of the prices of common and preferred shares at the BM&FBovespa as well as their American Deposit shares at the NYSE (i.e., 5 variables, including the exchange rate), whereas the Petrobras system also includes the ADR counterparts at the Arca trading platform. Note that we actually expect Arca to impound information more timely for Petrobras than the NYSE. Arca's smart order router does not restrict attention exclusively to NYSE's quotes, executing orders at the trading venue with the best available quote across all stock exchanges in the US (including NASDAq). Finally, to better understand how the price discovery mechanism changes across different market cycles, we estimate IS measures for the periods ranging from January to June 2008, July to December 2008, January to June 2009, and July to November 2009. This is motivated by our prior believe that the share of information flows differently depending on the market cycle. (Blanchard, 1981) and (Veronesi, 1999) bring a theoretical analysis of asset value changes and states of the economy.

4.1 Petrobras

Figure 2 plots the prices of the Petrobras shares at the BM&FBovespa (in both BRL and USD terms) as well as their corresponding ADR prices in the US market. It is striking how the prices move in tandem, even if not surprising, given that they all relate to the same fundamental value. We separate the subperiods we consider by dashed lines so as to highlight how different they are. Petrobras share prices are clearly trending up in the first subsample running from January to June 2008, but then stock prices plummet in the second half of 2008 as a reaction to the steady decline in the price of oil. Petrobras share prices show some recovery in the last two subsamples, reflecting to some extent the steady rise in oil prices as from January 2009. Share prices do not recover fully probably because of investors' fears that Petrobras' primary raison d'etre is to serve the nation in whatever way the Brazilian government sees fit rather than to make a profit.

For each subperiod, we carry out a price discovery analysis relying on the spectral-based IS measure of Section 2. We bootstrap the VECM residuals as in (Li and Maddala, 1997) to compute the standard errors of the information shares. In particular, we consider 1,000 bootstrap samples. The top panel of Table 3 reports the results for the first half of 2008. There are 4 cointegrating vectors and hence 3 common factors. The first cointegrating vector takes the difference between NYSE and Arca prices of Petrobras common shares. As both these ADRs have voting rights and prices in US dollars, their price difference essentially eliminates the common factor given by the fundamental value of Petrobras. Voting rights aside, the same reasoning applies to the second cointegrating vector, which considers the difference between the prices of the preferred ADRs at the NYSE and Arca trading platforms.

The third cointegrating vector dictates that prices in Brazil and in the US must not drift apart once we consider them in the same currency. This indicates that the second common factor is attributable to the efficient exchange rate. Finally, the fourth cointegrating vector corresponds to the difference between the BM&FBovespa and NYSE *observed* dual-class premia.[3] This means that the dual-premium class indeed is a common factor driving the price dynamics, otherwise we would not have to take the difference between the observed dual-class premia in Brazil and in the US to get stationarity. This may come as a surprise, especially at such a high frequency. However, it is consistent with the Brazilian government expropriating preferred shareholders as a class during this period.

As for the IS estimates, the preferred share is much more informative than the common share in Brazil, whereas the opposite is true in the US. This may sound puzzling, but it actually reflects well the difference in their liquidity as seen in Section 3.1. The trading of common shares through the ADR program indeed responds for 20% of the total shares, which is extremely high in view that the Brazilian government detains about 55% of the common shares. Table 3 also confirms our prediction that Arca's smart order route contributes more to the impounding of information into security prices than the NYSE. Further, we also find that the exchange rate is not completely exogenous as one would normally expect (Grammig, Melvin, and Schlag, 2005). This is probably due to the fact that the system does not account for international oil prices, which affect both Petrobras share prices and the strength of the US dollar. In fact, the correlation between changes in the oil price and in the BRL/USD exchange rate is over 0.42 in the sample period. Finally, it is also interesting to observe that it is the US market that absorbs shocks in the efficient exchange rate.

The bottom panel of Table 3 reports the estimates of the spectral IS measures as well

[3] The price gap between common and preferred shares differs from the latent dual-class premium because of transient market microstructure effects.

as of the cointegrating vectors for the second half of 2008. This is when the financial crisis finally hits Brazil: The IBOVESPA drops about one third of its value and the Brazilian real devaluates over 50% against the US dollar in this period. The financial distress seems to strongly affect the price discovery process. To begin with, there are now 5 cointegrating vectors and hence only two common factors. In particular, the dual-class premium becomes stationary, characterizing the fifth cointegrating vector. The fact that investors do not price the voting premium anymore as an asset is still consistent with our private benefit story. It is much easier to expropriate the shareholders with no control power in periods of boom. As crises shut down most opportunities for extracting private benefits, the difference between common and preferred shares starts to reflect much more liquidity issues than anything else. Additionally, the contribution of Petrobras shares at the BM&FBovespa to the price discovery mechanism tanks in this period. This drop is particularly strong for the preferred shares. At the same time, the Arca platform gains in importance. As opposed to the first half of 2008, it is now the Brazilian market that incorporates shocks in the efficient exchange rate.

Table 4 documents a similar pattern for the first half of 2009 in that the dual-class premium remains stationary and the BM&FBovespa keeps losing importance in the price discovery process. In turn, the second half of 2009 resembles more the pre-crisis period, with the efficient exchange rate, the fundamental value of the company and the dual-class premium driving the stochastic trends in the system. The only difference is that the BM&FBovespa does not recover relative importance, whereas the NYSE starts playing a more significant role probably due to the increase in the frequency and value of block trades as from September 2009. This is when Brazil obtains the investment grade rating from Moody's, allowing foreign pension funds to invest in Brazilian ADRs.

As a robustness check, we estimate the IS measures using prices at the 60-second interval. The results are very similar and qualitatively exactly the same. We also carry out the price discovery analysis using the complete sample period (i.e., January 2008 to November 2009) as well as by years (i.e., January to December 2008 and January to November 2009). We find similar information shares, confirming that the foreign market contributes more to the price discovery mechanism than the home market. This is particularly true for the ADR prices of the common shares and for Arca, ratifying that liquidity matters.

4.2 Vale

In the absence of enough trades at the Arca platform, we focus on a system of 5 market prices: common and preferred shares at the BM&FBovespa (VALE3 and VALE5, respectively) and their corresponding ADRs at the NYSE (RIO.N and RIOp.N, respectively), plus the exchange rate. We expect Vale to feature a price discovery process similar to Petrobras. As before, the system does not include international metal prices and hence we do not expect the exchange rate to move in a completely exogenous manner relative to Vale's fundamental value. Note that the extension 5 in Vale's preferred shares defines them as 'class A', so that preferred shareholders have the right to vote in General Assembly deliberations, just as common shareholders. The only difference is that preferred shareholders do not have say in the composition of the Board of Directors. We thus expect Vale's preferred shares to contribute relatively more to the price discovery than Petrobras' preferreds.

Figure 3 displays the prices of Vale's common and preferred shares and of their ADRs. The pattern it depicts is very similar to that of Petrobras in that the second half of 2008 witnesses a huge drop in prices, with a slow recovery afterwards. Table 5 reveals the information shares we obtain for each half of 2008 and 2009, respectively. As in the case of Petrobras, the dual-class premium is a common factor in the first half of 2008, but then becomes stationary from July 2008 to June 2009. In this turbulent period, the preferred shares lose most of their importance (especially in the NYSE) and hence the price discovery takes place through the common shares. Shocks in the dual-premium class regain its permanent impact only as from July 2009. As before, the NYSE is more informative than the BM&FBovespa regardless of the share class. The contribution of the NYSE to the price discovery actually increases

Further, we also reject the exogeneity of the exchange rate. This is not surprising given that the sample correlation between the changes in the BRL/USD and in the S&P industrial metals spot index is pretty high at 0.53. We also find that it is the ADR prices that adjust for shocks in the efficient exchange rate.

The main difference relative to what we observe for Petrobras is that preferred shares play a much more significant part for Vale. The higher information shares we uncover for the preferred ADRs are likely due to the 'class A' nature of VALE5. In contrast, common and preferred shares at the B&FBovespa entail similar contributions to the price discovery (though weaker than their ADR counterparts). The financial crisis seems to have a significant impact in this pattern. The information shares of the preferred shares are indeed much lower from July to December 2008, though they start to recover in the first half of 2009, regaining their full importance in the price discovery mechanism only by the second half of 2009. Also, we observe that, similarly to what happens with Petrobras, the BM&FBovespa loses importance for the price discovery in Vale shares after the financial crisis. Finally, the second half of 2009 marks the return of the dual-class premium as a common factor driving the price dynamics.

Apart from sampling the prices at 60-second frequency, we also compute information shares for each year and for the overall sample. As before, we do not observe any qualitative change in the IS estimates. All in all, we conclude that (1) the foreign market impounds more information than the home market, (2) common and preferred shares have similar contributions to the impounding of information into securities prices, (3) the exchange rate is not entirely exogenous to the variations in Vale share prices, and (4) Vale's dual-class premium is a common factor only in normal times.

4.3 External validity

The main goal of this subsection is to check whether the information flow between markets also changes over time for other stocks. For external validation purposes, we perform the information share analysis for other dual-listed Brazilian stocks, namely, Bradesco (banking), Gerdau (steel), BrTelecom (telecommunication), and Ambev (beverage). These firms do not have both classes of shares being actively traded in the Brazilian market and/or in the US market and hence yield a price system with a lower dimension than in the case of Petrobras and Vale. Figure 4 displays the prices of their preferred shares both in Brazil and US.

Tables 6 to 9 report our findings. First, it is interesting to observe that the exchange rate is much more exogenous for Ambev and BrTelecom, exactly the firms that do not trade commodities. This is consistent with our conjecture that the lack of exogeneity of the exchange rate in Petrobras' and Vale's price systems relates to their involvement with commodity markets. Second, we find that Arca gains importance for all the stocks as from the financial crisis. The only exception is the information share of BrTelecom, which seems pretty stable over time, probably because of liquidity reasons. BrTelecom does not trade as often in Arca as it trades in other exchanges (see table 1 and 2). It is especially liquid at BM&FBovespa, which does not lose much importance for BrTelecom after the crisis as a result. All in all, the results corroborate the evidence for Petrobras and Vale that the price discovery role of NYSE increases in 2009.

5 Conclusion

We conduct a price discovery analysis for dual-class shares that trade at different markets. In particular, we focus on the common and preferred shares of Petrobras and Vale at the BM&FBovespa and their ADR counterparts at the NYSE. Once we account for the BRL/USD exchange rate, this leads to a system with 5 variables for Vale and 7 variables for Petrobras given that we also observe transactions at the NYSE Arca for the latter. We gauge the contribution of each share class and market by means of (Hasbrouck, 1995) information share measure. Unfortunately, the standard framework does not work well for large systems because the Cholesky decomposition it employs imposes *ex-ante* restrictions on which share class and market leads the price discovery process. To circumvent such a constraint, one would have to average the IS measures across all possible permutations of the variables that integrate the system. We thus develop an alternative IS measure that rests on the eigendecomposition of the covariance matrix of the reduced-form errors. In stark contrast to the Cholesky decomposition, the spectral-based approach is order invariant and hence corresponds to an agnostic price discovery analysis that imposes no *a priori* lead-lag pattern in the price dynamics.

Examining both common and preferred shares allows us not only to gather more information about the fundamental value of the company, but also say something about the dual-class premium. The evidence we uncover for Petrobras and Vale are compatible either with the expropriation of preferred shareholders as a class or with the majority shareholder extracting private benefits from their control rights. In both cases, we identify the Brazilian government as the main beneficiary of the dual-class premium. It detains not only Petrobras' control by holding over 55% of the voting shares, but also Vale's indirect control through a consortium of state pension funds. Note that the dual-class premium is a common factor governing the dynamics of the system only in normal times given that it becomes stationary in periods of financial distress. We also find that the foreign market is more important than the home market for the price discovery in both Petrobras and Vale. As a matter of fact, we notice that the IS estimates we obtain are by a long chalk increasing with the trade intensity of the corresponding price and hence the dominance of the NYSE. This pattern actually becomes more pronounced in the aftermath of the financial crisis, with the BM&FBovespa losing much of its importance for Petrobras and Vale in this period.

As for the exchange rate, we observe that it is the ADR prices that incorporate any shock in the efficient exchange rate. Our results also indicate that the efficient exchange rate is not exogenous to changes in the fundamental values of Petrobras and Vale. We conjecture that this is an artifact due to the omission of commodity indices in the analysis. The correlation between changes in commodity prices and the exchange rate variation is normally very high and hence we predict that augmenting the systems would probably recover the expected exogeneity of the exchange rate.

Appendix

.1 Cholesky versus spectral decomposition in price discovery

This section examines the implications of decomposing the covariance matrix by Cholesky and by the spectral approach as what concerns the estimation of information shares. We simulate three price discovery models. In the simplest setup M_1, the ADR price p_t^f follows the share price p_t^h at the home market and the exchange rate e_t is entirely exogenous, namely,

$$\begin{aligned} e_t &= e_{t-1} + u_t^e \\ p_t^h &= p_{t-1}^h + u_t^h \\ p_t^f &= p_{t-1}^h + e_{t-1} + u_t^f, \end{aligned}$$

where all prices are in logs and (u_t^e, u_t^h, u_t^f) is a vector of Gaussian white noises. In the other two settings, we also consider that there are both common and preferred shares (indexed by subscripts c and p, respectively) at the home and foreign markets.

The model M_2 assumes that the prices of the common and preferred shares are independent at the home market and that the ADR prices in the foreign market follow their counterparts in the home market:

$$\begin{aligned} e_t &= e_{t-1} + u_t^e \\ p_{p,t}^h &= p_{p,t-1}^h + u_{p,t}^h \\ p_{c,t}^h &= p_{c,t-1}^h + d + u_{c,t}^h \\ p_{p,t}^f &= p_{p,t-1}^h + e_{t-1} + u_{p,t}^f \\ p_{c,t}^f &= p_{c,t-1}^h + e_{t-1} + d + u_{c,t}^f, \end{aligned}$$

where $(u_t^e, u_{c,t}^h, u_{p,t}^h, u_{c,t}^f, u_{p,t}^f)$ is a vector of Gaussian white noises. Last but not least, M_3 posits that the prices of the common share at the home market and of both ADRs in the foreign market follow the price of the preferred share at home market, that is to say,

$$\begin{aligned} e_t &= e_{t-1} + u_t^e \\ p_{p,t}^h &= p_{p,t-1}^h + u_{p,t}^h \\ p_{c,t}^h &= p_{p,t-1}^h + d + u_{c,t}^h \\ p_{p,t}^f &= p_{p,t-1}^h + e_{t-1} + u_{p,t}^f \\ p_{c,t}^f &= p_{p,t-1}^h + d + e_{t-1} + u_{c,t}^f, \end{aligned}$$

Note that both M_2 and M_3 assume a constant dual-premium class of d for the sake of simplicity.

We simulate 1,000 replications of every model, each with a sample size of 10,000 observations. Note that we discard the first 500 observations in order to alleviate any dependence on the initial values. We consider two cases for the covariance matrix of the errors. The first imposes an identity covariance matrix, implying a unique Cholesky decomposition that does not vary with the ordering of the variables. The second case assumes the following nondiagonal covariance matrices:

$$\Omega_1 = \begin{pmatrix} 1 & 0.4 & 0.1 \\ 0.4 & 1 & 0.5 \\ 0.1 & 0.5 & 1 \end{pmatrix} \qquad \Omega_2 = \begin{pmatrix} 1 & 0.1 & 0.3 & 0.4 & 0.1 \\ 0.1 & 1 & 0.2 & 0.4 & 0.4 \\ 0.3 & 0.2 & 1 & 0.4 & 0.4 \\ 0.4 & 0.4 & 0.4 & 1 & 0.2 \\ 0.1 & 0.4 & 0.4 & 0.2 & 1 \end{pmatrix} \qquad \Omega_3 = \begin{pmatrix} 1 & 0.5 & 0.5 & 0.2 & 0.5 \\ 0.5 & 1 & 0.7 & 0.8 & 0.9 \\ 0.5 & 0.7 & 1 & 0.5 & 0.7 \\ 0.2 & 0.8 & 0.5 & 1 & 0.7 \\ 0.5 & 0.9 & 0.7 & 0.7 & 1 \end{pmatrix},$$

where Ω_j is the covariance matrix for the model M_j. The idea is to assess the behavior of the IS measures based on the Cholesky decomposition in view that the ordering of the variables now matters.

Table A1 documents the true information shares and their estimates based on the Cholesky and spectral decompositions for the case of diagonal covariance matrix. For the sake of brevity, we report the results only for M_1 because both estimators perform extremely well regardless of the setup we consider. In particular, they are both very accurate and precise, featuring no bias in the IS estimation. This means that the price we pay for the agnosticism of the eigendecomposition is negligible.

Tables A2 to A4 report the results for the nondiagonal covariance matrices. The Cholesky decomposition now depends on the ordering of the variables and hence we compute the IS measure for two system configurations. The first considers the exchange rate and the (preferred) share price at the home market as the first and last variables of the system, respectively. This entails a upper bound for the IS of the exchange rate and a lower bound for the IS of the (preferred) share price at the home market. The second configuration inverts the roles of these two variables and hence gives way to a lower bound for the IS of the exchange rate and a upper bound for the IS of the home price. We find a considerable gap between the lower and upper bounds of the Cholesky-based IS estimates. Averaging the bounds (or across all possible permutations) improves the performance, but not enough to get closer to the true IS values. As we increase the correlation between the markets (i.e., from Ω_2 to Ω_3), the problem becomes even more severe, with the Choleski decomposition rendering very dissimilar information shares according to the ordering of the variables. This confirms that incorrectly imposing a lower-triangular structure for the system is potentially very damaging for a price discovery analysis. In stark contrast, the eigendecomposition renders unique IS estimates that are pretty close to the corresponding theoretical values.

.2 Benefits of our methodology

This section examines the differences between our proposed methodology and the MIS introduced by (Lien and Shrestha, 2009). We perform a simple simulation exercise taking as main model M_3, presented in the previous section. We compute the information share measures with both methodologies for M_3. We present results for five scenarios. The first two have higher correlation among markets, whereas the second two present a lower correlation. We use a decomposed covariance matrix to generate the data. This matrix is not symmetric, which is the restriction that our methodology imposes. We chose a non symmetric matrix exactly to avoid advantages to our methodology. As we do not know what restrictions MIS methodology imposes, we do not try to avoid any shape specifically regarding MIS. The last scenario is computed with a decomposed matrix that mimics the estimated Ω. As we retrieve estimates of Ω, we need to decompose it in some way. We use our methodology then. This is the reason why we rename the true value as theoretical value in this scenario. We try to be as fair as possible.

As before, we perform 1,000 replications with a data size equal to 10,000 and discard the first 500 observations. We present the mean and standard deviations of the estimates. We then show relative measure on the mean squared errors (RMSE). We find clear evidence that our proposed way of computing price discovery measures outperforms the competitor for the majority of parameters of information share computed. There are some parameters (at most ten out of twenty five among all scenarios) where the competitor outperforms our methodology. However the differences are considerably smaller than the ones where our method outperforms. As we assume all parameters to have the same importance, we present an average of the RMSE showing that it is always lower than one, meaning our proposed methodology outperforms the competitor.

Another important point to raise is that the restrictions imposed by the competitor methodology are not clear. In this matter, Cholesky and our methodology are much more elucidative, given that the restrictions imposed are known and easy to interpret. Cholesky decomposition delivers the well known lower triangular matrix, leading to the problem of ordering of variables mattering, whereas our proposed methodology imposes a symmetric decomposed matrix delivering an order invariant measure of price discovery. Tables A5 to A8 have the results.

Table A1
Information shares for M_1 with a diagonal covariance matrix

We report the mean estimates of the information shares using the spectral and Cholesky decompositions as well as their standard errors within parentheses. All results rest on 1,000 samples of 10,0000 observations of model M_1, fixing the covariance matrix of the errors to identity.

	theoretical			spectral			Cholesky		
	e	p^f	p^h	e	p^f	p^h	e	p^f	p^h
e	1	0	0	1.00 (0.002)	0.00 (0.001)	0.00 (0.002)	1.00 (0.002)	0.00 (0.001)	0.00 (0.002)
p^f	0.5	0	0.5	0.50 (0.032)	0.00 (0.001)	0.50 (0.032)	0.50 (0.032)	0.00 (0.002)	0.50 (0.032)
p^h	0	0	1	0.00 (0.002)	0.00 (0.002)	1.00 (0.002)	0.00 (0.002)	0.00 (0.002)	1.00 (0.002)

Table A2
Information shares for M_1 with a nondiagonal covariance matrix

We report the mean estimates of the information shares using the spectral decomposition as well as the average lower and upper bounds of the Cholesky-based IS estimates relative to the exchange rate, with their standard errors within parentheses. We also inform the mean and standard error of the midpoint between the lower and upper bounds. All results rest on 1,000 samples of 10,0000 observations of model M_1, with the covariance matrix of the errors given by Ω_1.

	theoretical			spectral			Cholesky (midpoint)		
	e	p^f	p^h	e	p^f	p^h	e	p^f	p^h
e	0.96	0.04	0.00	0.96 (0.013)	0.04 (0.013)	0.00 (0.002)	0.91 (0.013)	0.08 (0.012)	0.01 (0.003)
p^f	0.46	0.10	0.45	0.46 (0.031)	0.10 (0.019)	0.45 (0.031)	0.46 (0.030)	0.10 (0.018)	0.44 (0.029)
p^h	0.00	0.07	0.93	0.00 (0.002)	0.07 (0.016)	0.93 (0.016)	0.01 (0.004)	0.13 (0.014)	0.87 (0.014)

	theoretical			Cholesky (upper)			Cholesky (lower)		
	e	p^f	p^h	e	p^f	p^h	e	p^f	p^h
e	0.96	0.04	0.00	1.00 (0.029)	0.00 (0.029)	0.00 (0.007)	0.82 (0.002)	0.16 (0.001)	0.01 (0.001)
p^f	0.46	0.10	0.45	0.55 (0.030)	0.12 (0.021)	0.34 (0.031)	0.37 (0.031)	0.08 (0.017)	0.55 (0.031)
p^h	0.00	0.07	0.93	0.01 (0.001)	0.25 (0.001)	0.74 (0.002)	0.00 (0.007)	0.00 (0.025)	1.00 (0.025)

Table A3

Information shares for M_2 with a nondiagonal covariance matrix

We report the mean estimates of the information shares using the spectral decomposition as well as the average lower and upper bounds of the Cholesky-based IS estimates relative to the exchange rate, with their standard errors within parentheses. We also inform the mean and standard error of the midpoint between the lower and upper bounds. All results rest on 1,000 samples of 10,0000 observations of model M_2, with the covariance matrix of the errors given by Ω_2.

	theoretical					spectral					Cholesky (midpoint)				
	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h
e	0.94	0.00	0.02	0.04	0.00	0.94	0.00	0.02	0.04	0.00	0.90	0.00	0.04	0.05	0.01
						(0.015)	(0.002)	(0.009)	(0.012)	(0.003)	(0.013)	(0.003)	(0.009)	(0.010)	(0.004)
p_c^h	0.00	0.92	0.00	0.04	0.04	0.00	0.92	0.00	0.04	0.04	0.01	0.91	0.00	0.00	0.08
						(0.002)	(0.018)	(0.004)	(0.013)	(0.012)	(0.004)	(0.013)	(0.001)	(0.001)	(0.013)
p_p^f	0.46	0.02	0.05	0.03	0.44	0.45	0.02	0.05	0.03	0.44	0.46	0.04	0.04	0.02	0.44
						(0.031)	(0.010)	(0.014)	(0.011)	(0.032)	(0.030)	(0.010)	(0.013)	(0.005)	(0.029)
p_c^f	0.45	0.44	0.02	0.07	0.02	0.45	0.44	0.02	0.07	0.02	0.46	0.44	0.02	0.02	0.06
						(0.032)	(0.032)	(0.008)	(0.017)	(0.010)	(0.030)	(0.031)	(0.006)	(0.007)	(0.011)
p_p^h	0.00	0.04	0.04	0.00	0.92	0.00	0.04	0.04	0.00	0.91	0.01	0.08	0.05	0.00	0.86
						(0.002)	(0.013)	(0.013)	(0.004)	(0.019)	(0.004)	(0.012)	(0.010)	(0.003)	(0.016)

	theoretical					Cholesky (upper)					Cholesky (lower)				
	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h
e	0.94	0.00	0.02	0.04	0.00	1.00	0.00	0.00	0.00	0.00	0.81	0.01	0.08	0.10	0.01
						(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.025)	(0.005)	(0.018)	(0.020)	(0.007)
p_c^h	0.00	0.92	0.00	0.04	0.04	0.01	0.99	0.00	0.00	0.00	0.00	0.84	0.00	0.00	0.16
						(0.007)	(0.007)	(0.001)	(0.002)	(0.001)	(0.002)	(0.025)	(0.001)	(0.002)	(0.025)
p_p^f	0.46	0.02	0.05	0.03	0.44	0.55	0.07	0.05	0.00	0.33	0.37	0.00	0.04	0.04	0.55
						(0.032)	(0.017)	(0.014)	(0.004)	(0.030)	(0.032)	(0.003)	(0.012)	(0.013)	(0.032)
p_c^f	0.45	0.44	0.02	0.07	0.02	0.55	0.45	0.00	0.00	0.00	0.37	0.44	0.04	0.04	0.11
						(0.032)	(0.032)	(0.001)	(0.002)	(0.002)	(0.031)	(0.033)	(0.012)	(0.014)	(0.022)
p_p^h	0.00	0.04	0.04	0.00	0.92	0.01	0.15	0.10	0.01	0.72	0.00	0.00	0.00	0.00	1.00
						(0.007)	(0.024)	(0.021)	(0.005)	(0.031)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)

Table A4

Information shares for M_3 with a nondiagonal covariance matrix

We report the mean estimates of the information shares using the spectral decomposition as well as the average lower and upper bounds of the Cholesky-based IS estimates relative to the exchange rate, with their standard errors within parentheses. We also inform the mean and standard error of the midpoint between the lower and upper bounds. All results rest on 1,000 samples of 10,0000 observations of model M_3, with the covariance matrix of the errors given by Ω_3.

	theoretical					spectral					Cholesky (midpoint)				
	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h
e	0.87	0.04	0.04	0.00	0.04	0.87	0.04	0.05	0.00	0.04	0.80	0.01	0.02	0.05	0.13
						(0.021)	(0.014)	(0.014)	(0.002)	(0.013)	(0.016)	(0.004)	(0.006)	(0.010)	(0.014)
p_c^h	0.04	0.19	0.09	0.08	0.59	0.04	0.19	0.09	0.09	0.59	0.13	0.28	0.00	0.00	0.59
						(0.013)	(0.026)	(0.018)	(0.018)	(0.033)	(0.015)	(0.017)	(0.003)	(0.001)	(0.014)
p_p^f	0.43	0.14	0.08	0.03	0.32	0.43	0.14	0.09	0.03	0.32	0.47	0.10	0.01	0.02	0.41
						(0.032)	(0.023)	(0.018)	(0.011)	(0.031)	(0.026)	(0.014)	(0.006)	(0.006)	(0.019)
p_c^f	0.43	0.14	0.08	0.03	0.32	0.43	0.14	0.09	0.03	0.32	0.47	0.10	0.01	0.02	0.41
						(0.032)	(0.023)	(0.018)	(0.011)	(0.031)	(0.026)	(0.014)	(0.006)	(0.006)	(0.019)
p_p^h	0.04	0.19	0.09	0.08	0.59	0.04	0.19	0.09	0.09	0.59	0.13	0.28	0.00	0.00	0.59
						(0.013)	(0.026)	(0.018)	(0.018)	(0.033)	(0.015)	(0.017)	(0.003)	(0.001)	(0.014)

	theoretical					Cholesky (upper)					Cholesky (lower)				
	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h
e	0.87	0.04	0.04	0.00	0.04	1.00	0.00	0.00	0.00	0.00	0.60	0.01	0.04	0.09	0.25
						(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.031)	(0.008)	(0.013)	(0.020)	(0.028)
p_c^h	0.04	0.19	0.09	0.08	0.59	0.25	0.56	0.01	0.00	0.18	0.00	0.00	0.00	0.00	1.00
						(0.030)	(0.033)	(0.006)	(0.002)	(0.027)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
p_p^f	0.43	0.14	0.08	0.03	0.32	0.74	0.19	0.00	0.00	0.06	0.20	0.01	0.01	0.03	0.75
						(0.029)	(0.026)	(0.004)	(0.002)	(0.016)	(0.025)	(0.005)	(0.008)	(0.012)	(0.028)
p_c^f	0.43	0.14	0.08	0.03	0.32	0.74	0.19	0.00	0.00	0.06	0.20	0.01	0.01	0.03	0.75
						(0.029)	(0.026)	(0.004)	(0.002)	(0.016)	(0.025)	(0.005)	(0.008)	(0.012)	(0.028)
p_p^h	0.04	0.19	0.09	0.08	0.59	0.25	0.56	0.01	0.00	0.18	0.00	0.00	0.00	0.00	1.00
						(0.030)	(0.033)	(0.006)	(0.002)	(0.027)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)

Table A5

Benefits of our methodology: high correlation

We report the mean estimates of the information shares using the spectral decomposition as well as using the MIS methodology proposed by (Lien and Shrestha, 2009), with their standard errors within parentheses. All results rest on 1,000 samples of 10,0000 observations of model M_3. The decomposed matrix used to generate the data is not symmetric, in order not to give advantage to our methodology. The first table has the results for scenario 1 where the decomposed matrix used is (1 0.8 0.9 0.8 0.7; 0.8 1 0.9 0.8 0.7; 0.9 0.7 1 0.8 0.7; 0.9 0.8 0.7 1 0.7; 0.9 0.8 0.7 0.8 1), followed by scenario 2 with (1 0.6 0.7 0.6 0.5; 0.6 1 0.7 0.6 0.5; 0.7 0.5 1 0.6 0.5; 0.7 0.6 0.5 1 0.5; 0.7 0.6 0.5 0.6 1)

	true					spectral					MIS				
	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h
e	0.28	0.18	0.23	0.18	0.14	0.29 (0.029)	0.16 (0.024)	0.20 (0.026)	0.20 (0.026)	0.16 (0.024)	0.25 (0.028)	0.17 (0.024)	0.19 (0.026)	0.20 (0.026)	0.19 (0.026)
p_c^h	0.23	0.18	0.14	0.18	0.28	0.22 (0.026)	0.17 (0.025)	0.15 (0.024)	0.17 (0.025)	0.29 (0.031)	0.19 (0.025)	0.18 (0.025)	0.15 (0.023)	0.17 (0.025)	0.32 (0.032)
p_p^f	0.25	0.18	0.18	0.18	0.20	0.26 (0.028)	0.17 (0.024)	0.17 (0.025)	0.19 (0.026)	0.21 (0.028)	0.22 (0.027)	0.17 (0.024)	0.17 (0.025)	0.19 (0.026)	0.25 (0.029)
p_c^f	0.25	0.18	0.18	0.18	0.20	0.26 (0.028)	0.17 (0.024)	0.17 (0.025)	0.19 (0.026)	0.21 (0.028)	0.22 (0.027)	0.17 (0.024)	0.17 (0.025)	0.19 (0.026)	0.25 (0.029)
p_p^h	0.23	0.18	0.14	0.18	0.28	0.22 (0.026)	0.17 (0.025)	0.15 (0.024)	0.17 (0.025)	0.29 (0.031)	0.19 (0.025)	0.18 (0.025)	0.15 (0.023)	0.17 (0.025)	0.32 (0.032)

	true					spectral					MIS				
	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h
e	0.41	0.15	0.20	0.15	0.10	0.40 (0.032)	0.13 (0.022)	0.18 (0.024)	0.17 (0.024)	0.13 (0.022)	0.36 (0.032)	0.14 (0.023)	0.18 (0.024)	0.17 (0.024)	0.15 (0.024)
p_c^h	0.20	0.15	0.10	0.15	0.41	0.18 (0.025)	0.13 (0.023)	0.11 (0.019)	0.14 (0.022)	0.44 (0.031)	0.15 (0.023)	0.14 (0.023)	0.11 (0.019)	0.13 (0.022)	0.48 (0.031)
p_p^f	0.31	0.15	0.15	0.15	0.24	0.30 (0.03)	0.14 (0.023)	0.15 (0.022)	0.16 (0.024)	0.26 (0.028)	0.26 (0.029)	0.14 (0.023)	0.15 (0.022)	0.16 (0.024)	0.29 (0.029)
p_c^f	0.31	0.15	0.15	0.15	0.24	0.30 (0.03)	0.14 (0.023)	0.15 (0.022)	0.16 (0.024)	0.26 (0.028)	0.26 (0.029)	0.14 (0.023)	0.15 (0.022)	0.16 (0.024)	0.29 (0.029)
p_p^h	0.20	0.15	0.10	0.15	0.41	0.18 (0.025)	0.13 (0.023)	0.11 (0.019)	0.14 (0.022)	0.44 (0.031)	0.15 (0.023)	0.14 (0.023)	0.11 (0.019)	0.13 (0.022)	0.48 (0.031)

Table A6
Benefits of our methodology: low correlation

We report the mean estimates of the information shares using the spectral decomposition as well as using the MIS methodology proposed by (Lien and Shrestha, 2009), with their standard errors within parentheses. All results rest on 1,000 samples of 10,0000 observations of model M_3. The decomposed matrix used to generate the data is not symmetric, in order not to give advantage to our methodology. The first table has the results for scenario 3 where the decomposed matrix used is (1 0.4 0.5 0.4 0.3; 0.4 1 0.5 0.4 0.3; 0.5 0.3 1 0.4 0.3; 0.5 0.4 0.3 1 0.3; 0.5 0.4 0.3 0.4 1), followed by scenario 4 with (1 0.2 0.3 0.2 0.1; 0.2 1 0.3 0.2 0.1; 0.3 0.1 1 0.2 0.1; 0.3 0.2 0.1 1 0.1; 0.3 0.2 0.1 0.2 1)

	true					spectral					MIS				
	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h
e	0.60	0.10	0.15	0.10	0.05	0.57 (0.031)	0.09 (0.018)	0.14 (0.023)	0.12 (0.021)	0.08 (0.017)	0.55 (0.031)	0.09 (0.019)	0.14 (0.023)	0.13 (0.021)	0.10 (0.019)
p_c^h	0.15	0.10	0.05	0.10	0.60	0.12 (0.021)	0.08 (0.018)	0.06 (0.015)	0.08 (0.018)	0.67 (0.031)	0.10 (0.019)	0.08 (0.018)	0.05 (0.015)	0.08 (0.018)	0.69 (0.031)
p_p^f	0.38	0.11	0.11	0.11	0.29	0.36 (0.03)	0.09 (0.019)	0.11 (0.02)	0.11 (0.021)	0.32 (0.03)	0.34 (0.03)	0.10 (0.02)	0.11 (0.02)	0.12 (0.021)	0.34 (0.031)
p_c^f	0.38	0.11	0.11	0.11	0.29	0.36 (0.03)	0.09 (0.019)	0.11 (0.02)	0.11 (0.021)	0.32 (0.03)	0.34 (0.03)	0.10 (0.02)	0.11 (0.02)	0.12 (0.021)	0.34 (0.031)
p_p^h	0.15	0.10	0.05	0.10	0.60	0.12 (0.021)	0.08 (0.018)	0.06 (0.015)	0.08 (0.018)	0.67 (0.031)	0.10 (0.019)	0.08 (0.018)	0.05 (0.015)	0.08 (0.018)	0.69 (0.031)

	true					spectral					MIS				
	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h
e	0.85	0.03	0.08	0.03	0.01	0.81 (0.025)	0.03 (0.011)	0.07 (0.017)	0.06 (0.015)	0.03 (0.011)	0.80 (0.025)	0.03 (0.011)	0.07 (0.017)	0.06 (0.016)	0.03 (0.011)
p_c^h	0.08	0.03	0.01	0.03	0.85	0.04 (0.012)	0.02 (0.009)	0.01 (0.005)	0.02 (0.009)	0.92 (0.019)	0.03 (0.012)	0.02 (0.009)	0.01 (0.005)	0.02 (0.009)	0.92 (0.018)
p_p^f	0.50	0.05	0.05	0.05	0.36	0.46 (0.031)	0.03 (0.012)	0.04 (0.013)	0.05 (0.014)	0.41 (0.032)	0.44 (0.031)	0.04 (0.012)	0.05 (0.014)	0.05 (0.014)	0.42 (0.032)
p_c^f	0.50	0.05	0.05	0.05	0.36	0.46 (0.031)	0.03 (0.012)	0.04 (0.013)	0.05 (0.014)	0.41 (0.032)	0.44 (0.031)	0.04 (0.012)	0.05 (0.014)	0.05 (0.014)	0.42 (0.032)
p_p^h	0.08	0.03	0.01	0.03	0.85	0.04 (0.012)	0.02 (0.009)	0.01 (0.005)	0.02 (0.009)	0.92 (0.019)	0.03 (0.012)	0.02 (0.009)	0.01 (0.005)	0.02 (0.009)	0.92 (0.018)

Table A7
Benefits of our methodology: empirical correlation

We report the mean estimates of the information shares using the spectral decomposition as well as using the MIS methodology proposed by (Lien and Shrestha, 2009), with their standard errors within parentheses. All results rest on 1,000 samples of 10,0000 observations of model M_3. In scenario 5, the empirical covariance matrix is retrieved, and decomposed using the spectral methodology. The small differences between the theoretical value and the spectral estimates come from rounding effects (for instance 0.19 on position 24 of the theoretical value is actually 0.1852, whereas on the spectral estimate is 0.1849).

	theoretical					spectral					MIS				
	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h	e	p_c^h	p_p^f	p_c^f	p_p^h
e	0.90	0.01	0.00	0.06	0.03	0.90 (0.019)	0.01 (0.006)	0.00 (0.003)	0.06 (0.015)	0.03 (0.012)	0.94 (0.015)	0.01 (0.006)	0.00 (0.003)	0.03 (0.01)	0.02 (0.009)
p_c^h	0.01	0.10	0.08	0.19	0.63	0.01 (0.005)	0.10 (0.019)	0.08 (0.018)	0.18 (0.025)	0.63 (0.031)	0.02 (0.009)	0.12 (0.021)	0.08 (0.018)	0.15 (0.023)	0.64 (0.031)
p_p^f	0.12	0.08	0.08	0.12	0.59	0.12 (0.022)	0.08 (0.018)	0.08 (0.018)	0.12 (0.021)	0.59 (0.034)	0.08 (0.018)	0.11 (0.02)	0.08 (0.018)	0.11 (0.02)	0.62 (0.033)
p_c^f	0.12	0.08	0.08	0.12	0.59	0.12 (0.021)	0.08 (0.018)	0.08 (0.018)	0.12 (0.021)	0.59 (0.034)	0.08 (0.018)	0.11 (0.02)	0.08 (0.018)	0.11 (0.02)	0.62 (0.033)
p_p^h	0.01	0.10	0.08	0.19	0.63	0.01 (0.005)	0.10 (0.019)	0.08 (0.018)	0.18 (0.025)	0.63 (0.031)	0.02 (0.009)	0.12 (0.021)	0.08 (0.018)	0.15 (0.023)	0.64 (0.031)

Table A8
Relative Mean Squared Error

We report the relative mean squared error (RMSE) computed with our methodology as numerator and MIS as denominator. Hence, RMSE lower than 1 shows our estimator outperforming MIS. Scenarios 1 to 5 have 25 parameters each and their position on the IS matrix is specified in the first column. We also show the mean among all parameters, where we find that our estimator on average outperforms the competitor in all five scenarios.

parameters	1	2	3	4	5
IS_{11}	0.65	0.39	0.44	0.69	0.23
IS_{21}	0.35	0.36	0.53	0.84	0.09
IS_{31}	0.46	0.38	0.41	0.69	0.24
IS_{41}	0.46	0.38	0.41	0.69	0.24
IS_{51}	0.35	0.36	0.53	0.84	0.09
IS_{12}	1.19	1.19	1.11	0.99	1.06
IS_{22}	1.02	1.03	0.98	0.98	0.44
IS_{32}	1.11	1.13	1.12	1.08	0.40
IS_{42}	1.11	1.13	1.12	1.08	0.40
IS_{52}	1.02	1.03	0.98	0.98	0.44
IS_{13}	0.95	1.04	1.11	1.05	0.58
IS_{23}	1.11	1.12	1.04	1.01	0.99
IS_{33}	0.97	0.99	1.00	1.00	1.03
IS_{43}	0.97	0.99	1.00	1.00	1.03
IS_{53}	1.11	1.12	1.04	1.01	0.99
IS_{14}	1.00	0.92	0.82	0.85	0.24
IS_{24}	0.95	0.89	0.88	0.97	0.30
IS_{34}	1.03	1.02	0.98	0.95	0.82
IS_{44}	1.03	1.02	0.98	0.95	0.82
IS_{54}	0.95	0.89	0.88	0.97	0.30
IS_{15}	0.33	0.37	0.49	0.77	0.61
IS_{25}	0.36	0.39	0.61	0.88	1.02
IS_{35}	0.34	0.35	0.47	0.78	0.54
IS_{45}	0.34	0.35	0.47	0.78	0.54
IS_{55}	0.36	0.39	0.61	0.88	1.02
mean	0.78	0.77	0.80	0.91	0.58

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Figure 1
Intersection in trading hours (São Paulo time, UTC −3 hours)

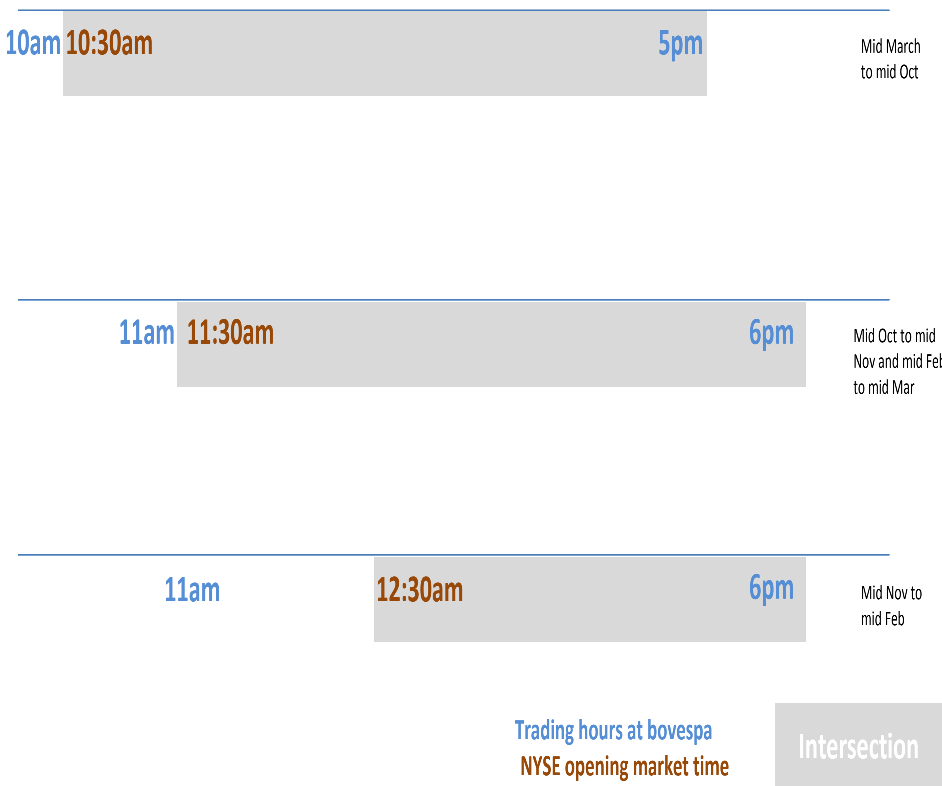
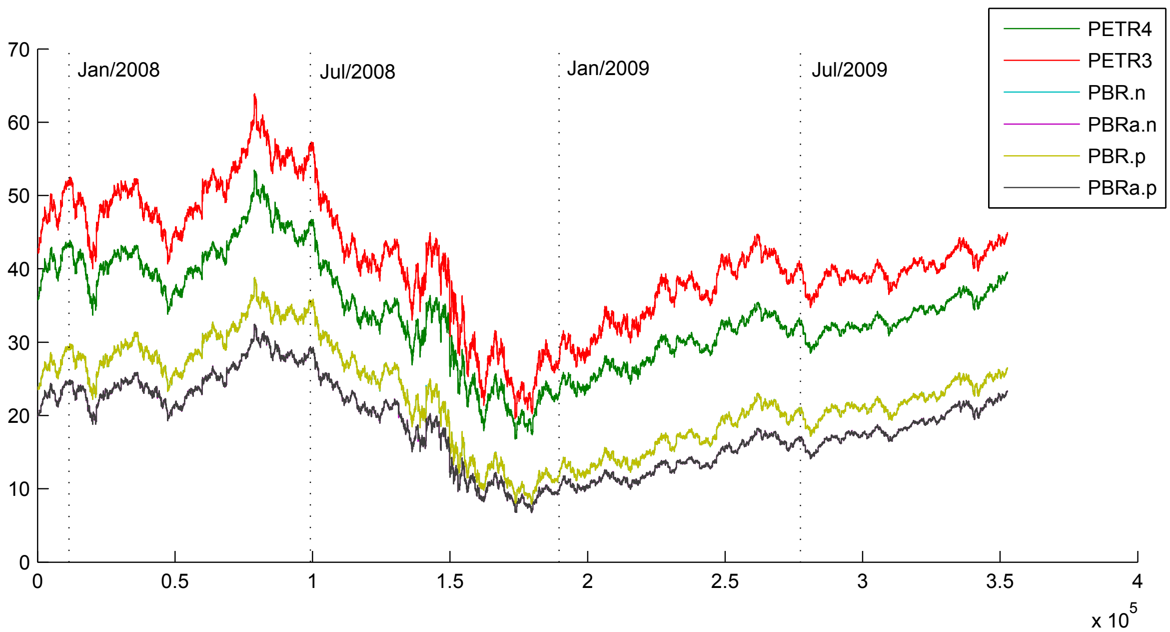


Figure 2
The prices of Petrobras' shares and their ADR counterparts

The first plot depicts share prices in Brazilian reais and ADR prices in US dollars, whereas the second chart displays all prices in US dollars. PETR3 and PETR4 correspond to common and preferred shares at the BM&FBovespa, respectively. Similarly, PBR and PBRa are the symbols for Petrobras' common and preferred ADRs, with extensions indicating the trading platform: N for NYSE and P for Arca.



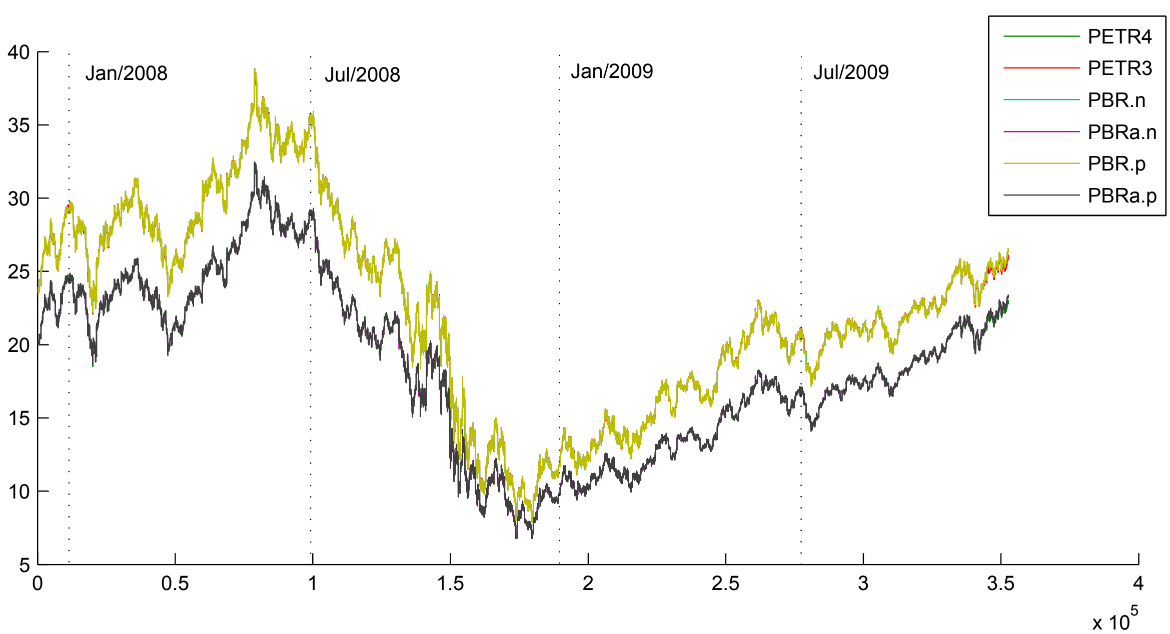


Figure 3
The prices of Vale's shares and their ADR counterparts

The first plot depicts share prices in Brazilian reais and ADR prices in US dollars, whereas the second chart displays all prices in US dollars. VALE3 and VALE5 correspond to common and preferred shares at the BM&FBovespa, respectively. Similarly, RIO and RIOp are the symbols for Vale's common and preferred ADRs at the NYSE.

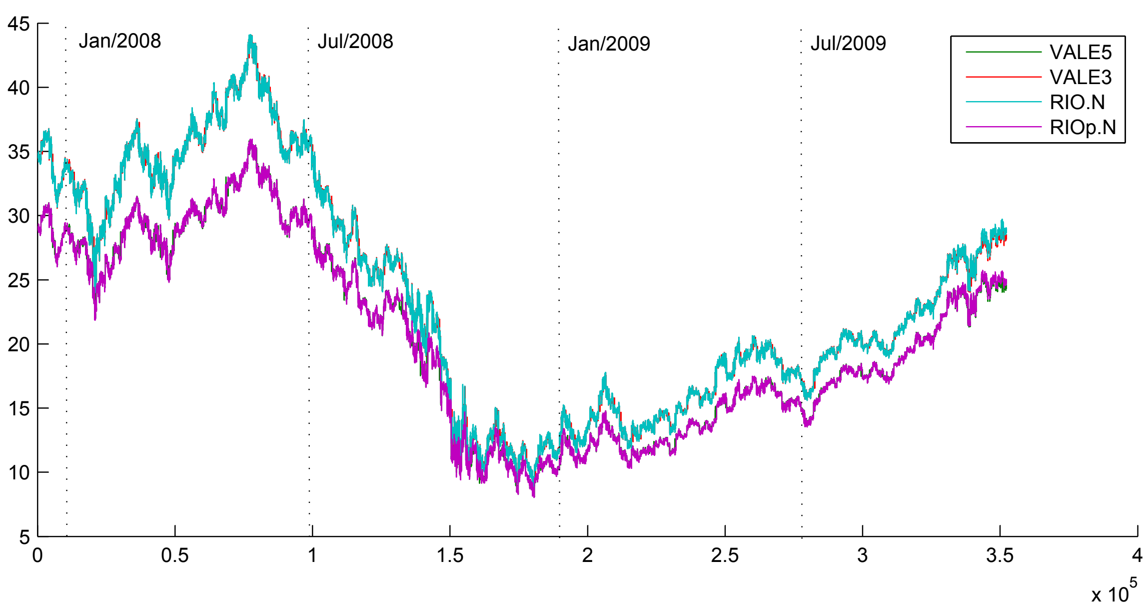


Figure 4
The prices of Bradesco's, Gerdau's, Ambev's and BrTelecom's shares and their ADR counterparts

The plots on the upper panel depict the share and ADR prices for Bradesco (left) and Gerdau (right). The lower panel displays the share and ADR prices for BrTelecom (left) and Ambev (right). Tick names ending with 4 correspond to preferred shares at the BM&FBovespa, whereas those with N and P correspond to preferred shares at NYSE and ARCA, respectively. All share prices at the BM&FBovespa are in Brazilian reais, whereas all ADR prices are in US dollars.

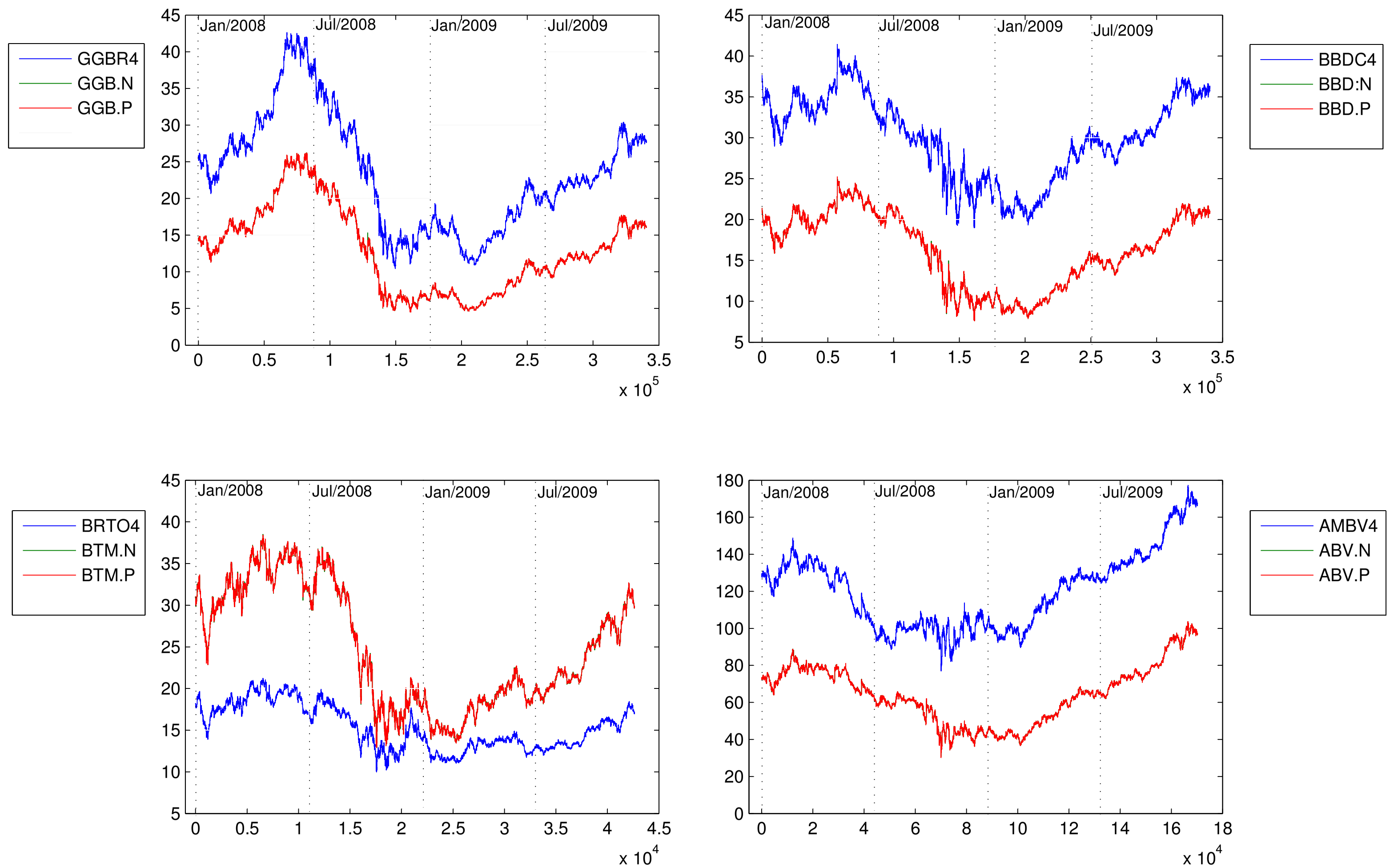


Table 1
Sample sizes before and after discarding outlier

We filter out any price entry p_i that does not conform to $|p_i - \bar{p}_i(k, 0.10)| < 3s_i(k) + 0.01$, where $\bar{p}_i(k, 0.10)$ and $s_i(k)$ are respectively the 10%-trimmed sample mean and the sample standard deviation of a neighborhood of k observations around i. We fix k according to the trade intensity, ranging from 20 to 60 observations. The column 'trading platform' informs the market at which the asset trades, 'company' reports which firm the asset is, 'class' reveals whether the share class is common (ON) or preferred (PN), and 'symbol' documents the asset symbol in the trading platform. We report the sample sizes (in millions) for both raw and clean data, i.e., respectively before and after excluding outliers (in thousands).

trading platform	company	class	symbol	raw data	outliers	clean data
BM&Bovespa	Petrobras	ON	PETR3	2.11	4,812	2.10
		PN	PETR4	9.07	7,353	9.06
	Vale	ON	VALE3	2.07	8,139	2.06
		PN	VALE5	6.39	5,236	6.38
	Ambev	PN	AMBV4	0.72	4,109	0.72
	BR Telecom	PN	BRTO4	0.56	1,564	0.55
	Gerdau	PN	GGBR4	3.24	3,000	3.23
	Bradesco	PN	BBDC4	2.96	3,909	2.95
Nyse	Petrobras	ON	PBR.N	7.91	3,318	7.91
		PN	PBRa.N	5.02	4,485	5.02
	Vale	ON	Rio.N	6.93	1,159	6.93
		PN	Riop.N	3.58	1,823	3.58
	Ambev	PN	ABV.N	1.12	1,645	1.12
	BR Telecom	PN	BTM.N	0.20	521	0.20
	Gerdau	PN	GGB.N	2.83	723	2.83
	Bradesco	PN	BBD.N	3.60	959	3.60
Arca	Petrobras	ON	PBR.P	11.82	3,460	11.82
		PN	PBRa.P	4.87	2,501	4.87
	Ambev	PN	ABV.P	0.51	1,190	0.50
	BR Telecom	PN	BTM.P	0.11	391	0.11
	Gerdau	PN	GGB.P	4.16	871	4.16
	Bradesco	PN	BBD.P	6.09	1,038	6.09
exchange rate			BRLUSD	4.09	600	4.09

Table 2
Aggregating tick data into fixed time intervals

We aggregate tick data into regular intervals of 30 seconds, giving way to a sample size of over 350,000 observations for each market price from January 2008 to November 2009 for Petrobras and Vale. For the firms on the validation test we use other sampling frequencies due to liquidity issues. To aggregate the data we use the methodology proposed by (Harris, McInish, Shoesmith, and Wood, 1995). The first 4 columns are as in Table 1. The column 'tick data' reports the initial sample size of irregularly-spaced-in-time data (in millions). It differs from the sample size of the clean data in Table 1 mainly because of holidays in Brazil and in the US. Finally, 'missing' informs how many 30-second intervals feature at least one missing observation across the different markets and share classes (also in millions), whereas 'zero returns' documents the proportion of zero returns due to missing observations.

frequency	trading platform	company	class	symbol	tick data	missing	% Missing
30"	BM&Bovespa	Petrobras	ON	Petr3	1.94	0.10	28%
			PN	Petr4	7.79	0.00	1%
		Vale	ON	Vale3	2.06	0.09	25%
			PN	Vale5	6.38	0.01	2%
		Gerdau	PN	GGBR4	2.78	0.12	35%
		Bradesco	PN	BBDC4	2.60	0.12	35%
60"		Ambev	PN	AMBV4	0.65	0.04	25%
240"		BR Telecom	PN	BRTO4	0.49	0.00	6%
30"	Nyse	Petrobras	ON	PBR.N	7.42	0.00	1%
			PN	PBRa.N	4.80	0.02	5%
		Vale	ON	Rio.N	6.92	0.01	2%
			PN	Riop.N	3.57	0.04	10%
		Gerdau	PN	GGB.N	2.55	0.04	11%
		Bradesco	PN	BBD.N	3.21	0.03	8%
60"		Ambev	PN	ABV.N	1.01	0.03	16%
240"		BR Telecom	PN	BTM.N	0.18	0.01	22%
30"	Arca	Petrobras	ON	PBR.P	11.19	0.01	3%
			PN	PBRa.P	4.63	0.04	13%
		Gerdau	PN	GGB.P	3.78	0.10	27%
		Bradesco	PN	BBD.P	5.53	0.07	20%
60"		Ambev	PN	ABV.P	0.46	0.07	38%
240"		BR Telecom	PN	BTM.P	0.10	0.02	42%
30"				BRLUSD	2.84	0.03	10%
60"				BRLUSD	2.84	0.01	6%
240"				BRLUSD	2.84	0.00	3%

Table 3
Information shares for Petrobras in 2008

We report the IS estimates based on the eigendecomposition of the covariance matrix of the reduced-form errors, and their bootstrap-based standard errors. The first subsample covers 87,781 observations from the first half of 2008, whereas the second subsample has 90,431 observations from the second half of 2008. BRLUSD refers to the exchange rate, PETR3 and PETR4 are the common and preferred shares of Petrobras at the BM&FBovespa, PBR and PBRa are the common and preferred ADRs of Petrobras. The extensions N and P are for NYSE and Arca, respectively.

January to June	information shares							cointegrating vector			
	BRLUSD	PETR4	PETR3	PBR.N	PBRa.N	PBR.P	PBRa.P				
BRLUSD	0.53 (0.027)	0.00 (0.002)	0.04 (0.007)	0.05 (0.008)	0.07 (0.009)	0.16 (0.017)	0.15 (0.014)	-0.02	0.00	0.01	1.00
PETR4	0.00 (0.001)	0.38 (0.025)	0.03 (0.007)	0.12 (0.015)	0.10 (0.012)	0.25 (0.023)	0.11 (0.015)	0.02	0.00	1.00	-0.01
PETR3	0.00 (0.002)	0.23 (0.019)	0.06 (0.010)	0.20 (0.023)	0.06 (0.008)	0.39 (0.026)	0.06 (0.010)	0.00	0.00	-1.00	-1.00
PBR.N	0.02 (0.004)	0.16 (0.017)	0.03 (0.006)	0.20 (0.023)	0.07 (0.010)	0.42 (0.027)	0.09 (0.014)	1.00	0.00	1.01	1.00
PBRa.N	0.04 (0.006)	0.26 (0.021)	0.01 (0.004)	0.13 (0.016)	0.12 (0.014)	0.29 (0.024)	0.15 (0.017)	0.00	1.00	-1.00	0.00
PBR.P	0.02 (0.004)	0.16 (0.017)	0.03 (0.006)	0.20 (0.023)	0.07 (0.010)	0.42 (0.027)	0.09 (0.014)	-1.00	0.00	0.00	-0.04
PBRa.P	0.04 (0.006)	0.26 (0.021)	0.01 (0.004)	0.13 (0.016)	0.12 (0.014)	0.29 (0.024)	0.15 (0.017)	-0.02	-1.00	0.00	0.04

July to December	information shares							cointegrating vector				
	BRLUSD	PETR4	PETR3	PBR.N	PBRa.N	PBR.P	PBRa.P					
BRLUSD	0.38 (0.071)	0.04 (0.027)	0.00 (0.006)	0.09 (0.045)	0.04 (0.029)	0.29 (0.105)	0.14 (0.082)	0.00	0.00	1.00	1.00	-0.04
PETR4	0.04 (0.016)	0.14 (0.056)	0.05 (0.017)	0.17 (0.053)	0.07 (0.037)	0.36 (0.105)	0.17 (0.094)	0.00	0.00	-0.01	-1.00	0.00
PETR3	0.04 (0.015)	0.14 (0.057)	0.05 (0.017)	0.17 (0.053)	0.07 (0.037)	0.36 (0.105)	0.17 (0.093)	0.00	0.00	-1.00	-0.01	0.00
PBR.N	0.00 (0.007)	0.05 (0.032)	0.02 (0.013)	0.19 (0.057)	0.08 (0.041)	0.45 (0.114)	0.21 (0.107)	1.00	0.00	0.00	0.00	1.00
PBRa.N	0.01 (0.007)	0.05 (0.031)	0.02 (0.013)	0.19 (0.057)	0.08 (0.041)	0.45 (0.114)	0.21 (0.108)	0.00	1.00	0.00	0.00	-1.00
PBR.P	0.00 (0.007)	0.05 (0.032)	0.02 (0.013)	0.19 (0.057)	0.08 (0.041)	0.45 (0.114)	0.21 (0.107)	-1.00	0.00	1.00	0.00	0.00
PBRa.P	0.01 (0.007)	0.05 (0.031)	0.02 (0.013)	0.19 (0.057)	0.08 (0.041)	0.45 (0.114)	0.21 (0.108)	0.00	-1.00	0.00	1.00	-0.04

Table 4
Information shares for Petrobras in 2009

We report the IS estimates based on the spectral decomposition of the covariance matrix of the reduced-form errors, and their bootstrap-based standard errors. The first subsample covers 87,797 observations from the first half of 2009, whereas the second subsample has 75,010 observations from July to November 2009. BRLUSD refers to the exchange rate, PETR3 and PETR4 are the common and preferred shares of Petrobras at the BM&FBovespa, PBR and PBRa are the common and preferred ADRs of Petrobras. The extensions N and P are for NYSE and Arca, respectively.

January to June	information shares							cointegrating vector				
	BRLUSD	PETR4	PETR3	PBR.N	PBRa.N	PBR.P	PBRa.P					
BRLUSD	0.39 (0.042)	0.00 (0.017)	0.02 (0.004)	0.10 (0.022)	0.10 (0.031)	0.14 (0.044)	0.25 (0.056)	0.00	0.00	1.00	1.00	0.00
PETR4	0.00 (0.002)	0.08 (0.053)	0.05 (0.008)	0.26 (0.037)	0.06 (0.024)	0.41 (0.078)	0.14 (0.042)	0.00	0.00	-0.03	-1.00	1.00
PETR3	0.00 (0.004)	0.09 (0.056)	0.06 (0.010)	0.26 (0.037)	0.06 (0.022)	0.41 (0.078)	0.12 (0.038)	0.00	0.00	-1.00	-0.01	-1.00
PBR.N	0.03 (0.010)	0.06 (0.048)	0.02 (0.005)	0.24 (0.037)	0.08 (0.027)	0.38 (0.075)	0.18 (0.047)	1.00	0.00	0.00	0.00	0.00
PBRa.N	0.06 (0.016)	0.05 (0.044)	0.01 (0.004)	0.23 (0.035)	0.09 (0.029)	0.35 (0.072)	0.21 (0.050)	0.00	1.00	0.00	0.00	0.00
PBR.P	0.03 (0.010)	0.06 (0.048)	0.02 (0.005)	0.24 (0.037)	0.08 (0.027)	0.38 (0.075)	0.18 (0.047)	-1.00	0.00	1.00	0.00	0.97
PBRa.P	0.06 (0.016)	0.05 (0.044)	0.01 (0.004)	0.23 (0.035)	0.09 (0.029)	0.35 (0.072)	0.21 (0.050)	0.00	-1.00	0.02	1.00	-0.97

July to November	information shares							cointegrating vector			
	BRLUSD	PETR4	PETR3	PBR.N	PBRa.N	PBR.P	PBRa.P				
BRLUSD	0.47 (0.072)	0.00 (0.010)	0.01 (0.011)	0.13 (0.015)	0.09 (0.017)	0.15 (0.019)	0.15 (0.021)	0.01	0.00	0.00	1.00
PETR4	0.02 (0.014)	0.09 (0.046)	0.01 (0.005)	0.21 (0.014)	0.18 (0.017)	0.24 (0.017)	0.25 (0.018)	-0.01	0.00	1.00	-0.17
PETR3	0.03 (0.016)	0.03 (0.025)	0.02 (0.013)	0.33 (0.017)	0.09 (0.014)	0.37 (0.018)	0.13 (0.015)	0.00	0.00	-1.00	-1.00
PBR.N	0.01 (0.008)	0.02 (0.019)	0.01 (0.007)	0.32 (0.017)	0.12 (0.015)	0.36 (0.018)	0.18 (0.016)	1.00	0.00	1.01	1.00
PBRa.N	0.02 (0.012)	0.05 (0.033)	0.00 (0.005)	0.22 (0.015)	0.19 (0.018)	0.25 (0.017)	0.27 (0.019)	0.00	1.00	-1.00	0.00
PBR.P	0.01 (0.008)	0.02 (0.019)	0.01 (0.007)	0.32 (0.017)	0.12 (0.015)	0.36 (0.018)	0.18 (0.016)	-1.00	0.00	0.00	0.03
PBRa.P	0.02 (0.012)	0.05 (0.033)	0.00 (0.005)	0.22 (0.015)	0.19 (0.018)	0.25 (0.017)	0.27 (0.019)	0.01	-1.00	0.00	0.06

Table 5
Information shares for Vale

We report the IS estimates based on the spectral decomposition of the covariance matrix of the reduced-form errors, and their bootstrap-based standard errors. There are 87,966 observations in the first half of 2008, 90,143 in the second half of 2008, 86,256 in the first half of 2009, and 76,311 observations from July to November 2009. BRLUSD refers to the exchange rate, VALE3 and VALE5 are the common and preferred shares of Vale at the BM&FBovespa, RIO.N and RIOp.N are the common and preferred ADRs of Vale at the NYSE.

January to June 2008	information shares					cointegrating vector		
	BRLUSD	VALE5	VALE3	RIO.N	RIOp.N			
BRLUSD	0.42	0.01	0.00	0.21	0.36		1.00	0.00
	(0.039)	(0.006)	(0.002)	(0.021)	(0.029)			
VALE5	0.00	0.24	0.14	0.22	0.41		0.04	1.00
	(0.003)	(0.028)	(0.019)	(0.020)	(0.029)			
VALE3	0.00	0.10	0.25	0.42	0.23		-1.05	-0.99
	(0.003)	(0.018)	(0.026)	(0.026)	(0.023)			
RIO.N	0.02	0.06	0.18	0.45	0.30		1.02	0.99
	(0.007)	(0.014)	(0.022)	(0.026)	(0.026)			
RIOp.N	0.02	0.14	0.09	0.27	0.48		0.00	-0.99
	(0.008)	(0.022)	(0.017)	(0.021)	(0.031)			

July to December 2008	information shares					cointegrating vector		
	BRLUSD	VALE5	VALE3	RIO.N	RIOp.N			
BRLUSD	0.54	0.04	0.01	0.32	0.10	1.00	-1.02	0.14
	(0.050)	(0.032)	(0.006)	(0.053)	(0.070)			
VALE5	0.00	0.03	0.23	0.71	0.03	0.00	1.00	1.00
	(0.002)	(0.032)	(0.026)	(0.064)	(0.034)			
VALE3	0.00	0.04	0.24	0.69	0.02	-0.99	0.00	-0.84
	(0.005)	(0.036)	(0.027)	(0.065)	(0.030)			
RIO.N	0.05	0.01	0.17	0.72	0.05	0.99	0.00	0.00
	(0.016)	(0.018)	(0.022)	(0.059)	(0.047)			
RIOp.N	0.09	0.00	0.14	0.71	0.06	0.00	-1.01	0.00
	(0.022)	(0.014)	(0.021)	(0.058)	(0.051)			

January to June 2009	information shares					cointegrating vector		
	BRLUSD	VALE5	VALE3	RIO.N	RIOp.N			
BRLUSD	0.40	0.04	0.01	0.26	0.29	1.00	-1.00	0.16
	(0.043)	(0.044)	(0.012)	(0.051)	(0.083)			
VALE5	0.01	0.00	0.27	0.48	0.23	0.00	1.00	1.00
	(0.006)	(0.020)	(0.035)	(0.064)	(0.076)			
VALE3	0.02	0.01	0.29	0.47	0.22	-1.02	0.00	-0.78
	(0.009)	(0.022)	(0.036)	(0.064)	(0.072)			
RIO.N	0.01	0.00	0.22	0.49	0.28	1.01	0.00	0.00
	(0.004)	(0.016)	(0.032)	(0.063)	(0.085)			
RIOp.N	0.02	0.00	0.19	0.49	0.30	0.00	-1.00	0.00
	(0.009)	(0.017)	(0.031)	(0.062)	(0.089)			

July to November 2009	information shares					cointegrating vector		
	BRLUSD	VALE5	VALE3	RIO.N	RIOp.N			
BRLUSD	0.49	0.00	0.01	0.19	0.31		1.00	0.00
	(0.046)	(0.006)	(0.012)	(0.020)	(0.045)			
VALE5	0.00	0.19	0.08	0.28	0.44		0.15	1.00
	(0.003)	(0.041)	(0.029)	(0.022)	(0.052)			
VALE3	0.00	0.08	0.11	0.49	0.31		-1.36	-1.02
	(0.005)	(0.026)	(0.035)	(0.027)	(0.042)			
RIO.N	0.02	0.05	0.09	0.48	0.36		1.13	0.99
	(0.009)	(0.021)	(0.032)	(0.026)	(0.045)			
RIOp.N	0.04	0.11	0.07	0.33	0.46		0.00	-0.97
	(0.011)	(0.031)	(0.027)	(0.022)	(0.052)			

Table 6
Information shares for Gerdau

We report the IS estimates based on the spectral decomposition of the covariance matrix of the reduced-form errors, and their bootstrap-based standard errors. There are 87,928 observations in the first half of 2008, 88,555 in the second half of 2008, 87,734 in the first half of 2009, and 76,265 observations from July to November 2009. BRLUSD refers to the exchange rate, GGBR4 is the preferred share of Gerdau at the BM&FBovespa, GGB.N is the preferred ADR of Gerdau at the NYSE and GGB.P is the preferred ADR of Gerdau at the Arca.

January to June 2008	information shares				cointegrating vector	
	BRLUSD	BBDC4	BBD.N	BBD.P		
BRLUSD	0.78	0.00	0.09	0.13	0.00	-1.02
	(0.025)	(0.001)	(0.014)	(0.02)		
GGBR4	0.02	0.56	0.16	0.27	0.00	1.00
	(0.004)	(0.032)	(0.017)	(0.025)		
GGB.N	0.11	0.43	0.17	0.29	1.00	0.00
	(0.011)	(0.03)	(0.018)	(0.026)		
GGB.P	0.11	0.43	0.17	0.29	-1.00	-1.00
	(0.011)	(0.03)	(0.018)	(0.026)		

July to December 2008	information shares				cointegrating vector	
	BRLUSD	BBDC4	BBD.N	BBD.P		
BRLUSD	0.74	0.00	0.03	0.22	0.00	-0.97
	(0.035)	(0.001)	(0.011)	(0.03)		
GGBR4	0.00	0.42	0.12	0.45	0.00	1.00
	(0.002)	(0.038)	(0.017)	(0.033)		
GGB.N	0.10	0.28	0.12	0.50	1.00	0.00
	(0.012)	(0.034)	(0.018)	(0.034)		
GGB.P	0.11	0.28	0.12	0.50	-1.00	-0.99
	(0.012)	(0.034)	(0.018)	(0.034)		

January to June 2009	information shares				cointegrating vector	
	BRLUSD	BBDC4	BBD.N	BBD.P		
BRLUSD	0.73	0.01	0.07	0.20	0.00	-0.95
	(0.024)	(0.005)	(0.012)	(0.022)		
GGBR4	0.02	0.34	0.17	0.47	0.00	1.00
	(0.004)	(0.032)	(0.019)	(0.026)		
GGB.N	0.12	0.25	0.17	0.47	1.00	0.00
	(0.011)	(0.028)	(0.019)	(0.026)		
GGB.P	0.12	0.25	0.17	0.47	-1.00	-0.98
	(0.011)	(0.028)	(0.019)	(0.026)		

July to December 2009	information shares				cointegrating vector	
	BRLUSD	BBDC4	BBD.N	BBD.P		
BRLUSD	0.66	0.00	0.15	0.19	0.00	-0.89
	(0.053)	(0.015)	(0.035)	(0.039)		
GGBR4	0.01	0.33	0.27	0.39	0.00	1.00
	(0.005)	(0.085)	(0.045)	(0.05)		
GGB.N	0.08	0.24	0.28	0.40	1.00	0.00
	(0.018)	(0.075)	(0.047)	(0.051)		
GGB.P	0.08	0.24	0.28	0.40	-1.00	-0.96
	(0.018)	(0.075)	(0.047)	(0.051)		

Table 7
Information shares for Bradesco

We report the IS estimates based on the spectral decomposition of the covariance matrix of the reduced-form errors, and their bootstrap-based standard errors. There are 87,956 observations in the first half of 2008, 88,568 in the second half of 2008, 87,718 in the first half of 2009, and 76,268 observations from July to November 2009. BRLUSD refers to the exchange rate, BBDC4 is the preferred share of Bradesco at the BM&FBovespa, BBD.N is the preferred ADR of Bradesco at the NYSE and BBD.P is the preferred ADR of Bradesco at the Arca.

January to June 2008	information shares				cointegrating vector	
	BRLUSD	BBDC4	BBD.N	BBD.P		
BRLUSD	0.66	0.00	0.10	0.23	0.00	-1.00
	(0.034)	(0.003)	(0.016)	(0.026)		
BBDC4	0.00	0.38	0.16	0.46	0.00	1.00
	(0.002)	(0.033)	(0.019)	(0.03)		
BBD.N	0.07	0.26	0.18	0.50	1.00	0.00
	(0.009)	(0.028)	(0.021)	(0.03)		
BBD.P	0.07	0.26	0.18	0.50	-1.00	-1.00
	(0.009)	(0.028)	(0.021)	(0.03)		

July to December 2008	information shares				cointegrating vector	
	BRLUSD	BBDC4	BBD.N	BBD.P		
BRLUSD	0.64	0.01	0.13	0.22	0.00	-1.00
	(0.038)	(0.005)	(0.02)	(0.021)		
BBDC4	0.00	0.32	0.14	0.54	0.00	1.00
	(0.001)	(0.032)	(0.02)	(0.028)		
BBD.N	0.09	0.16	0.19	0.57	1.00	0.00
	(0.011)	(0.023)	(0.023)	(0.026)		
BBD.P	0.09	0.16	0.19	0.57	-1.00	-1.00
	(0.011)	(0.023)	(0.023)	(0.026)		

January to June 2009	information shares				cointegrating vector	
	BRLUSD	BBDC4	BBD.N	BBD.P		
BRLUSD	0.66	0.00	0.16	0.18	0.00	-1.00
	(0.025)	(0.001)	(0.018)	(0.018)		
BBDC4	0.00	0.35	0.31	0.33	0.00	1.00
	(0.002)	(0.025)	(0.018)	(0.017)		
BBD.N	0.12	0.21	0.32	0.35	1.00	0.00
	(0.01)	(0.02)	(0.02)	(0.018)		
BBD.P	0.12	0.21	0.32	0.35	-1.00	-1.00
	(0.01)	(0.02)	(0.02)	(0.018)		

July to December 2009	information shares				cointegrating vector	
	BRLUSD	BBDC4	BBD.N	BBD.P		
BRLUSD	0.69	0.00	0.03	0.27	0.00	-1.04
	(0.06)	(0.018)	(0.021)	(0.058)		
BBDC4	0.00	0.35	0.14	0.50	0.00	1.00
	(0.006)	(0.099)	(0.045)	(0.066)		
BBD.N	0.12	0.23	0.13	0.53	1.00	0.00
	(0.034)	(0.078)	(0.044)	(0.074)		
BBD.P	0.12	0.23	0.13	0.53	-1.00	-1.00
	(0.034)	(0.078)	(0.044)	(0.074)		

Table 8
Information shares for Ambev

We report the IS estimates based on the spectral decomposition of the covariance matrix of the reduced-form errors, and their bootstrap-based standard errors. There are 43,947 observations in the first half of 2008, 44,304 in the second half of 2008, 43,869 in the first half of 2009, and 38,131 observations from July to November 2009. BRLUSD refers to the exchange rate, AMBV4 is the preferred share of Ambev at the BM&FBovespa, ABV.N is the preferred ADR of Ambev at the NYSE and ABV.P is the preferred ADR of Ambev at the Arca.

January to June 2008	information shares				cointegrating vector	
	BRLUSD	AMBV4	ABV.N	ABV.P		
BRLUSD	0.80	0.00	0.15	0.04	0.00	-1.00
	(0.027)	(0.003)	(0.021)	(0.01)		
AMBV4	0.00	0.52	0.32	0.16	0.00	1.00
	(0.001)	(0.032)	(0.025)	(0.019)		
ABV.N	0.07	0.38	0.38	0.17	1.00	0.00
	(0.01)	(0.03)	(0.027)	(0.021)		
ABV.P	0.07	0.38	0.38	0.17	-1.00	-1.00
	(0.01)	(0.03)	(0.027)	(0.021)		

July to December 2008	information shares				cointegrating vector	
	BRLUSD	AMBV4	ABV.N	ABV.P		
BRLUSD	0.80	0.00	0.04	0.17	0.00	-1.00
	(0.035)	(0.001)	(0.012)	(0.033)		
AMBV4	0.00	0.65	0.06	0.29	0.00	1.00
	(0.002)	(0.04)	(0.013)	(0.035)		
ABV.N	0.23	0.34	0.08	0.36	1.00	0.00
	(0.021)	(0.037)	(0.016)	(0.039)		
ABV.P	0.23	0.34	0.08	0.36	-1.00	-1.00
	(0.021)	(0.037)	(0.016)	(0.039)		

January to June 2009	information shares				cointegrating vector	
	BRLUSD	AMBV4	ABV.N	ABV.P		
BRLUSD	0.78	0.00	0.11	0.10	0.00	-0.99
	(0.022)	(0.001)	(0.015)	(0.015)		
AMBV4	0.00	0.32	0.37	0.31	0.00	1.00
	(0.001)	(0.023)	(0.019)	(0.019)		
ABV.N	0.17	0.16	0.37	0.31	1.00	0.00
	(0.015)	(0.017)	(0.021)	(0.02)		
ABV.P	0.17	0.16	0.37	0.31	-1.00	-1.00
	(0.015)	(0.017)	(0.021)	(0.02)		

July to December 2009	information shares				cointegrating vector	
	BRLUSD	AMBV4	ABV.N	ABV.P		
BRLUSD	0.86	0.00	0.06	0.08	0.00	-0.86
	(0.037)	(0.014)	(0.021)	(0.025)		
AMBV4	0.00	0.34	0.26	0.40	0.00	1.00
	(0.002)	(0.095)	(0.045)	(0.058)		
ABV.N	0.15	0.22	0.26	0.37	1.00	0.00
	(0.026)	(0.078)	(0.047)	(0.06)		
ABV.P	0.15	0.22	0.26	0.37	-1.00	-0.94
	(0.026)	(0.078)	(0.047)	(0.06)		

Table 9
Information shares for BrTelecom

We report the IS estimates based on the spectral decomposition of the covariance matrix of the reduced-form errors, and their bootstrap-based standard errors. There are 11,015 observations in the first half of 2008, 11,078 in the second half of 2008, 10,984 in the first half of 2009, and 9,564 observations from July to November 2009. BRLUSD refers to the exchange rate, BRTO4 is the preferred share of BrTelecom at the BM&FBovespa, BTM.N is the preferred ADR of BrTelecom at the NYSE and BTM.P is the preferred ADR of BrTelecom at the ARCA.

January to June 2008	information shares				cointegrating vector	
	BRLUSD	BRTO4	BTM.N	BTM.P		
BRLUSD	0.85	0.00	0.09	0.06	0.00	-0.98
	(0.027)	(0.006)	(0.021)	(0.018)		
BRTO4	0.00	0.36	0.23	0.41	0.00	1.00
	(0.002)	(0.036)	(0.027)	(0.031)		
BTM.N	0.06	0.29	0.25	0.40	1.00	0.00
	(0.01)	(0.033)	(0.028)	(0.031)		
BTM.P	0.06	0.29	0.25	0.40	-1.00	-1.00
	(0.01)	(0.033)	(0.028)	(0.031)		

July to December 2008	information shares				cointegrating vector	
	BRLUSD	BRTO4	BTM.N	BTM.P		
BRLUSD	0.86	0.00	0.06	0.08	0.00	-0.99
	(0.039)	(0.007)	(0.018)	(0.022)		
BRTO4	0.00	0.44	0.28	0.28	0.00	1.00
	(0.002)	(0.052)	(0.031)	(0.031)		
BTM.N	0.16	0.28	0.27	0.30	1.00	0.00
	(0.023)	(0.044)	(0.031)	(0.033)		
BTM.P	0.16	0.28	0.27	0.30	-1.00	-1.00
	(0.023)	(0.044)	(0.031)	(0.033)		

January to June 2009	information shares				cointegrating vector	
	BRLUSD	BRTO4	BTM.N	BTM.P		
BRLUSD	0.78	0.00	0.12	0.10	0.00	-0.98
	(0.033)	(0.002)	(0.025)	(0.023)		
BRTO4	0.02	0.46	0.34	0.18	0.00	1.00
	(0.006)	(0.039)	(0.033)	(0.026)		
BTM.N	0.18	0.28	0.33	0.20	1.00	0.00
	(0.02)	(0.034)	(0.034)	(0.028)		
BTM.P	0.18	0.28	0.33	0.20	-1.00	-0.98
	(0.02)	(0.034)	(0.034)	(0.028)		

July to December 2009	information shares				cointegrating vector	
	BRLUSD	BRTO4	BTM.N	BTM.P		
BRLUSD	0.86	0.00	0.10	0.04	0.00	-0.93
	(0.039)	(0.008)	(0.031)	(0.018)		
BRTO4	0.01	0.38	0.43	0.18	0.00	1.00
	(0.006)	(0.072)	(0.068)	(0.032)		
BTM.N	0.16	0.24	0.42	0.17	1.00	0.00
	(0.025)	(0.063)	(0.069)	(0.034)		
BTM.P	0.16	0.24	0.42	0.17	-1.00	-0.96
	(0.025)	(0.063)	(0.069)	(0.034)		

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