Deviations from covered interest parity: The role of fundamentals, financial and political turmoil, and market frictions

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Emerson Fernandes Marçal‡

Abstract Recent studies of mature markets on covered interest parity suggest that deviations are mean-reverting, but persistent, particularly after the 2008 crisis (Du et al., 2018). Our study contributes to the literature by modeling the deviations from covered interest rate parity (CIP) of an important emerging-market economy. We focus on Brazilian data, given the importance of its derivative market. One of the strengths of our study is the use of an agnostic approach, based on an automatic model-selection technique that is robust to structural change, the Autometrics algorithm (Hendry and Doornik, 2014), to unveil the possible determinants of CIP deviations from a wide information data set. We show that CIP deviations are highly sensitive to changes in Brazilian federal government total debt, level of reserves, inflation, and degree of trade openness. We also document the existence of instability in the model due to financial and political turmoil. We reach these conclusions based on the algorithm’s intercept correction, which can be seen as a byproduct of our methodology. Finally, we find evidence that, even after correction for fundamentals and instability points, CIP deviations still have persistence, suggesting that market frictions play an important role in the dynamics of CIP deviations.

Keywords: Automatic model selection; Covered interest rate parity; Country risk; Exchange rate; Interest rate.

JEL Code: F31, C22, C55.

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1. Introduction

The covered interest rate parity (CIP) condition implies that the interest rate differential between similar financial assets with the same maturity, but denominated in different currencies, should be equal to the cost of hedging the currency risk on a forward market. The interest rate differential; that is, the spread between the domestic and foreign interest rates, is a key variable

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for emerging countries. In these countries, this spread is usually positive, which entails a higher cost of capital than in developed economies. This differential between interest rates varies over time, notably increasing in periods of financial turbulence. Smaller spreads represent lower loan costs for both public and private sectors, and consequently, higher growth (Calvo, 1998; Schmukler and Servén, 2002).

In a recent paper, Du et al. (2018) document that CIP deviations for mature markets after the 2008 financial crisis events became large and persistent, allowing systematic arbitrage opportunities. This contrasts with evidence from the period prior to the crisis. The authors suggest that financial constraints limit the provision of a sufficient currency hedge, which may be one important determinant to explain the lack of fully exploited arbitrage opportunities. Along the same lines, Borio et al. (2016) highlight that important deviations from the CIP condition began to prevail after the global financial crisis, and, even more puzzling, in some cases from 2004 onward. They suggest that an increased demand for hedges with limits to arbitrage due lower balance-sheet capacity explains these violations. Cerutti et al. (2019) also note that CIP deviations increased significantly since the financial crisis, and argue that the potential macro-financial drivers of the variation in CIP deviations also became significant. For these authors, the variation in CIP deviations seems to be associated with multiple factors, not only regulatory changes.

We investigate whether similar results hold for emerging markets. We focus our analysis on Brazil. This country has one of the most developed derivatives markets for an emerging-market economy:

Virtually alone among emerging economies, Brazil boasts relatively large and well developed onshore derivatives exchanges that trade FX and interest rate contracts in addition to stock and commodity instruments. (...) Owing to its depth and high level of development, the Brazilian derivatives market has been innovative and resilient to financial distress. During many episodes of financial turbulence, including the East Asian financial crisis (1997), the Russian debt moratorium (1998), the abandonment of the real peg (1999), the Argentine default (2001), the Great Financial Crisis (2007-09) and the recent fiscal and political crisis in Brazil (2015), the Brazilian derivatives market arguably helped prevent more serious financial distress or a credit crunch. Upper and Vallim (2016, p. 75)

Deviations from covered interest parity are closely related to sovereign
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risk in emerging markets. Analyzing the determinants of local sovereign country risk is important because it affects investments, asset prices, exchange rates, and the term structure of the interest rate, among other economic variables. Macroeconomic factors, political instability and turmoil, the quality of institutions, and other elements may influence the high term premium. Developed markets tend to have a lower sovereign risk, compared to emerging markets.

This study investigates the determinants of deviations from CIP by decomposing them into three parts, according to fundamentals, financial and political turmoil, and market imperfections. We accomplish this using recent advances on model selection. We select the determinants of local risk using the agnostic approach given by the Autometrics algorithm. This algorithm follows a general-to-specific (Gets) approach, in line with the London School of Economics (LSE) tradition of econometrics. It allows analysts to unveil possible relationships from a wider group of indicators. The number of indicators used in the analysis does not determine the sample size. This algorithm also allows analysts to identify outliers and structural changes (Hendry and Doornik, 2014).

Our results suggest that four types of indicators explain the deviations from CIP: (1) those related to reserves, (2) those related to solvency issues, (3) those related to the level of inflation, and (4) indicators of trade openness and the current account balance. Our analysis allows us to show that CIP deviations had an important spike during 2002, which is not fully explained by the variables used in the analysis, given the presence of outliers and instability in the models. This spike was probably related to the increase in political risk during a presidential election held in that year. Another CIP spike arose from the political and economic crisis that culminated with the Brazilian president’s impeachment at the end of 2016.

This article proceeds as follows. In the next section, we review the determinants of CIP deviations and risk premiums. In the third section, we describe the Autometrics algorithm briefly. In the fourth section, we present and discuss the results. We provide our final remarks in the last section.

2. Methodology

CIP establishes that domestic and foreign interest rates should be equal when there is no difference in risk, compared with the same currency, and ignoring transaction costs. The forward premium tends to equal the interest differential between two countries (Sarno et al., 2003; Cuthbertson and
Nitzsche, 2004), calculated as follows:

\[ f_{t,t+k} - s_t = i_{t,t+k} - i^*_t \quad (1) \]

where \( f_{t,t+k} \equiv \ln F_{t,t+k} \) is the natural logarithm of the exchange rate on the futures market traded at \( t \) to be delivered at \( t + k \), \( s_t \equiv \ln S_t \) is the logarithm of the exchange rate on the spot market on day \( t \), and \( i_t, i^*_t \) are, respectively, the logarithm of the domestic and foreign interest rates on day \( t \).

Assuming no risk and market frictions, deviations from Equation (1) result in arbitrage opportunities. If (1) does not hold, then some forces restore the balance and Equation (2) holds in the long run (Cuthbertson and Nitzsche, 2004):

\[ CIP_t \equiv i_t - i^*_t - (f_{t,t+k} - s_t) = 0. \quad (2) \]

In the presence of a time-varying risk but no market frictions, deviations from CIP provide an estimate of country risk. If the risk is stationary, then the CIP series is stationary. Prior evidence suggests that covered interest parity holds for developed countries, with minor deviations explained by transaction costs, differences in tax treatment, and liquidity differences between foreign securities and domestic securities, at least up to 2008 (Du et al., 2018).

For emerging markets, Equations (1) and (2) are not directly applicable, due to the existence of a time-varying risk premium and possible market frictions. For a foreign investor to invest in an emerging market, the interest rate paid by a bond issued in the market’s local currency must be equal to the risk-free foreign interest rate plus a risk premium. Thus, Equation (2) requires an additional risk premium (Garcia and Didier, 2003; Aliber, 1973):

\[ i_t = i^*_t + f_{t,t+k} - s_t + \text{risk\_premium}_t. \quad (3) \]

Additionally, according to these authors, with the forward premium \( f_{t,t+k} \), and the values of \( i \) and \( i^* \), we can estimate the difference in country risk:

\[ CIP_t = i_t - i^*_t - (f_{t,t+k} - s_t) \approx RP_t. \quad (4) \]

If the risk premium (RP) is persistent over time, then deviations from CIP are also persistent.

Finally, if a country’s derivatives and futures markets are not deep enough to provide a sufficient hedge for a foreign investor, then we must include an additional term in (3). The memory observed in the CIP time series should be a mix of the term premium and market frictions dynamics, as in (5):

\[ CIP_t = i_t - i^*_t - (f_{t,t+k} - s_t) \approx RP_t + MF_t. \quad (5) \]
Assume that $X_t$ is a vector of observed determinants of $RP_t$ and $MF_t$, and that $RP_t$, $MP_t$, and $X_t$ follow a multivariate VAR process. Then, under certain conditions $CIP_t$ can be well described by an autoregressive distributed lag (ADL) model:

$$\tilde{\phi}(L)CIP_t = \tilde{\Psi}(L)X_t + v_t$$

(6)

where $v_t \sim IID(0, \sigma_v^2)$.

Based on an extensive list of indicators, we can identify the determinants of country risk, and using the Autometrics algorithm, we can estimate (6). Using indicator saturation techniques available in Autometrics, we can also identify instability points and permanent level changes in the CIP’s data generating process (DGP). Lagged terms on CIP significantly higher than order one provide evidence of relevant market frictions. Table 1 provides an extensive list of indicators usually associated with the risk premium. We will use all of these indicators to investigate whether they can be linked to CIP deviations.

### Table 1

<table>
<thead>
<tr>
<th>Variables associated with the risk premium</th>
<th>references</th>
</tr>
</thead>
<tbody>
<tr>
<td>potential risk determinants</td>
<td></td>
</tr>
<tr>
<td>need to finance public debt</td>
<td>Garcia and Didier (2003)</td>
</tr>
<tr>
<td>central government debt</td>
<td>Arora and Cerisola (2001)</td>
</tr>
<tr>
<td>foreign debt / GDP</td>
<td>Min (1999), Schimmelpfennig et al. (2003), Rowland and Torres (2004), Bellas et al. (2010), Dumicic and Ridzak (2011)</td>
</tr>
</tbody>
</table>

1 See Appendix A for details.
2 In the paper we restrict our analysis to indicators that are closely linked to risk premium.
Continuation of Table 1

<table>
<thead>
<tr>
<th>potential risk determinants</th>
<th>references</th>
</tr>
</thead>
<tbody>
<tr>
<td>exports (volume rate of change)</td>
<td>Doumpos and Zopounidis (2001)</td>
</tr>
<tr>
<td>imports (rate of change)</td>
<td>Min (1999), Schimmelpfennig et al. (2003), Maltritz and Molchanov (2014)</td>
</tr>
<tr>
<td>imports (volume rate of change)</td>
<td>Doumpos and Zopounidis (2001)</td>
</tr>
<tr>
<td>imports / GDP</td>
<td>Taffler and Abassi (1984), Haan et al. (1997)</td>
</tr>
<tr>
<td>imports / reserves</td>
<td>Feder and Just (1977)</td>
</tr>
<tr>
<td>trade balance / imports</td>
<td>Taffler and Abassi (1984)</td>
</tr>
<tr>
<td>trade balance / GDP</td>
<td>Ferrucci (2003), Schimmelpfennig et al. (2003), Maltritz and Molchanov (2014)</td>
</tr>
<tr>
<td>trade balance / international reserves</td>
<td>Taffler and Abassi (1984)</td>
</tr>
<tr>
<td>trade openness = (imports + exports) / GDP</td>
<td>Detragiache and Spilimbergo (2001), Ferrucci (2003), Schimmelpfennig et al. (2003), Dailami et al. (2008), Bellas et al. (2010), Maltritz and Molchanov (2014)</td>
</tr>
</tbody>
</table>
## Continuation of Table 1

<table>
<thead>
<tr>
<th>potential risk determinants</th>
<th>references</th>
</tr>
</thead>
<tbody>
<tr>
<td>reserves / imports</td>
<td>Feder and Uy (1985), Cosset and Roy (1991), Cosset et al. (1992), Oral et al. (1992), Haan et al. (1997)</td>
</tr>
<tr>
<td>terms of exchange (rate of change)</td>
<td>Feder and Uy (1985), Shapiro (1985), Min (1999), Detragiache and Spilimbergo (2001), Tiffin et al. (2003), Gupta et al. (2008), Hilscher and Nosbusch (2010)</td>
</tr>
<tr>
<td>current transactions (rate of change)</td>
<td>Detragiache and Spilimbergo (2001)</td>
</tr>
<tr>
<td>current transactions / exports</td>
<td>Haan et al. (1997)</td>
</tr>
<tr>
<td>conditions of domestic financial market</td>
<td>Ramcharran (1999), Garcia and Didier (2003)</td>
</tr>
<tr>
<td>conditions of international financial markets</td>
<td>Gupta et al. (2008), Gupta et al. (2008), Bellas et al. (2010), Hilscher and Nosbusch (2010), Dumicic and Ridzak (2011)</td>
</tr>
</tbody>
</table>
3. Reduction theory and the Autometrics algorithm

Reduction theory aims to underpin and clarify empirical models involving possibly non-stationary variables and their respective interconnections, that result from high-dimensional processes. It allows an approximation between the high-dimensional DGP (a set of several economic variables) and its respective “local” DGP, or LDGP (Hendry and Doornik, 2014).

Considering the distortions and inaccuracies that aspects such as population size, heterogeneity, and possibly non-stationary data can cause in modeling, the LDGP seeks to reduce the model to a controllable size by deriving the joint density of the relevant variables for the phenomenon under analysis. Reduction theory formulates the LDGP in general terms. Thus, the empirical model seeks to discover the properties of the unknown DGP, developing the quantitative models with all available information, and investigating the phenomena for which the reality is not yet established (Hendry and Doornik, 2014).

Model selection becomes challenging when the number of regressors grows due to the exponential increase in the set of candidate models. When \( k \) variables occur in the subset, \( 2^k \) specifications will be within the set of candidate models. Moreover, these procedures do not ensure congruence. Thus, a model with specification errors may be selected (Castle et al., 2011; Greene, 2012; Hendry and Doornik, 2014).

The LSE approach considers the choice of an econometric model based on Gets modeling. The initial or general model encompasses all available variables that could initially be part of the DGP (Doornik, 2008; Souza, 2015). The following steps are taken: a) formulation of a general unrestricted model (GUM) congruent with the data; b) application of a series of tests to detect the specification errors; c) elimination of variables with non-significant coefficients; and d) the formulation and selection of a congruent and more compact format, called the specific model (Doornik, 2009). The specific model, in turn, should not only overlap rival models, but also meet the criteria of comprehension and the diagnosis adopted, without the threat of losing an understanding of the phenomenon (Doornik, 2009; Souza, 2015).

Targeting the Gets model starts with a general, super-parameterized, dynamic model containing more lags than would be considered necessary. The model is reduced progressively through a sequence of simplification tests. The significance levels of the test sequence are known. Only after these steps should an analyst test their economic theories (Hendry, 1995).

This approach faces a considerable challenge in treating the data because...
it encompasses estimates, and statistical and diagnostic tests, that originate from the various sub-models generated. Their dimensions and stages would preclude manual execution and favor errors and distortions. Using an automatic model-selection algorithm allows researchers to save time and effort, thereby making the selection more robust (Doornik, 2008).

The first version of an automated model algorithm was developed by Hoover and Perez (1999) and Hendry and Krolzig (1999, 2001, 2003, 2005). Doornik (2009) developed the Autometrics algorithm, which is considered the third generation of the Gets approach. The algorithm uses multiple search paths, with scope and interactivity, through diagnostic tests, additional statistical suitability assessments, and pre-search simplification options. Additionally, Autometrics – in its search method – uses the decision tree concept with a refined pre-search and simplifications in the objective function.

Selection algorithms tend to perform better if regressors are orthogonal, identical, and independently distributed over time. In this environment, sequential tests are not dependent. Autometrics performs well even in case where regressors are not orthogonal and contain time dependence. Its search paths are designed to identify relevant variables from an ample set of variables for the LDGP by testing congruence, simplifying all estimated models at each step. Additionally, it tests terminal models to encompass their rivals. Its probabilistic framework allows broad application (Castle et al., 2012).

According to Hendry and Doornik (2014), formulating and implementing the Gets approach has six main steps: specification of the GUM, verification of congruence, formulation of the selection criterion, selection under the null hypothesis, retention of relevant variables, and repetition of the tests. Oxmetrics 7 software implements the Autometrics algorithm.

3.1 Dealing with structural changes

We can use three types of dummies to model instability and structural changes: impulsive indicator saturation (IIS), step indicator saturation (SIS), and first difference indicator saturation (DIIS). An impulsive dummy for year XXXX and period YY (I:XXXX(YY)) has a value of one if the observation is for the period XXXX(YY), and zero otherwise. The step dummy for year XXXX and period YY (S:XXXX(YY)) has a value of one if the observation is for the period XXXX(YY) or before, and zero otherwise. The difference impulsive dummy (DI:XXXX(YY)) for year XXXX(YY) is the first of I:XXXX(YY). We make the selection using the Autometrics algorithm. We add various subsets of the dummies to model and evaluate their relevance. The following offer detailed explanations of the procedure: Castle
et al. (2015), Castle et al. (2012), Ericsson (2017), and Hendry and Johansen (2015).

3.2 Comparing *Autometrics* with other algorithms

In this section we discuss similarities, strengths, and limitations of *Autometrics*, and possible complementarities with other algorithms such as least absolute shrinkage and selection operator (LASSO) and adaptive LASSO (AdaLASSO).

Tibshirani (1996) proposes the LASSO method based on the following minimization problem:

$$
\hat{\beta}^{\text{LASSO}} = \arg\min_{\beta_0, \beta_1, \ldots, \beta_k} \sum_{i=1}^{n} \left( y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ji} \right)^2 + \lambda \sum_{j=1}^{k} |\beta_j| \tag{7}
$$

where $\lambda \geq 0$ is a tuning parameter and LASSO requires a method to obtain a value for $\lambda$. The first term is the sum of square of residuals. The second term is a shrinkage penalty. $\sum_{j=1}^{k} |\beta_j|$ is the $\ell^1$ norm of a coefficient vector $\beta$. The $\ell^1$ penalty forces some of the coefficient estimates to be equal to zero when $\lambda$ is sufficiently large. When $\lambda = 0$, LASSO estimates equal ordinary least squares estimates. Therefore, the LASSO technique performs variable selection. Cross-validation is usually the method to obtain the $\lambda$ value.

Zou (2006) warns that LASSO can lead to inconsistent selection of variables that may keep noisy variables for a given $\lambda$. The author also shows that LASSO can lead to the right selection of variables with biased estimates for large coefficients. This leads to sub-optimal prediction rates. In order to solve these problems Zou (2006) introduces the adaptive LASSO, which considers weights $\omega_j$ that adjust the penalty to be different for each coefficient. AdaLASSO seeks to minimize

$$
\hat{\beta}^{\text{AdaLASSO}} = \arg\min_{\beta_0, \beta_1, \ldots, \beta_k} \sum_{i=1}^{n} \left( y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ji} \right)^2 + \lambda \sum_{j=1}^{k} \omega_j |\beta_j| \tag{8}
$$

where $\omega_j = |\hat{\beta}_j^{\text{ridge}}| - \tau$, $\tau > 0$. AdaLASSO considers that large (small) coefficients have small (large) weights – and small (large) penalties. The coefficients estimated by ridge regression $\hat{\beta}_j^{\text{ridge}}$ generate the weight $\omega_j$. Ridge regression uses a quadratic penalty function:

$$
\hat{\beta}^{\text{ridge}} = \arg\min_{\beta_0, \beta_1, \ldots, \beta_k} \sum_{i=1}^{n} \left( y_i - \beta_0 - \sum_{j=1}^{k} \beta_j x_{ji} \right)^2 + \lambda \sum_{j=1}^{k} \beta_j^2 \tag{9}
$$
Deviations from Covered Interest Parity

where the penalty is the $\ell^2$ norm of the $\beta$ vector. Ridge regression is not a method of variable selection, because this regression obtains non-zero estimates for all coefficients.

Finally, the Autometrics algorithm can relate to a robust estimation of the parameters of a regression. A robust estimator can be formulated from the Huber loss function Huber (1964):

$$L(\beta) = \begin{cases} 
  \frac{r^2}{2}, & \text{if } |r| \leq \delta \\
  \frac{r^2}{2} - \delta^2 / 2, & \text{if } |r| > \delta
\end{cases}$$

(10)

where $\delta$ is a parameter to be set according some criteria. Murphy (2012, Chapter 7) discusses the probability interpretation of LASSO, ridge and Huber estimators. Johansen and Nielsen (2016) proves that the IIS outlier detection algorithm implemented in Autometrics can be seen as a generalization of a robust estimator. Berenguer-Rico et al. (2019a,b) also provide a theoretical, statistical basis for the algorithm. If no selection on the set of regressors is performed, Autometrics estimates the parameters, minimizing the distortions that outliers may cause, and identifies them with high probability. The Autometrics algorithm also search for relevant regressors, similar to LASSO and AdaLASSO.

Another issue that Autometrics addresses is the model specification. The algorithm is in line with the concept of congruence of a statistical model, as defined by Hendry (1995). LASSO and AdaLASSO algorithms are only selection devices. For example, Berenguer-Rico and Wilms (2021) show that the White test for heteroskedasticity (White, 1980) continues to have asymptotically chi-square distribution when robust algorithms estimate the model. This paper provides an initial result towards addressing outliers and specification tests simultaneously.

Epprecht et al. (2019) perform a Monte Carlo study to compare Autometrics with LASSO and AdaLASSO. When the number of relevant regressors is small compared to the sample size, the methods’ performances are equivalent, and near the oracle properties. However, when the number of irrelevant regressors is higher than sample size, the performance of LASSO and AdaLASSO decreases substantially. One pitfall of their simulation is that they rely on DGPs that do not contain outliers. Their evaluation is restricted to the case where Autometrics was used as a selection algorithm device. In a environment where outliers are relevant, our guess is that the performance of Autometrics can be improved. But even in the case analyzed here, Autometrics performs at least as well as LASSO and AdaLASSO in most scenarios.
Table 2
Components of the dependent variable

<table>
<thead>
<tr>
<th>acronym</th>
<th>operational definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_t$</td>
<td>CDI rate, published by Cetip (% per month)</td>
</tr>
<tr>
<td>$I_t^*$</td>
<td>3-month treasury constant maturity rate published by the United States Federal Reserve Board of Governors - FED (% per month)</td>
</tr>
<tr>
<td>$S_t$</td>
<td>selling price of the spot exchange rate published by the Central Bank of Brazil.</td>
</tr>
<tr>
<td>$F_{t+1}^*$</td>
<td>selling price of the forward exchange rate on last working day of month $t$ to a contract referring to the last working day of the following month ($t+1$) obtained in the contracts negotiated on B3.</td>
</tr>
</tbody>
</table>

* Small letters denote the natural logarithm of the variables.

4. Results

4.1 Database description

The dataset covers the period from January 1995 to July 2018. Our database frequency is monthly. Our sample covers 283 months and encompasses the period seen by Garcia and Didier (2003), who analyze CIP deviations from May 1999 to June 2001 with weekly data. According to the authors, this led to the limited strength of their conclusions. We can add almost two decades to their information set. We opt to work with monthly data due to the characteristics of the Brazilian derivatives market, in which all contracts are set to the last working day of the month. The most liquid forward contract is for one-month-ahead delivery (Table 2). No contract has a maturity of weeks. In order to avoid any distortions that weekly data can have, and due to the fact that our sample size is big, we think that working with monthly data is the best choice.

The study-dependent variable is the CIP. Figure 1 illustrates the CIP deviations.

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3Find the data and codes to replicate these results at https://data.mendeley.com/data sets/hsx3ztsy8w/1.
We formulate a general model with as potentially drivers of risk as possible, called the GUM. We identify explanatory variables based on an analysis of 50 studies on country risk, credit, and default. We are working with a very long time span, which can restrict the number of selected indicators. Some series are available for the most recent period, whereas others were available for an early period, but may be discontinued in the primary sources. In order to satisfy the comprehensive condition of the resulting model (with the GUM including the following aspects: institutional knowledge, historical contingencies, data availability, measurement information, theoretical aspects, transformations of functional forms, possibility of structural breaks, number of lags, and order of integration for time series), for this study, we select 39 explanatory variables based on macroeconomic fundamentals, as in Table 3. The criterion we establish for this selection is the availability of data at a monthly frequency for the study period. Our sample covers virtually the entire period after the “Real Macroeconomic Stabilization Plan” that brought Brazilian inflation to an unprecedented low level by Brazilian standards.
<table>
<thead>
<tr>
<th>independent variables</th>
<th>acronym</th>
<th>expected sign</th>
<th>database</th>
</tr>
</thead>
<tbody>
<tr>
<td>need for public sector financing / GDP</td>
<td>1_NFSF_PIB</td>
<td>−</td>
<td>(1)</td>
</tr>
<tr>
<td>total debt / exports</td>
<td>2_DIVT_EXP</td>
<td>+</td>
<td>(1) and (2)</td>
</tr>
<tr>
<td>central government debt</td>
<td>3_LNDIVT</td>
<td>+</td>
<td>(1)</td>
</tr>
<tr>
<td>total debt / GDP</td>
<td>4_DIVT_PIB</td>
<td>+</td>
<td>(1)</td>
</tr>
<tr>
<td>foreign debt / exports</td>
<td>5_DIV_EXT_EXP</td>
<td>+</td>
<td>(1)</td>
</tr>
<tr>
<td>foreign debt / GDP</td>
<td>6_DIV_EXT_PIB</td>
<td>+</td>
<td>(1) and (2)</td>
</tr>
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<td>exports (rate of change)</td>
<td>7_LN_EXP and 8_VAR_EXP</td>
<td>−/+</td>
<td>(2)</td>
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<td>exports (volume rate of change)</td>
<td>9_LN_VEXP</td>
<td>−/+</td>
<td>(2)</td>
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<td>exports / GDP</td>
<td>10_EXP_PIB</td>
<td>+</td>
<td>(1) and (2)</td>
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<td>−/+</td>
<td>(2)</td>
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<td>imports (volume rate of change)</td>
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<td>−/+</td>
<td>(1) and (2)</td>
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<td>imports / GDP</td>
<td>14_IMP_PIB</td>
<td>−</td>
<td>(1) and (2)</td>
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<td>imports / reserves</td>
<td>15_IMP_RES</td>
<td>+</td>
<td>(1) and (2)</td>
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<td>16_BaC_EXP</td>
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<td>(2)</td>
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<td>trade balance / imports</td>
<td>17_BaC_IMP</td>
<td>+</td>
<td>(2)</td>
</tr>
<tr>
<td>trade balance / GDP</td>
<td>18_BaC_PIB</td>
<td>−</td>
<td>(2)</td>
</tr>
<tr>
<td>trade balance / international reserves</td>
<td>19_BaC_RES</td>
<td>−</td>
<td>(1) and (2)</td>
</tr>
<tr>
<td>trade openness = (imports + exports) / GDP</td>
<td>20_Abert_Coml</td>
<td>−</td>
<td>(1) and (2)</td>
</tr>
<tr>
<td>consumer price index</td>
<td>21_INPC and 22_IPCA</td>
<td>+</td>
<td>(3)</td>
</tr>
<tr>
<td>inflation rate</td>
<td>23_JGPM</td>
<td>+</td>
<td>(4)</td>
</tr>
<tr>
<td>GDP (rate of change)</td>
<td>24_LNPIB; 25_VLPIB_ACC_12M; 26_BACEN_PIBMETA</td>
<td>−</td>
<td>(1)</td>
</tr>
<tr>
<td>reserves (rate of change)</td>
<td>27_VAR_RES</td>
<td>−</td>
<td>(1)</td>
</tr>
<tr>
<td>reserves (growth rate)</td>
<td>28_LN_RES</td>
<td>−</td>
<td>(1)</td>
</tr>
<tr>
<td>reserves / imports</td>
<td>29_RES_IMP</td>
<td>−</td>
<td>(1) and (2)</td>
</tr>
<tr>
<td>reserves / GDP</td>
<td>30_RES_PIB</td>
<td>−</td>
<td>(1)</td>
</tr>
<tr>
<td>terms of exchange (rate of change)</td>
<td>31_VAR_TermT and 32_LN_TermT</td>
<td>+</td>
<td>(5)</td>
</tr>
<tr>
<td>current transactions (rate of change)</td>
<td>33_Var_TransC</td>
<td>−</td>
<td>(1)</td>
</tr>
<tr>
<td>current transactions / exports</td>
<td>34_TransC_EXP</td>
<td>−</td>
<td>(1) and (2)</td>
</tr>
<tr>
<td>current transactions / GDP</td>
<td>35_TransC_PIB</td>
<td>+</td>
<td>(1)</td>
</tr>
<tr>
<td>EMBI + Brazil (monthly average in points)</td>
<td>36_Embi_BR and 37_Var_Embi_BR</td>
<td>+</td>
<td>(6)</td>
</tr>
<tr>
<td>conditions of domestic financial market</td>
<td>38_Var_Ibovespa</td>
<td>−/+</td>
<td>(7)</td>
</tr>
<tr>
<td>conditions of international financial markets</td>
<td>39_VAR_VIX</td>
<td>−/+</td>
<td>(8)</td>
</tr>
</tbody>
</table>
4.2 Choosing the best model

The initial GUM has 12 lags and centered seasonal dummies (CSeasonal). The model uses the dummy saturation technique to identify outliers and possible structural breaks. Following the Gets modeling procedure, we remove the statistically non-significant variables. Our GUM is given by (11):

\[
\Phi(L)CIP_t = \mu + \sum_{h=0}^{\infty} \sum_{k=1}^{q_0} \theta_{0,k,h} X_{k,t-h}^h + \sum_{i=1}^{T} \theta_{1i} IIS_i + \sum_{j=1}^{T} \theta_{2j} DIIS_j + \sum_{k=1}^{T} \theta_{3k} SIS_k + \zeta(L)CSeasonal_t + \varepsilon_t. \tag{11}
\]

The augmented Dickey-Fuller (ADF) unit root test suggests that the following variables are non-stationary: total debt change, total debt to GDP, external debt to exports, external debt to GDP, change in imports, imports to reserves, GDP change, change in reserves, reserves to imports, reserves to GDP, change in trade terms, and Embi+BR. We use the first difference of these variables instead of their levels.

There are different ways to run the algorithm. The two key parameters are target p-value and type of intervention. We choose two target p-values: “minute” (0.01%) and “tiny” (0.1%). If we choose higher target p-values, then the algorithm tends to retain more irrelevant variables. We can calculate the expected value of irrelevant retention by multiplying the target p-value by the number of regressors in the initial model. If all regressors are irrelevant, the algorithm will have an expected (false) retention rate given by p-value*(# total regressors). If a total of 1000 regressors make up the initial set of variables, a tiny p-value is chosen, and none of them are relevant, a total of one regressor (on average) is retained (1000*0.001=1) (Hendry and Johansen, 2015).

Table 4 summarizes the number of parameters and information criteria of the terminal models associated with each configuration of the algorithm. We estimate thirteen configurations in total, and obtain the best model for the configuration with a tiny target p-value, IIS, and DIIS.
<table>
<thead>
<tr>
<th>final models</th>
<th>target size</th>
<th>outlier and structural detection</th>
<th># params.</th>
<th>log-lik.</th>
<th>SC</th>
<th>HQ</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 minute</td>
<td>IIS+SIS</td>
<td>11</td>
<td>1084.656</td>
<td>−7.8064</td>
<td>−7.8941</td>
<td>−7.953</td>
<td></td>
</tr>
<tr>
<td>2 minute</td>
<td>large residuals</td>
<td>11</td>
<td>1066.427</td>
<td>−7.6714</td>
<td>−7.7591</td>
<td>−7.818</td>
<td></td>
</tr>
<tr>
<td>3 minute</td>
<td>IIS</td>
<td>4</td>
<td>1041.366</td>
<td>−7.6309</td>
<td>−7.6628</td>
<td>−7.6842</td>
<td></td>
</tr>
<tr>
<td>4 minute</td>
<td>SIS</td>
<td>9</td>
<td>1069.934</td>
<td>−7.7388</td>
<td>−7.8106</td>
<td>−7.8588</td>
<td></td>
</tr>
<tr>
<td>5 minute</td>
<td>DIIS</td>
<td>8</td>
<td>1093.648</td>
<td>−7.6235</td>
<td>−7.6855</td>
<td>−7.7270</td>
<td></td>
</tr>
<tr>
<td>6 minute</td>
<td>DIIS+IIS</td>
<td>9</td>
<td>1080.017</td>
<td>−7.8135</td>
<td>−7.8853</td>
<td>−7.8853</td>
<td></td>
</tr>
<tr>
<td>7 tiny</td>
<td>IIS+SIS</td>
<td>17</td>
<td>1126.651</td>
<td>−7.9931</td>
<td>−8.1287</td>
<td>−8.2196</td>
<td></td>
</tr>
<tr>
<td>8 tiny</td>
<td>large residuals</td>
<td>14</td>
<td>1074.751</td>
<td>−7.6708</td>
<td>−7.7825</td>
<td>−7.8574</td>
<td></td>
</tr>
<tr>
<td>9 tiny</td>
<td>IIS</td>
<td>9</td>
<td>1078.755</td>
<td>−7.8042</td>
<td>−7.8759</td>
<td>−7.9241</td>
<td></td>
</tr>
<tr>
<td>10 tiny</td>
<td>SIS</td>
<td>19</td>
<td>1116.738</td>
<td>−7.8782</td>
<td>−8.0297</td>
<td>−8.1314</td>
<td></td>
</tr>
<tr>
<td>11 tiny</td>
<td>DIIS</td>
<td>15</td>
<td>1096.523</td>
<td>−7.8114</td>
<td>−7.931</td>
<td>−8.0113</td>
<td></td>
</tr>
<tr>
<td>12 tiny</td>
<td>DIIS+IIS</td>
<td>26</td>
<td>1146.734</td>
<td>−7.9552</td>
<td>−8.1626</td>
<td>−8.3017</td>
<td></td>
</tr>
<tr>
<td>13 tiny</td>
<td>DIIS+IIS</td>
<td>21</td>
<td>1146.208</td>
<td>−8.0550&lt;</td>
<td>−8.2225&lt;</td>
<td>−8.3349&lt;</td>
<td></td>
</tr>
</tbody>
</table>
Table 5 provides all of the details of the best model. Results of the specification tests are satisfactory. Conditioning on the information set and intercept correction, the model shows no sign of wrong specification, and meets the notion of congruence. The null hypotheses of no auto-correlation, homoskedasticity, and normality in errors are all not rejected, at the usual 5% level. The null of good linear specification from the Ramsey (1969) specification test (RESET) is also not rejected. About 70% of the variance of CIP can be explained by the variables in the final model.

4.3 Factors driving CIP deviations

Table 6 reports our final model, that incorporates all accepted simplifications. It contains four main factors:

- (F1) is lagged changes in reserves. This indicator is linked to liquidity issues. Positive changes in this factor affect the risk premium negatively.

\[ F1_t \equiv 27\_VAR\_RES_{t-4}; \]  

- (F2) contains indicators related to the level of trade openness and current account results. Positive changes in this factor induce lower levels of risk.

\[ F2_t \equiv 20\_Abert\_Coml_{t-3} - 35\_TransC\_PIB_{t-4}; \]  

- (F3) is a combination of several price indexes for Brazil, which suggests that inflation is directly related to country risk. A higher level of inflation increases the level of risk.

\[ F3_t = 21\_INPC_{t-4} - 22\_IPCA_{t-4} + (1/7)23\_IGPM_{t-1}; \]  

- (F4) is related to the Brazilian government’s level of debt. A positive change in this factor induces a higher level of risk.

\[ F4_t = 0.000293528 \times D3 - 2\_DIVT\_EXP_t \\
- 0.00620446 \times D4\_DIVT\_PIB_t - 1 \]  

and

\[ D3 - 2\_DIVT\_EXP_t = 2\_DIVT\_EXP_{t-2} + DIVT\_EXP_{t-3}. \]
## Table 5
Results of the best model

dependent variable: $CIP_t$

<table>
<thead>
<tr>
<th>variable</th>
<th>coefficient</th>
<th>std. error</th>
<th>t-value</th>
<th>p-value</th>
<th>% of $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CIP_{t-1}$</td>
<td>0.217502</td>
<td>0.04748</td>
<td>4.58</td>
<td>0</td>
<td>0.0792</td>
</tr>
<tr>
<td>$2 - DIVT - EXP_t$</td>
<td>0.000312994</td>
<td>4.78E-05</td>
<td>6.55</td>
<td>0</td>
<td>0.1495</td>
</tr>
<tr>
<td>$2 - DIVT - EXP_{t-3}$</td>
<td>−0.0002754</td>
<td>4.67E-05</td>
<td>−5.9</td>
<td>0</td>
<td>0.1247</td>
</tr>
<tr>
<td>$D4 - DIVT - PIB_{t-1}$</td>
<td>−0.00623442</td>
<td>0.001068</td>
<td>−5.84</td>
<td>0</td>
<td>0.1225</td>
</tr>
<tr>
<td>$27 - VAR - RES_{t-4}$</td>
<td>−0.0159942</td>
<td>0.004509</td>
<td>−3.55</td>
<td>5E−04</td>
<td>0.049</td>
</tr>
<tr>
<td>$20 - Abert - Coml_{t-3}$</td>
<td>−0.0771504</td>
<td>0.008849</td>
<td>−8.72</td>
<td>0</td>
<td>0.2375</td>
</tr>
<tr>
<td>$35 - TransC - PIB_{t-4}$</td>
<td>0.0810311</td>
<td>0.0123</td>
<td>6.59</td>
<td>0</td>
<td>0.151</td>
</tr>
<tr>
<td>$21 - INPC_{t-4}$</td>
<td>0.731112</td>
<td>0.169</td>
<td>4.32</td>
<td>0</td>
<td>0.0711</td>
</tr>
<tr>
<td>$22 - IPCA_{t-4}$</td>
<td>−0.712894</td>
<td>0.1916</td>
<td>−3.72</td>
<td>2E−04</td>
<td>0.0537</td>
</tr>
<tr>
<td>$23 - IGPM_{t-1}$</td>
<td>0.109022</td>
<td>0.0336</td>
<td>3.24</td>
<td>0.001</td>
<td>0.0414</td>
</tr>
<tr>
<td>constant</td>
<td>−0.56503</td>
<td>0.3097</td>
<td>−1.82</td>
<td>0.069</td>
<td>0.0135</td>
</tr>
<tr>
<td>DI:1999(9)</td>
<td>−0.00780495</td>
<td>0.002587</td>
<td>−3.02</td>
<td>0.003</td>
<td>0.036</td>
</tr>
<tr>
<td>DI:2001(11)</td>
<td>0.0118937</td>
<td>0.00264</td>
<td>4.5</td>
<td>0</td>
<td>0.0768</td>
</tr>
<tr>
<td>DI:2002(5)</td>
<td>−0.0138787</td>
<td>0.003047</td>
<td>−4.56</td>
<td>0</td>
<td>0.0784</td>
</tr>
<tr>
<td>DI:2002(6)</td>
<td>−0.00983857</td>
<td>0.003055</td>
<td>−3.22</td>
<td>0.002</td>
<td>0.0408</td>
</tr>
<tr>
<td>DI:2002(8)</td>
<td>0.0428593</td>
<td>0.003782</td>
<td>11.3</td>
<td>0</td>
<td>0.3448</td>
</tr>
<tr>
<td>DI:2002(9)</td>
<td>−0.0112109</td>
<td>0.004173</td>
<td>−2.69</td>
<td>0.008</td>
<td>0.0287</td>
</tr>
<tr>
<td>DI:2015(7)</td>
<td>0.0187597</td>
<td>0.003222</td>
<td>5.82</td>
<td>0</td>
<td>0.122</td>
</tr>
<tr>
<td>DI:2015(8)</td>
<td>0.0180553</td>
<td>0.003664</td>
<td>4.93</td>
<td>0</td>
<td>0.0905</td>
</tr>
<tr>
<td>DI:2015(9)</td>
<td>0.0116135</td>
<td>0.003194</td>
<td>3.64</td>
<td>3E−04</td>
<td>0.0514</td>
</tr>
<tr>
<td>DI:2016(11)</td>
<td>0.0109242</td>
<td>0.0026</td>
<td>4.2</td>
<td>0</td>
<td>0.0675</td>
</tr>
<tr>
<td>I:1999(3)</td>
<td>0.0160146</td>
<td>0.003868</td>
<td>4.14</td>
<td>0</td>
<td>0.0656</td>
</tr>
<tr>
<td>I:2002(3)</td>
<td>−0.0123709</td>
<td>0.003792</td>
<td>−3.26</td>
<td>0.001</td>
<td>0.0418</td>
</tr>
<tr>
<td>I:2002(9)</td>
<td>0.0716613</td>
<td>0.00782</td>
<td>9.16</td>
<td>0</td>
<td>0.256</td>
</tr>
<tr>
<td>I:2002(12)</td>
<td>0.0125106</td>
<td>0.003989</td>
<td>3.14</td>
<td>0.002</td>
<td>0.0388</td>
</tr>
<tr>
<td>I:2010(2)</td>
<td>−0.0128616</td>
<td>0.003784</td>
<td>−3.4</td>
<td>8E−04</td>
<td>0.0452</td>
</tr>
</tbody>
</table>

**Sigma**

\[
\sigma = 0.00364108
\]

**RSS**

\[
\text{RSS} = 0.003234818
\]

**$R^2$**

\[
R^2 = 0.709425
\]

**Adj. $R^2$**

\[
\text{Adj. } R^2 = 0.679653
\]

**log-likelihood**

\[
\text{log-likelihood} = 1146.73
\]

**no. of observations**

\[
\text{no. of observations} = 270
\]

**mean(CIP)**

\[
\text{mean(CIP)} = 0.0032771
\]

**no. of parameters**

\[
\text{no. of parameters} = 26
\]

**se(Y)**

\[
\text{se(Y)} = 0.00643309
\]

**AR 1-7 test:**

\[
F(7,237) = 2.0045[0.0553]
\]

**ARCH 1-7 test:**

\[
F(7,254) = 0.40492[0.8988]
\]

**Normality test:**

\[
\chi^2(2) = 0.93043[0.6280]
\]

**hetero test:**

\[
F(33,229) = 1.0857[0.3519]
\]

**RESET23 test:**

\[
F(2,247) = 0.29175[0.7472]
\]
All of the coefficients of these factors have the expected sign, according to theory. Our results strongly suggest that macroeconomic factors play a role in the dynamics of CIP in Brazil. The sample covers over twenty years, several of which were turbulent. During the 90s Brazil launched a macroeconomic stabilization plan, and financial turmoil affected many emerging markets. Local market issues due to political instability also had impacts on Brazilian economy.

Furthermore, our results highlight inflation control’s role in preventing volatility in the foreign exchange market, and its impact on the premiums. The flow of investments and stocks of Brazilian external accounts over time are related to solvency, making it straightforward to conclude that they are important in explaining CIP. Finally, reserves are also important to guarantee that the country will be less likely to face liquidity constraints in the future.

The work of García and Didier (2003) shares similarities with our work, given that they model the Brazilian risk premium. In their empirical example, they model the determinants of a stripped C-Bond. The authors highlight that this variable does not include the convertibility risk. Contrary to CIP, investors do not have to face border risks. Our measures of risk premium is thus broader than theirs, and contains all sources of sovereign risk. One possible future path of research could be to analyze other measures of risk using our approach, and unveil possible differences.

Our conclusions are line with those of García and Didier (2003), and provide complementary evidence in favor of their proposition that the high level of real interest rates faced by the Brazilian economy during the period studied were closely linked to macroeconomic imbalances.
### Results of the final model: Restricted version of the best model

<table>
<thead>
<tr>
<th>variable</th>
<th>coefficient</th>
<th>std. error</th>
<th>t-value</th>
<th>p-value</th>
<th>% of $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CIP_{t-1}$</td>
<td>0.224532</td>
<td>0.04432</td>
<td>5.07</td>
<td>0</td>
<td>0.0934</td>
</tr>
<tr>
<td>$F1_{t}$</td>
<td>-0.016271</td>
<td>0.004306</td>
<td>-3.78</td>
<td>0.0002</td>
<td>0.0542</td>
</tr>
<tr>
<td>$F2_{t}$</td>
<td>-0.079333</td>
<td>0.00824</td>
<td>-9.63</td>
<td>0</td>
<td>0.2713</td>
</tr>
<tr>
<td>$F3_{t}$</td>
<td>0.751364</td>
<td>0.135</td>
<td>5.57</td>
<td>0</td>
<td>0.1106</td>
</tr>
<tr>
<td>$F4_{t}$</td>
<td>0.999999</td>
<td>0.1213</td>
<td>8.25</td>
<td>0</td>
<td>0.2145</td>
</tr>
<tr>
<td>constant</td>
<td>-0.476357</td>
<td>0.08859</td>
<td>-5.38</td>
<td>0</td>
<td>0.104</td>
</tr>
<tr>
<td>DI:1999(9)</td>
<td>-0.00773559</td>
<td>0.002562</td>
<td>-3.02</td>
<td>0.0028</td>
<td>0.0353</td>
</tr>
<tr>
<td>DI:2001(11)</td>
<td>0.0119667</td>
<td>0.002593</td>
<td>4.61</td>
<td>0</td>
<td>0.0788</td>
</tr>
<tr>
<td>DI:2002(5)</td>
<td>-0.0137863</td>
<td>0.002988</td>
<td>-4.61</td>
<td>0</td>
<td>0.0788</td>
</tr>
<tr>
<td>DI:2002(6)</td>
<td>-0.0095911</td>
<td>0.003</td>
<td>-3.2</td>
<td>0.0016</td>
<td>0.0394</td>
</tr>
<tr>
<td>DI:2002(8)</td>
<td>0.0429896</td>
<td>0.003683</td>
<td>11.7</td>
<td>0</td>
<td>0.3537</td>
</tr>
<tr>
<td>DI:2002(9)</td>
<td>-0.0110197</td>
<td>0.004081</td>
<td>-2.7</td>
<td>0.0074</td>
<td>0.0285</td>
</tr>
<tr>
<td>DI:2015(7)</td>
<td>0.0188772</td>
<td>0.003173</td>
<td>5.95</td>
<td>0</td>
<td>0.1245</td>
</tr>
<tr>
<td>DI:2015(8)</td>
<td>0.0180645</td>
<td>0.003629</td>
<td>4.98</td>
<td>0</td>
<td>0.0905</td>
</tr>
<tr>
<td>DI:2015(9)</td>
<td>0.0115429</td>
<td>0.003155</td>
<td>3.66</td>
<td>0.0003</td>
<td>0.051</td>
</tr>
<tr>
<td>DI:2016(11)</td>
<td>0.0108379</td>
<td>0.00257</td>
<td>4.22</td>
<td>0</td>
<td>0.0666</td>
</tr>
<tr>
<td>I:1999(3)</td>
<td>0.0163508</td>
<td>0.003689</td>
<td>4.43</td>
<td>0</td>
<td>0.0731</td>
</tr>
<tr>
<td>I:2002(3)</td>
<td>-0.0121073</td>
<td>0.003684</td>
<td>-3.29</td>
<td>0.0012</td>
<td>0.0416</td>
</tr>
<tr>
<td>I:2002(9)</td>
<td>0.0712655</td>
<td>0.007428</td>
<td>9.59</td>
<td>0</td>
<td>0.2699</td>
</tr>
<tr>
<td>I:2002(12)</td>
<td>0.0125321</td>
<td>0.003805</td>
<td>3.29</td>
<td>0.0011</td>
<td>0.0418</td>
</tr>
<tr>
<td>I:2010(2)</td>
<td>-0.0125071</td>
<td>0.003676</td>
<td>-3.4</td>
<td>0.0008</td>
<td>0.0444</td>
</tr>
</tbody>
</table>

| sigma       | 0.00361136  | RSS = 0.003247443 |
| $R^2$       | 0.708291    | F(20,249) = 30.23 [0.001]** |
| Adj. $R^2$  | 0.684860    | log-likelihood = 1146.21 |
| no. of parameters | 270 | 21 |
| meanCIP)    | 0.0032771   | se(Y) = 0.00643309 |

AR 1-7 test: F(7,242) = 1.9411 [0.0639]
ARCH 1-7 test: F(7,256) = 0.38106 [0.9130]
Normality test: $\chi^2(2) = 1.2388 [0.5383]$
hetero test: F(23,239) = 1.2678 [0.1898]
RESET23 test: F(2,247) = 0.3709 [0.6911]

Note: See Equations (12) to (16) for the definitions of Factors 1 to 4.
4.4 The roles of financial crises and political turmoil

Figure 3 contains the intercept-corrected estimates obtained from all interventions. Each dummy is multiplied by its coefficient. Then all terms are added up for each point in time. The evolution of the resulting variable over time is plotted in Figure 3. Figure 3 gives a visual interpretation of the interventions presented in Table 6. As highlighted in 4, we run Autometrics using different configuration sets. We have a total of 13 final models, and we choose the one with the best information criteria. Our best model using the Autometrics algorithm contains no level dummies (SIS). This might indicate that the variables used for selection explain a great part of the variance in the data, and that changes in the risk premium are closely related to our information set. It is also worth noting that the final model does not have structural change in the mean, only outliers. Most of these are clearly related to political or crisis events.

We now discuss the rationale for the instability points the algorithm uncovered:

Russia’s moratorium in 1998 – called the Russian crisis – led to a general “flight-to-quality” movement away from emerging markets. Added to this factor, Brazil abandoned an almost-fixed exchange rate regime, and began letting its currency float, due to a shortage of reserves.

In November 2001, Argentina, an important Brazilian trade partner, aban-
doned its currency board regime. This had a contagion effect on Brazil. Marçal et al. (2011) provide a formal test of how financial events in emerging markets at that time are related.

According to Figure 3, spikes in the CIP series in 2002 relate to Brazilian sovereign risk. An election took place in that year, and there was fear that the new government would adopt an unsustainable macroeconomic policy, leading to possible default and debt repudiation in the next term. The presidential campaign that year generated strong repercussions on the foreign exchange market and assets in general.

Luís Inácio Lula da Silva became president. Contrary to initial expectations, he adopted conservative economic policies by maintaining a positive fiscal primary surplus target, consistent with healthy public-debt dynamics and falling inflation, in his first term, from 2003 to 2006. He was re-elected. During his second term, and increasingly during the two terms of President Dilma Rousseff, his successor, fiscal policy was reversed, and public debt started to follow an unsustainable path. The loss of investment-grade status of Brazilian Federal Government debt from the largest international rating agencies became inevitable in 2015. Starting in 2015, the main factor driving Brazilian sovereign risk was the political crisis that culminated in the impeachment of President Dilma Rousseff. Dummies of July, August, and September 2015 may be related to these downgrades. The dummy of November 2016 is related to the impeachment of Dilma Roussef.

The dummy variable of February 2010 captures the deterioration of global macroeconomic conditions. There was also an effect on Brazilian risk in the third quarter of 2014, given the deteriorating macroeconomic indicators, such as high inflation rates, weak economic growth, and a high risk of recession.

Finally, one might expect that variables related to the Brazilian stock market index (Ibovespa) and risk indicator (VIX) should be selected, in line with Garcia and Didier (2003). However, the dummy variables retained in the final model probably deal better with the instability of the DGP.
4.5 How mature is the Brazilian derivatives market?

The coefficient of the lagged dependent variable, $CIP_t$, is retained (Table 6). The value is almost 0.225, which gives a half-life of 0.465 months (about 13 days). The coefficient of the auto-regressive model of order 1 is 0.476642, which implies a half-life of 0.935 months (about 28 days). This result suggests that much, but not all, of the memory of the CIP series can be related to fundamentals risk and political turmoil. The fact that the final model still contains a lagged variable suggests that, even corrected for the determinants of the fundamentals risk premium and political events, the CIP series still show positive persistence. If only the factors related to the risk premium and political and financial turmoil drive $CIP_t$, we should not have evidence of a significant lagged term of $CIP_t$. The factors related to micro-structure of the Brazilian market may explain the remaining memory. We conjecture that we can take this as evidence that the Brazilian market does not show the depth of a mature market, and market frictions play an important role. More research on this topic would be valuable.

5. Final remarks

This study investigates the determinants of CIP deviations for an important emerging market by means of a Gets automatic model selection using the
Autometrics algorithm developed by Hendry and Doornik (2014).

The results show that the level of risk in Brazil is highly susceptible to changes in the factors driving fundamentals risk. Four main types of variables are important in explaining CIP dynamics: inflation, reserves, trade openness and current issues, and the level of government debt. We also stress the importance of political and financial turmoil in explaining the CIP, which can be captured by IIS techniques.

We also identify a conditional persistence in CIP deviations; that is, even after correcting for the risk premium, CIP still has a significant memory. Brazil is one of the most developed emerging derivatives markets, but our results suggest that it still lacks depth. Research on the micro-structure of Brazilian markets may explain these findings.

References


URL: https://ideas.repec.org/p/imf/imfwpa/2003-221.html


A. Appendix

If we assume that \(X_t\) satisfies the conditions for weak exogeneity as discussed by Pesaran (2015) and Hendry (1995), then the following conditional model can be a starting point of the analysis:

\[
\begin{bmatrix}
b_{11}(L) & b_{12}(L) \\
b_{21}(L) & b_{22}(L)
\end{bmatrix}
\begin{bmatrix}
RP_t \\
MF_t
\end{bmatrix} =
\begin{bmatrix}
c_1(L) \\
c_2(L)
\end{bmatrix}X_t + \begin{bmatrix}
\varepsilon_{1,t} \\
\varepsilon_{2,t}
\end{bmatrix}
\] (17)

\[
\begin{bmatrix}
\varepsilon_{1,t} \\
\varepsilon_{2,t}
\end{bmatrix} \sim IID(0, \Omega)
\] (18)

where \(b_{ij}(L)\) and \(c_i(L)\) denote polynomials.

Similar to Zellner et al. (1974) and after some algebra:

\[
\begin{bmatrix}
RP_t \\
MF_t
\end{bmatrix} = \frac{1}{\theta(L)} \begin{bmatrix}
b_{22}(L) & -b_{12}(L) \\
-b_{21}(L) & b_{11}(L)
\end{bmatrix} \begin{bmatrix}
c_1(L) \\
c_2(L)
\end{bmatrix}X_t + \begin{bmatrix}
\varepsilon_{1,t} \\
\varepsilon_{2,t}
\end{bmatrix}
\] (19)

\[
\theta(L) \begin{bmatrix}
RP_t \\
MF_t
\end{bmatrix} = \begin{bmatrix}
c_1(L)b_{22}(L) - b_{12}(L)c_2(L) \\
-c_1(L)b_{21}(L) + b_{11}(L)c_2(L)
\end{bmatrix}X_t + \begin{bmatrix}
b_{22}(L)\varepsilon_{1,t} - b_{12}(L)\varepsilon_{2,t} \\
-b_{21}(L)\varepsilon_{1,t} + b_{11}(L)\varepsilon_{2,t}
\end{bmatrix}
\] (20)

where \(\theta(L) = b_{11}(L)b_{22}(L) - b_{12}(L)b_{21}(L).\)

Note that (20) admits a VARMA representation. From (20) and (5) we can obtain

\[
\theta(L)CPI_t = \{c_1(L)(b_{22}(L) - b_{21}(L)) - c_2(L)(b_{12}(L) - b_{11}(L))\}X_t + \phi(L)\eta_t
\] (21)

Note that we can rewrite the last term of (21) as

\[
\phi(L)\eta_t = (b_{22}(L) - b_{21}(L))\varepsilon_{1,t} + (b_{11}(L) - b_{12}(L))\varepsilon_{2,t}.
\] (22)

If the roots of \(\phi(L)\) are outside the unit circle, then we can approximate the (22) CIP by an autoregressive distributed lag (ADL) model of a sufficiently high order.

If we assume that \(b_{12}(L) = b_{21}(L) = 0, b_{22}(L) = 1, b_{11}(L)\) has order one, and \(\sigma_1^2 \gg \sigma_2^2\), then CIP can be well approximated by an autoregressive distributed lag model with one lag for CIP and with no evidence of autocorrelation:

\[
\theta(L)CPI_t = \{c_1(L)(b_{22}(L)) + c_2(L)(b_{11}(L))\}X_t + \varepsilon_{1,t}.
\] (23)
The rationality for this hypothesis lies in the assumption that the dynamics of risk premium are fully addressed by the extensive list of fundamentals used in the selection, and remaining variance of CIP is driven basically by market frictions issues. Given our hypothesis, Equation (23) suggests that the relevance of lagged dependent variable in an ADL model may be interpreted as market friction. The Autometrics algorithm tends to unveil relevant political events by highlighting these as outliers.