Measuring Shift-Contagion with a Bayesian Time-Varying Coefficient Model

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Outline

- Motivation
- Related literature and our contribution
- Econometric framework
- Application to the Chilean FX market

Motivation

1. Financial crises appear correlated across mkts/countries

2. As a consequence, growing interest in "contagion", broadly defined as the transmission of shocks (or crises) across markets (or countries)

3. Crises may be transmitted either through stable channels/ linkages (FR call this interdependence) or through sudden (and temporary?) changes in these linkages (FR called this shift-contagion).

4. From a policy perspective, it is important to be able to discriminate between the two alternative transmission mechanisms: if it's (temporary) shift-contagion, it may make sense to "fight" the shock (e.g., intervene in the FX market); if it's interdependence (or a permanent shift in the transmission mechanism), the battle is unlikely to be worth fighting (e.g., don't waste reserves by intervening).

Contribution

1. We take one reasonable and well known definition of contagion from the literature and focus on measurement problems.

2. In particular, we show how a Bayesian Time-Varying Coefficient Model (BTVC) may be used to measure shift-contagion.

   (a) We model cross-market linkages as changing randomly all the time, estimate their time profile, and look for quantitatively sizable and economically plausible shifts in these linkages

   (b) We use the proposed framework to the investigate shift-contagion from the Argentine crisis in the Chilean foreign exchange market

On the definition of contagion used

1. Shift-contagion is defined by FR as a sudden change in cross-country linkages following a crisis in one or more countries (Forbes and Rigobon (2000, 2001)). Note that:

    (a) According to this definition, a strong association between two markets, both before and after a crisis in one market, is not an instance of "shift-contagion" but of "interdependence".

    (b) This definition does not distinguish between temporary and permanent (or persistent) shifts in linkages.

2. We shall define shift-contagion as a temporary shift in the linkages because this aspect of the definition is important for policy analysis

Existing methods to measure contagion

1. Ideally, two steps approach to measure contagion (Favero and Giavazzi, 2002):

   (a) identify the channels by estimating a model of interdependence;

   (b) and check whether the strength of the linkages changed significantly during a crisis

2. However, in practice there is a trade off between the efficiency costs of identifying all channels with large models and omitting relevant variables (observable or latent) which may bias the tests in smaller set ups.

3. In addition, by using existing methods to measure contagion (correlations, OLS-based regressions, or dummy variables approaches):

   (a) Not only the source but also the precise timing of the crisis ought to be known;

   (b) In limited information settings, (i) cross-market correlations may increase even without a shift in linkages when volatility increases in the crisis country (Rigobon (2001)); (ii) this (upward) bias can be corrected only if we do not have simultaneity and/or omitted variables. Otherwise, these methods are biased, and the bias is difficult to correct (Rigobon (2001));

   (c) Full information settings may not be available if channels are not observable (e.g., global risk aversion).

Measurement problems

1. If the DGP is

$$y_t = \beta_1 + \beta_2 x_t + u_t$$

   (a) correlation coefficient ρ_{y_x} depends positively on $V(x)$, therefore it is not a good measure of contagion, because an increase in volatility, typically during turmoils, might be misleadingly called contagion. We must use a corrected measure (FR, 2001)

   (b) OLS estimation of β_2 does not have this problem. Testing contagion has other problems: timing of the crisis must be known; too few observations to test; no distinction between contagion and structural break.

2. If the DGP is instead

$$y_t = \beta_1 + \beta_2 x_t + \beta_3 z_t + u_t$$

but we estimate

$$y_t = \beta_1 + \beta_2 x_t + u_t$$

then we have an omitted variable problem. OLS is biased and may induce the same problem as the correlation coefficient in testing contagion whenever volatility increases. But notice that:

(a) (classical omitted variable) If:

$$z_t = \gamma x_t + \eta_t$$

the bias is constant in turmoil periods (i.e. when $V(z)$ or $V(x)$ increase);

(b) (latent common factor) if

$$x_t = \gamma z_t + \eta_t$$

the bias changes in turmoil periods (i.e. it increases with $V(z)$ and decreases with $V(\eta)$.

On the measure of contagion proposed here

1. No need to know the timing of the crisis, as coefficients are allowed to change all the time.

2. It may distinguish between temporary shifts and structural breaks.

3. The model allows for both interdependence and shift-contagion:

   - Thus, may be specified as full or limited information model: a stable association between two markets before and after a crisis may be traced in the usual manner, while shift-contagion can be detected by a temporary shift in the model parameters;

- As in the case of OLS-based methods, it may provide evidence on the specific channels of transmission of shocks across markets and is not biased by shifts in volatility alone

- It works in the joint presence of heteroskedasticity and omitted variables in a limited information setting (because the estimator may be corrected for omitted variables)

- Can be more easily estimated in a full information setting by using hierarchical specifications (i.e., it's easier to estimate large models without running into overfitting problems using Bayesian procedures).

Econometric framework

The Model is a BTVC model (an old friend, Canova 1993 and Canova and Ciccarelli 2000, useful also for other purposes (Ciccarelli and Rebucci, 2001a)):

$$A_t(L)\,Y_t = B_t(L)\,W_t + D_t + U_t,$$

where

- $Y_t = [y_t^1, \cdots, y_t^n]'$ is a $n \times 1$ vector of asset prices or quantities

- $W_t = [w_t^1, \cdots, w_t^m]'$ is a $m \times 1$ vector of controls and sources of shocks/crises

- $A_t(L)$ and $B_t(L)$ are time-varying polynomial matrices in the lag operator L with lag length p, and D_t is a vector of deterministic variables

- $U_t = [u_t^1, \cdots, u_t^n]'$ is a $n \times 1$ vector of country or market specific shocks

Specification

The model can be written in reduced form as:

$$Y_t = X_t\beta_t + \varepsilon_t \tag{1}$$

Assumptions:

(i) $\varepsilon_t \mid X_t \sim iid$ with $E[\varepsilon_t \mid X_t] = 0$ and $E[\varepsilon_t\varepsilon_t' \mid X_t] = \Sigma$;

(ii) $\beta_t = G\beta_{t-1} + F\beta_0 + H\zeta_t$ with $\zeta_t \sim iidN\left(0, \Phi\right)$;

(iii) X_t, ε_t and ζ_t are conditionally independent;

(iv) $\varepsilon_t \mid X_t \sim iit_\nu\left(0, \Omega\right)$, with $\Omega = \frac{\nu-2}{\nu}\Sigma$ and $\nu > 2$ (so that $E[\varepsilon_t \mid X_t] = 0$ and $E[\varepsilon_t\varepsilon_t' \mid X_t] = \Sigma$).

with G, F, and H known matrices of conforming dimension.

On the assumptions

1. Under assumptions (i)-(iii), Y_t is a conditionally heteroskedastic process, with non-linear conditional mean and variance (shown and discussed in Canova, 1993)

2. Adding assumption (iv), Y_t becomes a non-normal process (i.e., with fat tails)

3. Hence, our BTVC model should capture well typical features of high frequency financial data.

Estimation

Estimation is Bayesian.

- $Y^T = (Y_1, ..., Y_T)$ denote the sample data
- $\psi = (\{\beta_t\}_t, \Sigma, \beta_o, \Phi, \nu)$ denotes the parameters of interest
- $p(\psi)$ is the prior distribution
- $f\left(Y^T \mid \psi\right)$ is the likelihood.

Then

$$p\left(\psi \mid Y^T\right) \propto p(\psi)\, f\left(Y^T \mid \psi\right)$$

Estimation based on Markov Chain Monte Carlo (MCMC) techniques (for a survey see Ciccarelli and Rebucci, 2002).

Posteriors of interest

- Posterior mean of coefficients

$$\beta_t \mid X_t, Y_t, \psi_{-\beta_t} \sim N\left(\hat{\beta}_t, \hat{V}_t\right),$$

with

$$\hat{\beta}_t = \hat{\beta}_{t-1} + \hat{V}_{t-1} X_t \left(h_t \boldsymbol{\Sigma} + X_t \hat{V}_{t-1} X_t'\right)^{-1} \left(Y_t - X_t \hat{\beta}_{t-1}\right)$$

$$\hat{V}_t = \hat{V}_{t-1} - \hat{V}_{t-1} X_t' \left(h_t \boldsymbol{\Sigma} + X_t \hat{V}_{t-1} X_t'\right)^{-1} X_t \hat{V}_{t-1}.$$

- Volatility of error term

$$h_t \mid X_t, Y_t, \psi_{-h} \sim \text{Inv-}\chi^2\left(\nu_t, s_t^2\right)$$

with

$$\nu_t s_t^2 = \nu_{t-1} s_{t-1}^2 + \left(Y_t - X_t' \beta_t\right)' \boldsymbol{\Sigma}^{-1} \left(Y_t - X_t' \beta_t\right)$$

Features

1. The estimator of β_t (Kalman filter with a standard prior) is as unbiased as the OLS, but more efficient if the prior information is not diffuse (i.e., is more than complete 'ignorance').

2. The posterior mean of h_t depends on present and past values of functions of ε_t^2 in an autoregressive way: there is a posterior GARCH structure in the variance of the error term (similar to the "prior" of Cogley and Sargent 2002).

3. But it is not robust to the omission of relevant variables, even though a correction can be easily implemented at a small computational cost

Omitted variables: the problem

Consider a non-stochastic linear regression function:

$$Y_t = X_t\beta + Z_t\gamma$$

Assume, for instance, that

$$Z \mid X = XR + \eta$$

Thus, the true model is

$$Y = X\beta + XR\gamma + \eta\gamma$$

If instead we estimate

$$Y = X\beta + \varepsilon,$$

we have the well known mis-specification problem unless either $R = 0$ (omitted variables are uncorrelated with the included variables) or $\gamma = 0$ (omitted variables have no effect on Y).

Omitted variable: one solution (Leamer)

Inferences about β, however, may be made by observing Y and X alone provided we have a (probabilistic) view about Z.

- The model

  $$Y = X\beta + X\beta^c + \xi,$$

  where $\beta^c = R\gamma$ and $\xi = \eta\gamma$, offers a closer approximation to the true one because it admits the possibility of omitted variables, even though it does not requires us to know them.

- The fundamental difference between this and the false model is that the latter includes a statement about the quality of the experiment (a prior about β^c), while a false model does not.

- The identification problem is solved in a Bayesian context with an appropriate prior (in a classical world we would have perfect collinearity).

Omitted variable: the performance

We run two Monte Carlo experiments:

Model 1 (standard omitted variable specification)

$$\begin{array}{rcl} y_t & = & \beta x_t + \gamma z_t + \varepsilon_t \qquad x_t = \rho x_{t-1} + \eta_t \\ z_t & = & \delta x_t + u_t, \qquad \delta \in \left\{\bar{\delta}/2, \bar{\delta}\right\} \qquad\qquad t = 1, ..., 200 \\ \beta & \sim & N\left(\bar{\beta}, 0.25\bar{\beta}\right) \quad \gamma \sim N\left(\bar{\gamma}, 0.25\bar{\gamma}\right) \\ \varepsilon_t & \sim & N\left(0, \sigma_{\varepsilon}^2\right) \qquad u_t \sim N\left(0, \sigma_u^2\right) \end{array}$$

where heteroskedasticity in x created by

$$\begin{array}{rcl} \eta_t & \sim & N\left(0, \sigma_{L,\eta}^2\right) \quad t = 1, 100 \\ \eta_t & \sim & N\left(0, \sigma_{H,\eta}^2\right) \quad t = 101, 200. \end{array}$$

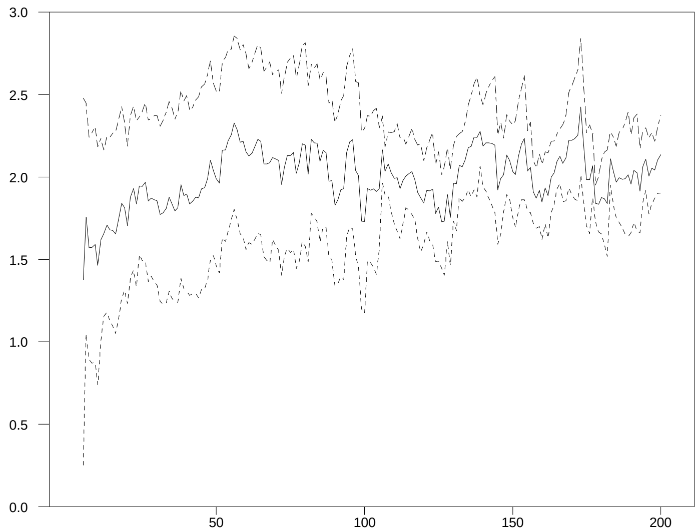
Parametrization replicates the worst case in FR (2001). Estimated models are:

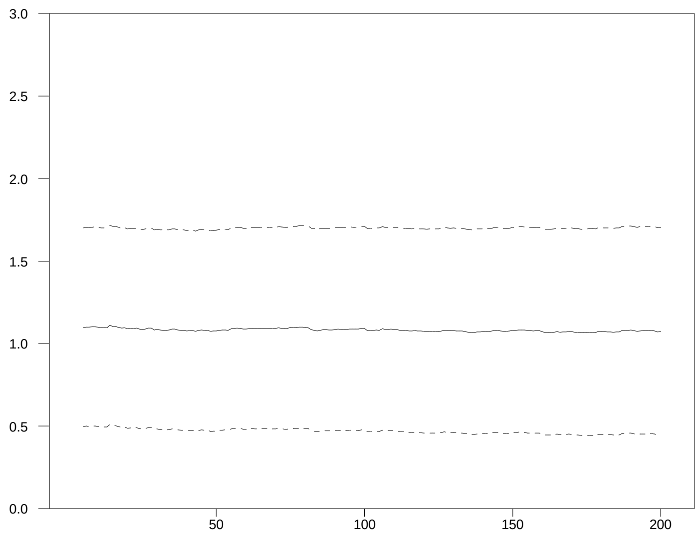
$$y_t = \beta_t x_t + \varepsilon_t$$

vs.

$$y_t = \beta_t x_t + \beta_t^c x_t + \varepsilon_t$$

Natural candidate for the prior mean of β_t: FR corrected correlation coefficient





Posterior distribution of β_t

Model 2 (The omitted variable is a common factor; see Rigobon, 2000 for a discussion)

$$\begin{aligned}
y_t &= \beta x_t + \gamma z_t + \varepsilon_t \qquad z_t = \rho z_{t-1} + \eta_t, \\
x_t &= \delta z_t + u_t \qquad \delta \in \left\{\bar{\delta}/2, \bar{\delta}\right\} \qquad\qquad t = 1, ..., 200 \\
\beta &\sim N\left(\bar{\beta}, 0.25\bar{\beta}\right) \quad \gamma \sim N\left(\bar{\gamma}, 0.25\bar{\gamma}\right) \\
\varepsilon_t &\sim N\left(0, \sigma_\varepsilon^2\right) \qquad u_t \sim N\left(0, \sigma_u^2\right)
\end{aligned}$$

and

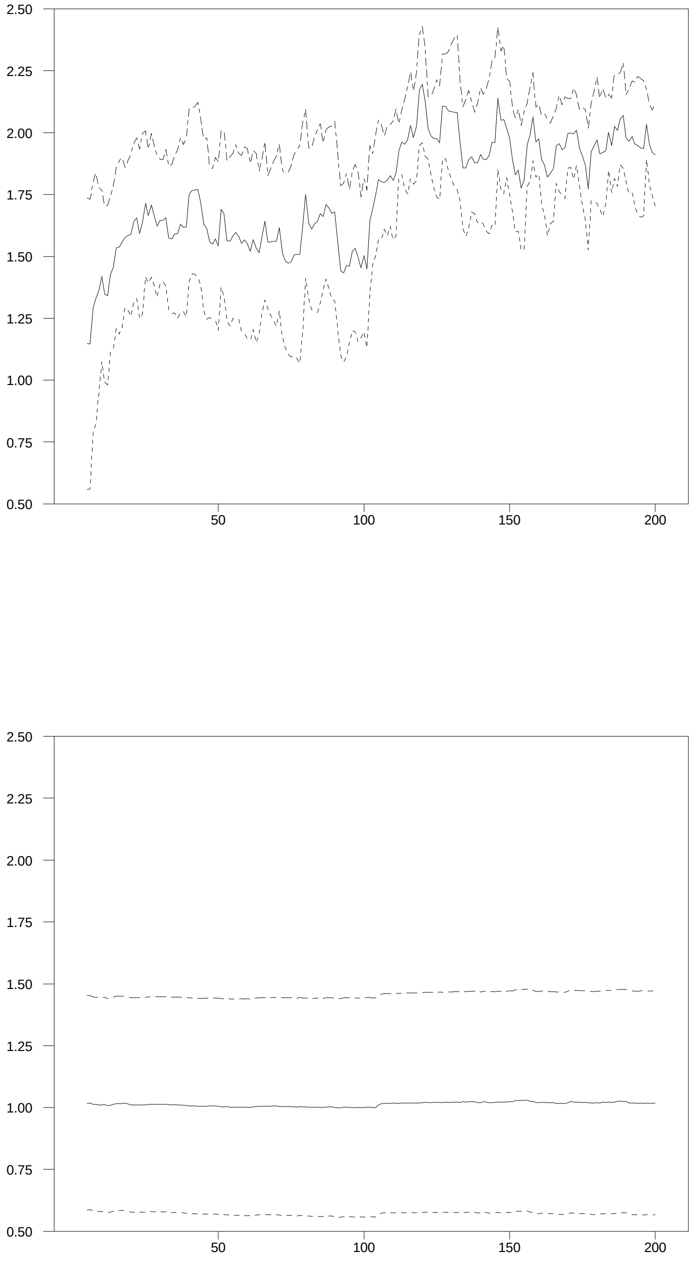
$$\begin{aligned}
\eta_t &\sim N\left(0, \sigma_{1,\eta}^2\right) \qquad\qquad t = 1, 100 \\
\eta_t &\sim N\left(0, \sigma_{2,\eta}^2\right) \qquad\qquad t = 101, 200.
\end{aligned}$$

The estimated models are:

$$y_t = \alpha_{1t} x_t + \varepsilon_t$$

vs

$$y_t = \alpha_{1t} x_t + \alpha_{1t}^c x_t + \varepsilon_t$$



Posterior distribution of α_{1t}

An application to the impact of the Argentine crisis on the Chilean FX market

An interesting case for several reasons:

- Because it's a natural experiment in which we can easily specify both an approximate "full" and a "limited" information model and compare results, with and without correction. In fact, there are no serious endogeneity problems and it is possible to consider a fairly comprehensive set of transmission channels.

- Because interesting also from a policy perspective: the BCCh intervened in the FX market in August-December 2001 for the first time since the free floatation of the peso in September 1999, motivating its decision by invoking "exceptional circumstances" consistent with its previously stated FX policy.

- Because it's a case in which other approaches would be difficult to apply:
  - The Argentine crisis unfolded slowly and is far from being over at this time;
  - It would be hard to define the right estimation windows for a "before and after crisis" approach;
  - Even assuming a window of interest could be established, there probably would be too few observations for efficient estimation after the crisis (our method can be applied in almost real time: sample period ends in January 2002);
  - Selecting a suitable number of dummy variables could also be difficult.

The background

- The Chilean peso depreciated very sharply in 2001, and there is no consensus on which were the main driving forces (copper price, domestic monetary policy, fundamental trade and investment linkages with Argentina, or pure contagion) (See Rebucci, 2002 for more details).

- We ask the question of whether this exchange rate was affected by "shift-contagion" from Argentina and, at the same time, whether the method we are proposing works well in practice.

What do we do?

1. We use two models: a "full" information model that considers a comprehensive set of potential explanatory factors and a "limited" information model that includes only two variables, as we would have to do in a multi-country context.

2. We estimate both of them, with and without the correction.

3. And finally we analyze and compare the results to address our question and assess the performance of the approach proposed, including particularly the effectiveness of the correction for omitted variable.

Model 1

Model 1 is a simple ADL (see Table 1 for detailed list of variables):

$$DLe_t = \alpha_t^0 + \alpha_t^1 DLe_{t-1} + \mathbf{Z}_t^{\prime}\gamma_t$$

$Dx_t = x_t - x_{t-1}$ and $Lx_t = \log(x_t)$

$\mathbf{Z}_t$ includes a comprehensive set of variables: (i) a terms of trade variable (copper price); (ii) domestic factors (a bunch of return differential with US comparable assets); (iii) regional factors (Argentine and Brazilian variables); (iv) and global factors (the dollar/euro rate and a semiconductor price index).

But may be omitting other variables, including observable domestic (e.g., a long run equilibrium relation with copper, a Chilean corporate bond spread), regional (e.g., Mexico), and global factors (e.g., US corporate bond spreads), and unobservable factors such as global risk aversion and the like.

Model 2

Model 2 is the analogous of a simple correlation coefficient, except for the lagged endogenous variable included to capture some persistence detected in the data (see Figure 3):

$$DLe_t = \alpha_t^0 + \alpha_t^1 DLe_{t-1} + \gamma_t^4 Di_t^{AR} + \varepsilon_t$$

This specification is known to omit, in addition to a bunch of control variables, an important (observable) common factor: the Brazilian variables included in model (1) (see correlation matrix in Table [2] and OLS regression in Table 4).

Actual specification and estimation

Defining $y_t \equiv DLe_t$ and collecting variables we have:

$$y_t = x_t' \beta_t + \varepsilon_t$$

Assume:

$$\beta_t = \beta_{t-1} + \zeta_t.$$

and estimate the model as explained in the previous section.

1. Initialize Model 1 with OLS estimates (Table 4); and Model 2 with RF corrected correlation

2. $\nu_o = 5$

3. $\Phi = \phi V_o^*$, with $\phi = 0.001$

4. 5000 iterations of the MCMC. Discard the first 2500. Convergence is already achieved after 1000 iterations.

Data

- Daily data from June 2, 1999 to January 31, 2002.

- Strong co-movements among the Chilean spot rate and Brazilian and Argentine variables on the one hand, and between Argentine and Brazilian variables on the other. (But Chile is small!)

- Importance of taking non-normality and conditional heteroskedasticity into consideration when modeling these series

Results: full information

Without correction

- Some instability characterizes the posterior distribution of all coefficients at some point over the sample period

- Much more visible in May-June, 2001. It is strikingly clear in the case of the Argentine risk indicators, but it is evident also for other variables.

- Note that (i) the shift is temporary and (ii) the Argentine spread has not decreased after January 2002.

With correction: Evidence of contagion is less striking, but there is not much difference (see error bands).

Hence the shift is not the artefact of volatility and omitted variables.

Results: limited information

Without correction:

- Bias in the estimation
- Not clear when contagion starts
- Comparable to rolling correlation coefficient

With correction:

- Almost no bias
- Comparable to the result obtained with "full information"

Conclusions and extensions

No need to know the timing of the crisis

Distinguish between temporary shifts and structural breaks

Much more favorable trade off full/limited information setting

The correction works reasonably well both in simulated and actual data.

We find evidence of shift-contagion.

The next step is a multivariate analysis of stocks, spreads and exchange rates in 1990s (work in progress: here there is also an endogeneity problem. Identification by size as in Ciccarelli and Rebucci, 2001).

Also possible in a multivariate context, perhaps, to find a way to estimate omitted, unobservable common factors by using dynamic principal component methods in a first stage of the analysis.

Table 1. The Set of Potential Explanatory Factors Considered

Acronimous	Name	Definition	Unit of Measure	Sampling	Source
DLe	Chilean spot rate	Log-change in the Chilean peso /U.S. dollar rate	Daily return in percent	Closing quote	Bloomberg
DLc	Copper price	Log-change in the London metal Exchange spot copper price	Daily return in percent	Closing quote	Bloomberg
m	Interest rate differential	Short-term interest rate differential (TAB-90 rate minus federal fund rate) (TAB-90 rate in UF)	Percentage point per year	Daily average	Bloomberg and Associacion de Bancos
Dm	Interest rate differential change	Change in short-term interest rate differential (TAB-90 rate minus federal fund rate)	Percentage point per year	Daily average	Bloomberg
DiCHL	Chilean sovereign risk	Change in the Chilean component of the EMBI Global index	Percentage point per year	Unknown	Bloomberg
DfCHL	Chilean currency risk	Change in the differential between the implied one-year NDF interest rate and the one-year U.S. Treasury yield (constant to maturity)	Percentage point per year	Mid-yield	Bloomberg and IMF ICM Department
s	Stock market differential	Stock market daily return differential (IGPA index minus S&P500 index)	Percentage point per day	Closing quote	Bloomberg
DiAR+	Argentine sovereign risk	Change in the Argentine component of the EMBI+ index	Percentage point per year	Closing quote	Bloomberg
DfAR	Argentine currency risk	Change in the differential between the implied one-year NDF interest rate and the one-year U.S. Treasury yield (constant to maturity)	Percentage point per year	Mid-yield	Bloomberg and IMF ICM Department
DLeAR	Argentine spot rate	Log-change in the Argentine peso/U.S. dollar rate	Daily return in percent	Closing quote	Bloomberg
DiBR+	Brazilian sovereign risk	Change in the Brazilian component of the EMBI+ index	Percentage point per year	Closing quote	Bloomberg
DfBR	Brazilian currency risk	Change in the differential between the implied one-year NDF interest rate and the one-year U.S. Treasury yield (constant to maturity)	Percentage point per year	Mid-yield	Bloomberg and IMF ICM Department
DLeBR	Brazilian spot rate	Log-change in the Brazilian real/US dollar rate	Daily return in percent	Closing quote	Bloomberg
DLb	Semiconductor price	Log-change in a semiconductor spot price (DRAM module, 100 mghz bus 128 MB)	Daily return in percent	Unknown	Datastream (DRMU03S)
DLeEU	Euro spot rate	Log-change in the Euro/U.S. dollar rate	Daily return in percent	Closing quote	Bloomberg

All exchange rates are expressed in units of national currencies per U.S. dollar.

Table 2. Sample Correlation Matrix (June 2, 1999 - January 31, 2002)

	Chilean Spot Rate Dle	Semi-conductor Price DLb	Euro Spot Rate DLeEU	Interest Rate Differen-tial m	Interest Rate Differen-tial Change Dm	Chilean Sovereign Risk DiCHLg	Chilean Currency Risk DfCHL	Stock Market Differen-tial s	Copper Price DLc	Brazilian Sovereign Risk DiBR+	Brazilian Currency Risk DfBR	Brazilian Spot Rate DLeBR	Argentine Sovereign Risk DiAR+	Argentine Currency Risk DfAR	Argentine Spot Rate DLeAR
Chilean spot rate	1,00														
Semiconductor price	-0,07	1,00													
Euro spot rate	0,01	0,03	1,00												
Interest rate differential	-0,06	0,15	0,01	1,00											
Interest rate differential change	-0,03	0,03	-0,01	0,11	1,00										
Chilean sovereign risk	0,01	0,00	-0,03	-0,03	-0,04	1,00									
Chilean currency risk	-0,07	0,00	0,01	-0,05	-0,07	0,06	1,00								
Stock market differential	0,09	-0,06	-0,06	0,01	-0,03	0,04	0,03	1,00							
Copper price	-0,04	0,14	-0,02	0,07	0,05	0,03	-0,02	-0,11	1,00						
Brazilian sovereign risk	0,33	-0,07	-0,07	-0,08	-0,11	0,10	0,07	0,22	-0,10	1,00					
Brazilian currency risk	0,15	-0,05	-0,01	-0,03	-0,05	0,03	0,05	0,05	0,00	0,24	1,00				
Brazilian spot rate	0,37	0,01	0,02	-0,06	-0,06	0,00	0,02	0,09	-0,08	0,41	0,18	1,00			
Argentine sovereign risk	0,19	-0,02	0,06	0,11	-0,02	0,02	-0,02	-0,01	0,01	0,36	0,14	0,19	1,00		
Argentine currency risk	0,18	-0,02	0,00	0,12	-0,03	-0,10	0,06	-0,06	0,03	0,25	0,18	0,22	0,34	1,00	
Argentine spot rate	0,05	0,03	0,02	0,22	0,00	0,02	-0,07	-0,03	0,01	0,02	0,01	0,06	0,11	-0,07	1,00

Sources: Bloomberg; Datastream; Fund database (ICM Dept.); and Fund staff calculations.

Table 3: Sample Descriptive Statistics (June 2, 1999-January 31, 2002)

	Chilean spot rate Dle	Semi-conductor Price DLb	Euro spot rate DLeEU	Interest rate differential m	Interest rate differential change Dm	Chilean sovereign risk DiCHLg	Chilean currency risk DfCHL	Stock market differential s	Copper price DLc	Brazilian sovereign risk DiBR+	Brazilian currency risk DfBR	Brazilian spot rate DLeBR	Argentine sovereign risk DiAR+	Argentine currency risk DfAR	Argentine spot rate DLeAR
Mean	0,05	-0,19	0,03	0,28	0,00	0,00	-0,01	0,05	0,02	0,00	0,00	0,05	0,06	0,21	0,10
Median	0,04	0,00	0,04	-0,04	0,00	0,00	-0,01	0,07	0,00	-0,01	-0,01	0,08	0,01	0,00	0,00
Standard Deviation	0,49	4,17	0,69	1,57	0,18	0,08	0,15	1,28	1,18	0,18	0,40	0,88	0,72	3,16	1,67
Kurtosis	2,62	27,48	3,17	3,15	19,35	15,74	4,42	1,67	6,18	1,73	5,86	4,51	45,13	65,17	266,33
Skewness	0,35	2,84	-0,56	1,88	0,02	-0,33	0,04	-0,08	0,77	0,27	0,68	-0,07	0,51	-0,60	14,26
Minimum	-1,92	-17,89	-4,47	-1,42	-1,41	-0,55	-0,72	-4,88	-4,77	-0,71	-1,96	-4,40	-7,96	-38,88	-7,84
Maximum	2,43	42,02	2,03	6,00	1,39	0,55	0,86	6,54	8,90	0,69	2,16	5,21	7,15	33,30	33,65
Number of observations	641	641	641	641	641	641	641	641	641	641	641	641	641	641	641

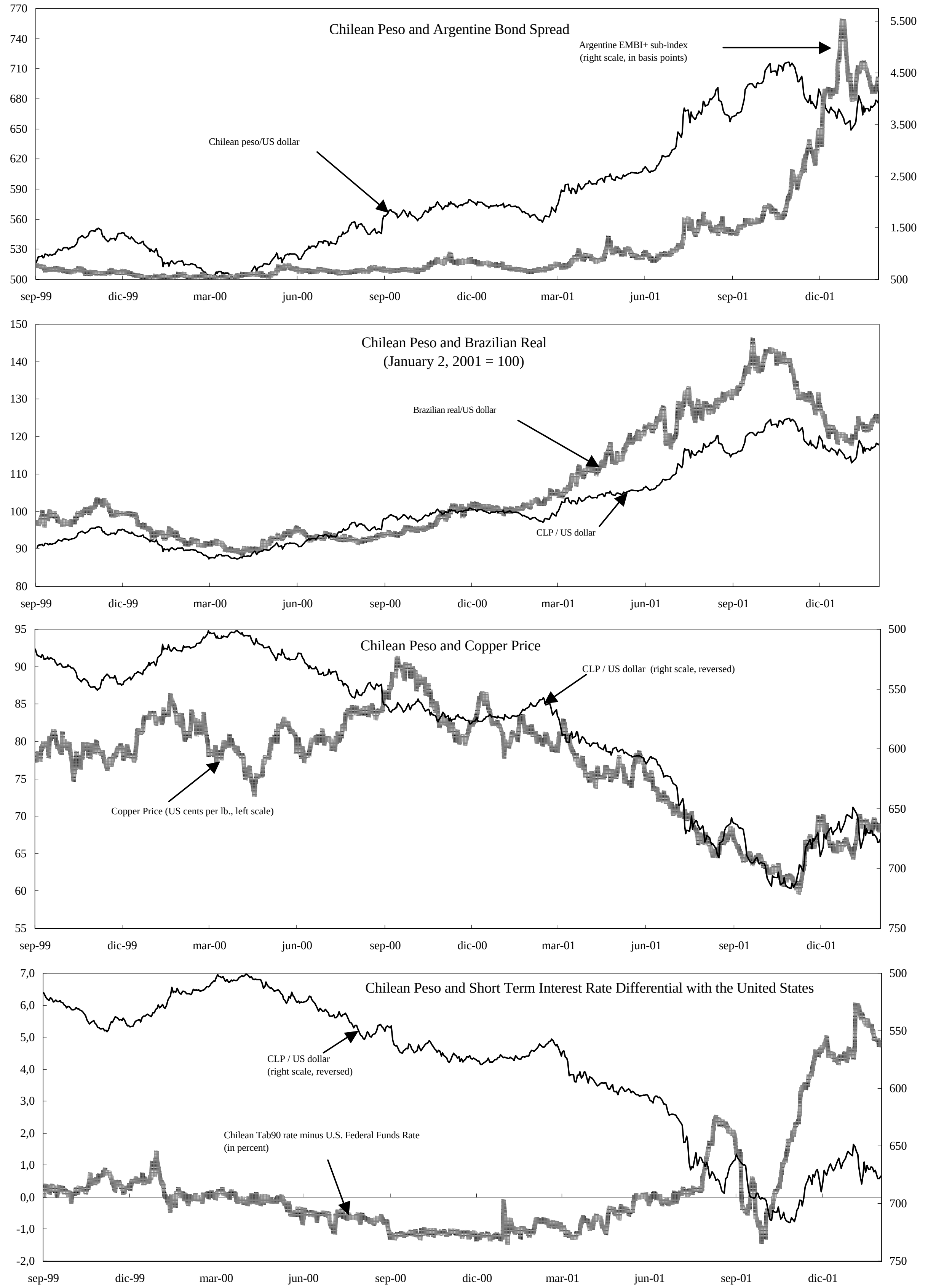
Sources: Bloomberg; Datastream; Fund database (ICM Dept.); and Fund staff calculations.

Table 4. Empirical Results from OLS Estimation with Time-Invariant Coefficients
(Sample: June 2, 1999 - January 31, 2002)

Model 1/	Corr. Coeff.	1	2	3
Independent variables 2/				
Lagged Chilean spot rate (log-change)	0,12	0,09	0,12	0,09
		1,80	2,57	1,89
Semiconductor price (log-change)	-0,07	-0,04	-0,03	-0,05
		-1,11	-0,77	-1,30
Euro spot rate (log-change)	0,01	0,01	0,00	0,01
		0,30	0,03	0,21
Interest rate differential (lagged level)	-0,06	-0,04	-0,09	-0,04
		-1,00	-1,51	-0,99
Interest rate differential change (lagged change)	-0,03	0,05	0,05	0,05
		1,92	1,62	2,12
Chilean sovereign risk (lagged change)	0,01	-0,02	-0,02	-0,02
		-0,63	-0,63	-0,65
Stock market differential (lagged level)	0,09	-0,002	0,05	0,00
		-0,04	1,26	0,04
Copper price (log-change)	-0,04	-0,01	-0,04	-0,01
		-0,16	-0,90	-0,24
Copper gap (lagged log-level)	0,04	na	na	-0,09
		na	na	-2,35
Brazilian sovereign risk (change)	0,33	0,16	na	0,16
		2,67	na	2,63
Brazilian currency risk (change)	0,15	0,04	na	0,03
		0,09	na	0,75
Brazilian spot rate (log-change)	0,37	0,26	na	0,26
		5,78	na	5,76
Argentine sovereign risk (change)	0,19	0,07	0,16	0,07
		1,48	2,60	1,59
Argentine currency risk (change)	0,18	0,07	0,15	0,07
		1,95	3,35	1,88
No. of observations	641	641	641	641
R-Square	na	0,19	0,09	0,20

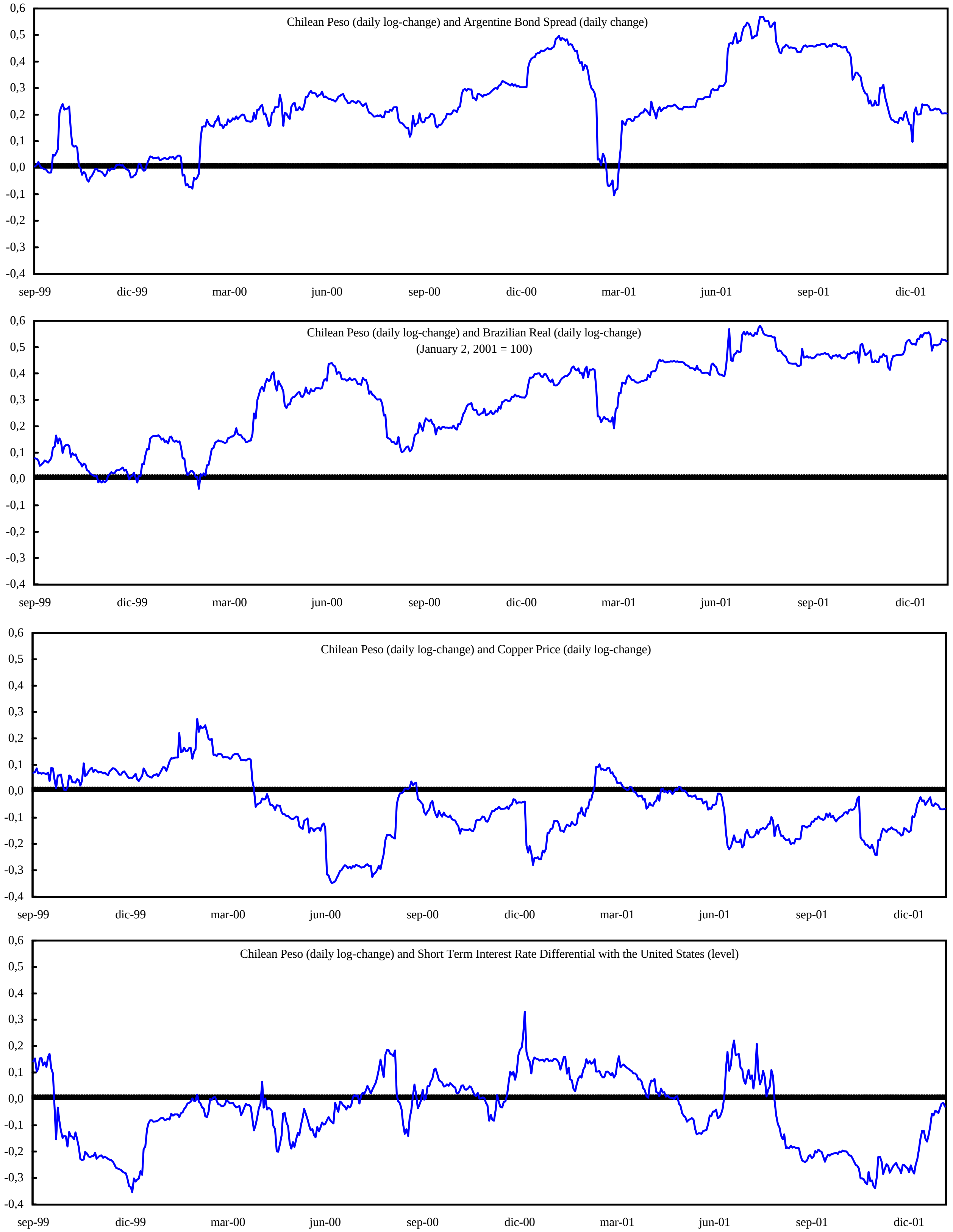
Sources: Bloomberg; Datastream; Fund database (ICM Dept.); and Fund staff calculations.
1/ The dependent variable is always the log-change in the peso/dollar rate.
2/ OLS regression coefficients and heteroskedastic consistent t-values, respectively, reported.
3/ ECM = Le - 8.53 + 0.3*Lc - 0.0004*Trend (+ means "undervalued" w.r.t. equilibrium, which is normalized to zero.)

Figure 1. The Chilean Peso/US Dollar Spot Rate and Selected Determinants 1/
(September 1999 - January 2002)



Sources: Bloomberg; and Fund staff estimates.
1/ All variables expressed in levels.

Figure 2. Rolling 80-Day Correlations with Selected Potential Determinants
(September 1999 - January 2002)



Sources: Bloomberg; and Fund staff estimates.

Figure 3. Persistence of Daily Exchange Rate Log-Changes and Squared Log-Changes 1/

Source: Fund staff estimates.

1/ ACF means auto-correlation function; SDLe is the log-change of the peso/dollar rate; SDLe2 is the square of the log-change.

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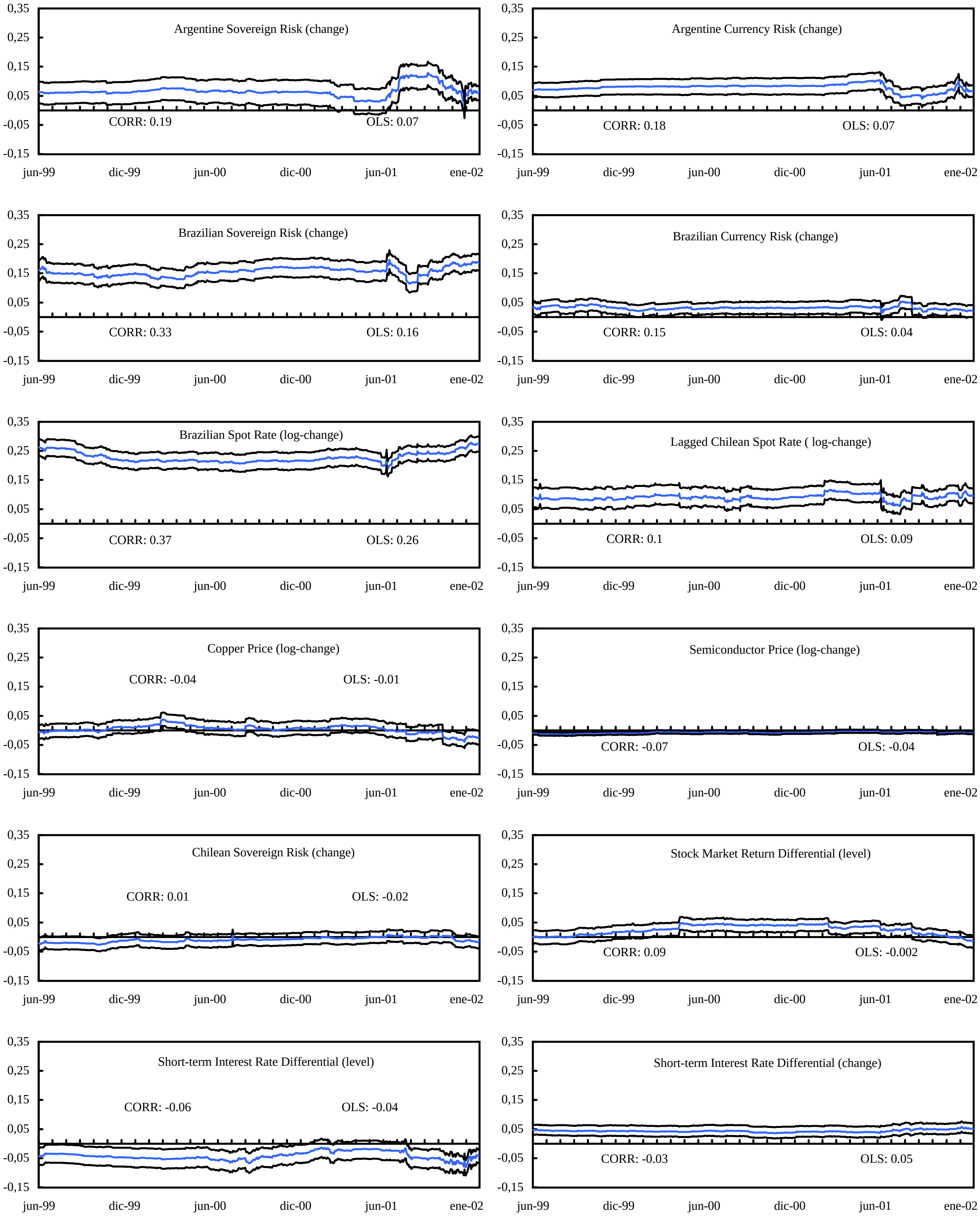
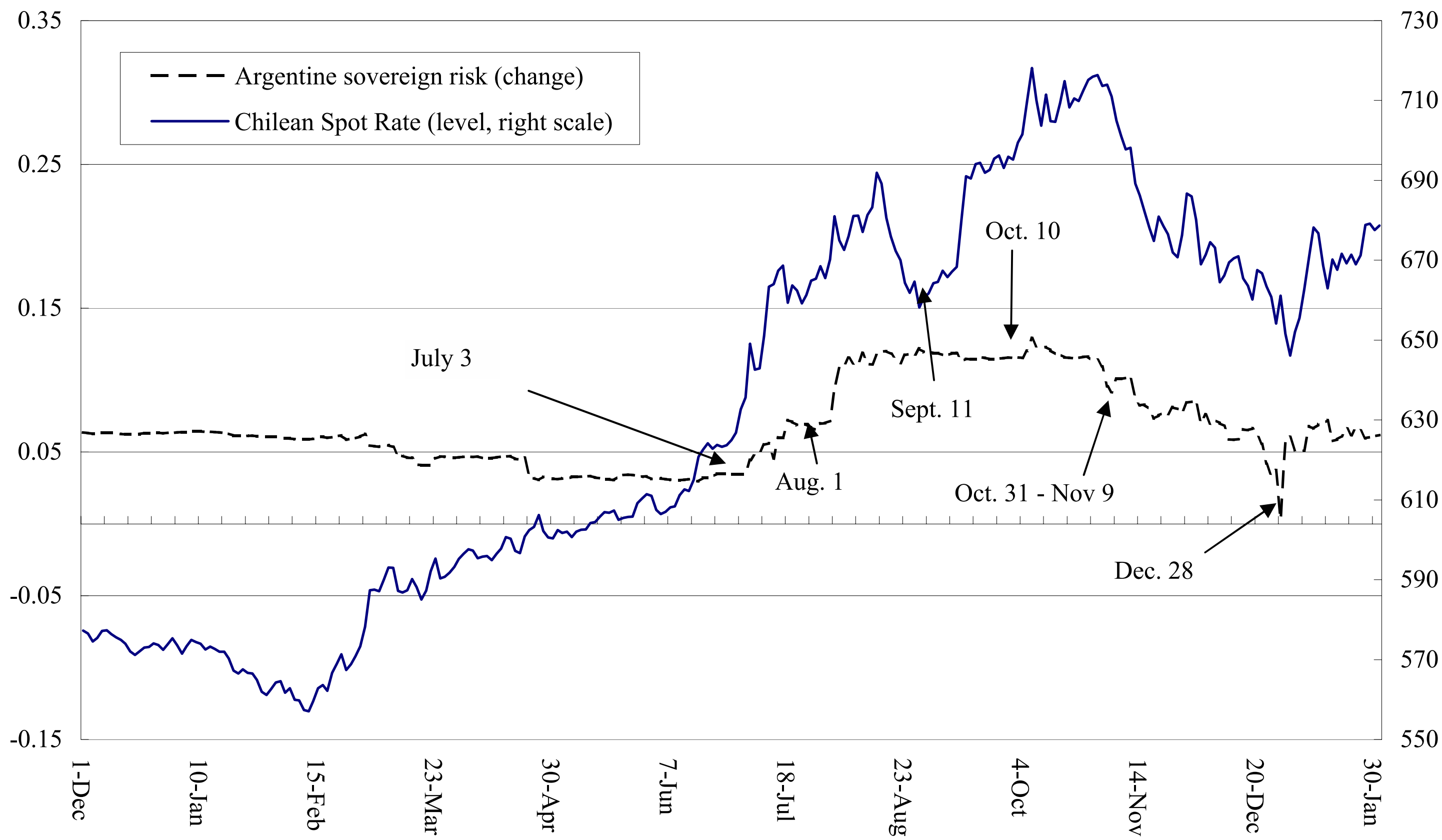
Figure 4. Empirical Results from Bayesian Estimation with Time-Varying Coefficients
(June 1, 2001 - January 31, 2002)



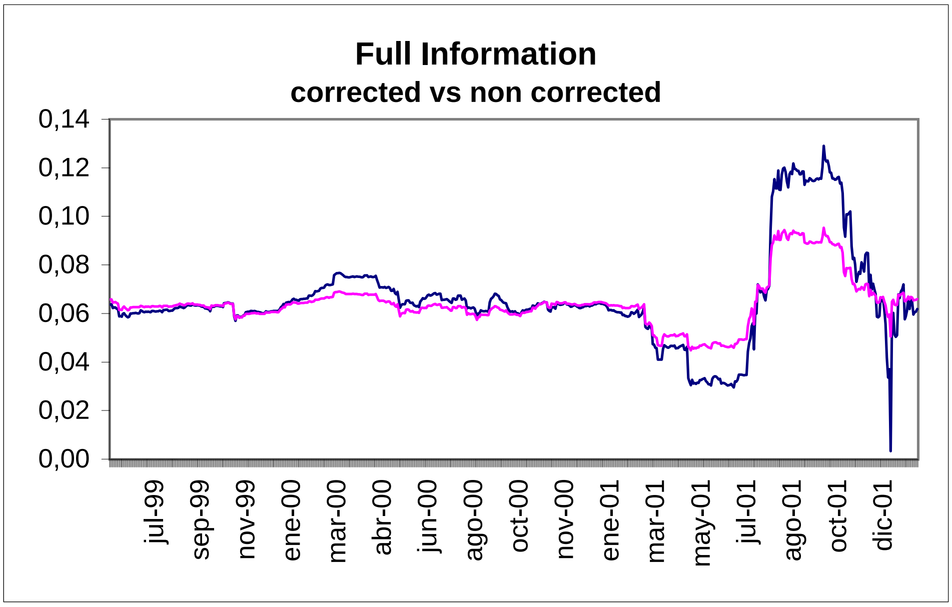
Sources: Bloomberg; Datastream; and Fund staff estimates.

1/ First quartile, mean, and third quartile of the posterior distribution reported.

Figure 5. Posterior Means of Key Regression Coefficients. (January 2001-January 2002)



Sources: Bloomberg; and Fund staff estimates.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0,08
0,06
0,04
0,02
0,00
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nov-99
ene-00
mar-00
abr-00
jun-00
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oct-00
nov-00
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mar-01
may-01
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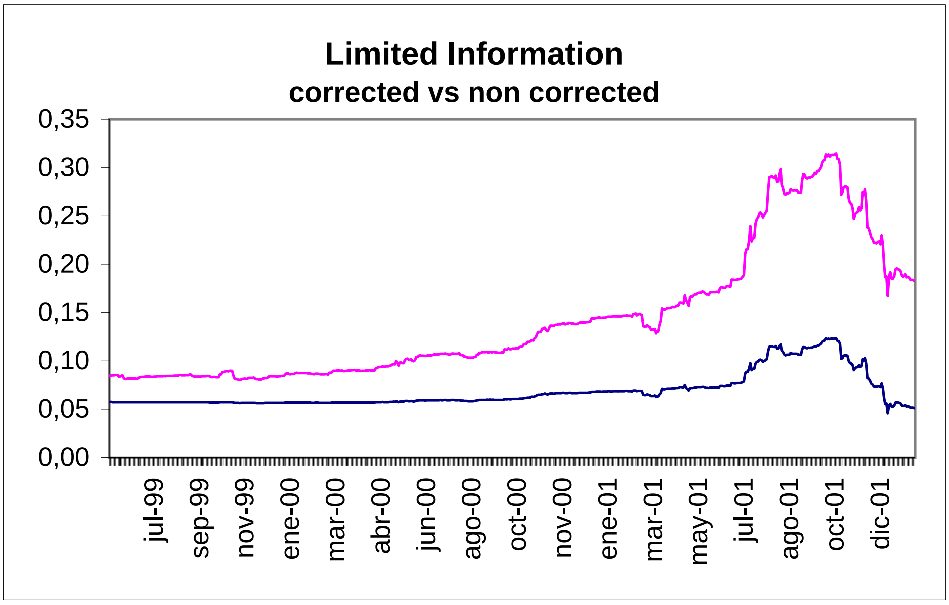
Limited Information
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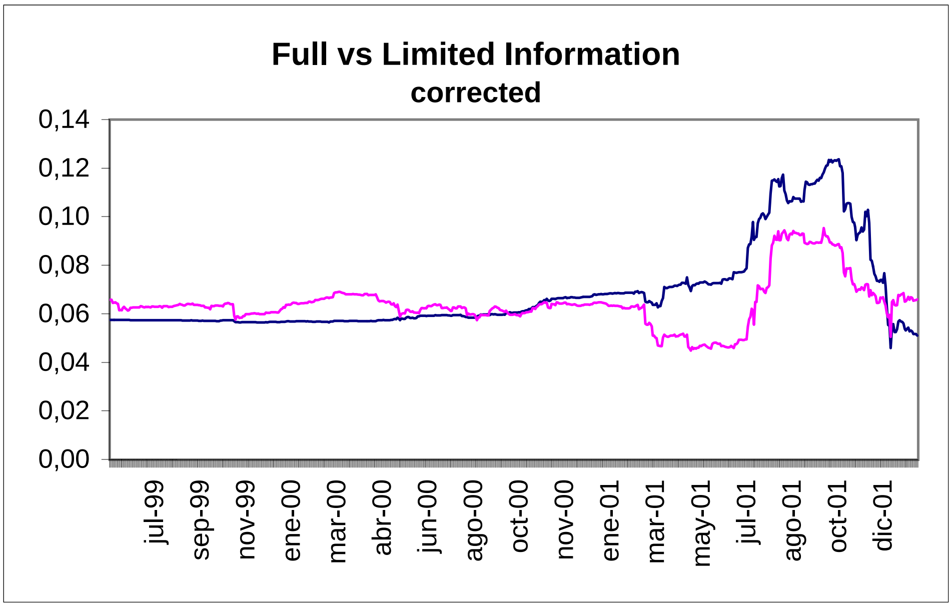
Full vs Limited Information
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0,08
0,06
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0,02
0,00
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sep-99
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ene-00
mar-00
abr-00
jun-00
ago-00
oct-00
nov-00
ene-01
mar-01
may-01
jul-01
ago-01
oct-01
dic-01

Rolling correlation and limited information not corrected