Currency Instability: Regime Switching versus Volatility Clustering

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In this paper, we demonstrate the importance of controlling for the volatility clustering effect when estimating regime-switching models. One can falsely report statistically significant distinct regimes that are, in fact, the ARCH effect. We provide statistical examples of this phenomenon. The simulation in our study further confirms the higher likelihood of falsely accepting regime switching when the ARCH effect is relatively pronounced. This is an important issue because of the recent interest in applying regime-switching models to capture currency instability and other financial crises in emerging countries.

Introduction

The financial instability in emerging markets has been debated without agreement as to what should be the proper policy prescriptions. There are those who blame the liberalization of capital and financial markets in the emerging countries for the resulting excessive volatility (Stiglitz, 2000). According to this diagnosis, one natural solution is the imposition of capital controls similar to those used by Chile from 1991 to 1998 (Krugman, 1998). Others point to structural problems in developing economies such as an inadequate banking system. Little attention has been paid to a definition of instability.

Recently, Bazdresch and Werner (2005) introduced a way to measure instability by applying a regime-switching model to the Mexican peso. They found evidence of two clearly identified regimes for data from January 1996 to December 2001. Based on a first-order autoregressive (AR) model, they found a regime with an insignificant

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trend and low volatility and another regime with a large depreciation trend and high volatility.

While dramatic changes in exchange rates can be a result of changes in the real sector of an economy, it is unlikely that the real sector will change drastically in the short run. As Mishkin (1999) argues, recent crises tend to be financial in origin. Regime-switching models therefore appear to provide a useful way to measure *ex post* currency instability. In fact, the estimated transition probabilities can provide policymakers a useful assessment of an *ex ante* speculative attack. Bazdresch and Werner's study is a promising first step toward the understanding of currency instability. There is, however, room for improvement. Daily exchange rate data are used in Bazdresch and Werner's study *without* accounting for the general autoregressive conditional heteroskedasticity (GARCH) effect. It is well known in financial econometrics that volatility clustering is common in high frequency financial data. The use of the GARCH-type techniques is a convenient way to address the volatility clustering problem. When the sum of the coefficients in a simple GARCH model is close to one, it indicates that shocks to the conditional variance are persistent over time. Lamoureux and Lastrapes (1990) and Hamilton and Susmel (1994) argue that high persistence of shocks to conditional variance is a sign of structural change in variance. The empirical distinction between the two phenomena is not obvious. It is therefore possible that what is reported as regime switching in Bazdresch and Werner's study may be volatility clustering.

The purpose of this paper is to examine empirically the relative importance of regime switching versus volatility clustering in the foreign currency market. We first provide some univariate statistics on the absence or presence of volatility clustering. We then re-estimate Bazdresch and Werner's regime-switching model ignoring volatility clustering to confirm their results. Further, we estimate their regime-switching model allowing for volatility clustering. If regime switching becomes statistically insignificant once volatility clustering is allowed, then it is less obvious that the currency in question has experienced a crisis. We also expand the sample to two other currencies to see how common regime switching is confused with volatility clustering. Simulations are performed to confirm the robustness of our results. The results may also apply to the studies by Engel and Hamilton (1990) and Engel (1994), who also use regime-switching models without allowing for the volatility clustering effects.[1]

[1]Volatility clustering may be less of a problem in these two studies as quarterly rather than daily data were used.

Exchange Rate Data and Summary Statistics

We obtain the daily exchange rates of the Mexican peso, the Chilean peso, and the Japanese yen from January 1996 to December 2001, which matches the time period considered by Bazdresch and Werner (2005).[2] To see if ignoring volatility clustering is appropriate in their study, we perform some simple univariate analyses on the log changes in each currency. As mentioned earlier, we also include two other currencies—the Chilean peso and the Japanese yen. The Chilean peso is chosen for the simple reason that it is the currency in the same region as Mexico.[3] The Japanese yen is used because it is a major currency that remains floating throughout the sample period, whereas most European currencies have been converted into the euro. Table 1 reports some statistics of the log daily changes of these three time series. All three currencies are found to be, on average, depreciating against the US$, with the Chilean peso exhibiting the largest average daily depreciation. With a daily standard deviation of close to 80 basis points, the Japanese yen is the most volatile among the three. They all have fat tails, which is an indication of conditional heteroskedasticity.

Table 1—Summary Statistics of Log Daily Changes in Foreign Exchange Rates from January 1996 to December 2001

	Mexican Peso	Chilean Peso	Japanese Yen
Mean ($\times 10^{-3}$)	0.12845	0.32257	0.13136
Standard Deviation ($\times 10^{-3}$)	5.478	3.945	7.930
Skewness	1.076	0.760	-0.953
Kurtosis	13.404	10.957	12.838
Autocorrelation Tests			
DW	1.9794	1.7933	2.0368
BG: p-value	0.9738	0.8013	0.9854
ARCH Tests			
ARCH1: p-value	0.0933	0.0165	0.0000
ARCH4: p-value	0.0906	0.1189	0.0022

DW: the standard Durbin-Watson statistics on serial correlation. BG: p-values corresponding to the Breusch (1978) and Godfrey (1978) LM test statistics for higher-order serial correlation. ARCH1 and ARCH4: p-values of tests for first- and fourth-order autoregressive conditional heteroskedasticity (ARCH)

[2]Same as Bazdresch and Werner (2005), we use the FIX transaction-weighted average Mexican peso exchange rate from Bank of Mexico. For the Chilean peso, we use the observed exchange rate from the Central Bank of Chile. Finally, the daily Japanese yen exchange rate is from the Federal Reserve Bank of New York. The reference currency is the US dollar.

[3]Chile has relied on controls on capital inflows from 1991 to 1998 in the form of the requirement to make noninterest bearing deposits at the Central Bank. This potentially could dampen the volatility of exchange rates. As Edwards (1999) and Reinhart and Rogoff (2004) suggest, the controls had little effects on the Chilean peso.

The standard Durbin-Watson (DW) statistics on serial correlation and the Breusch (1978) and Godfrey (1978) LM test statistics do not suggest statistically significant autocorrelation. The first- and fourth-order autoregressive conditional heteroskedasticity tests, however, suggest weak (Mexican peso) to strong (Japanese yen) ARCH effects.

Estimation of AR-GARCH Model

We first estimate an AR(1)-GARCH(1,1) model for each of the time series. It can serve as a benchmark model for our subsequent examination of any regime-switching effects in the next section. Specifically, we consider the following model for the exchange rate S_t.

$$\Delta s_t = \mu + \rho \Delta s_{t-1} + \varepsilon_t^{\sigma_t} \tag{1}$$

where:

$$\Delta s_t = \log(S_t) - \log(S_{t-1})$$

$$\varepsilon_t^{\sigma_t} \sim N(0, \sigma_{t_t}^2)$$

$$\sigma_t^2 = c + a\varepsilon_{t-1}^2 + b\sigma_{t-1}^2$$

The results are presented in Table 2. Consistent with the ARCH1 and ARCH4 tests reported in Table 1, we have significant GARCH effects for all three time series. The parameters governing the mean equations, however, are less significant. Only the Chilean peso has a statistically significant AR coefficient. Standard autoregressive conditional heteroskedasticity tests (not reported here) conducted on the standardized residuals cannot reject the null hypothesis that all heteroskedasticity effects have been removed after fitting with a GARCH(1,1) process. There is enough prima fascia evidence that volatility clustering should not be ignored.

Table 2—AR(1)-GARCH(1,1) Models of the Daily Changes in Exchange Rates from January 1996 to December 2001

	Mexican Peso	Chilean Peso	Japanese Yen
μ ($\times 10^{-3}$)	-0.1978^{+}	0.0468	0.3520*
	(0.1174)	(0.0561)	(0.1634)
ρ	-0.0185	0.1082**	0.0263
	(0.0314)	(0.0273)	(0.0289)
c ($\times 10^{-4}$)	0.03427**	0.00194**	0.00865**
	(0.00373)	(0.00033)	(0.00206)
a	0.3110**	0.2883**	0.0678**
	(0.0180)	(0.0159)	(0.0069)
b	0.5999**	0.7452**	0.9185**
	(0.0262)	(0.0115)	(0.0085)

Note: $^{+}$, * and ** denote 10 percent, 5 percent, and 1 percent significant levels, respectively. Estimated parameters are presented with their respective standard errors (in parentheses)

Estimation of Regime-Switching (RS) Models

In this section, we examine RS models with and without incorporating the ARCH effects. Specifically, we consider the following model for the exchange rate S_t.

$$\Delta s_t = \mu_{i_t} + \rho_{i_t} \Delta s_{t-1} + \varepsilon_t^{\sigma_{i_t}} \tag{2}$$

where:

$$\Delta s_t = \log(S_t) - \log(S_{t-1})$$

$$\text{Regime } i_t \in \{0,1\}$$

$$\varepsilon_t^{\sigma_{i_t}} \sim N\left(0, \sigma_{i_t}^2\right)$$

$$\sigma_{i_t}^2 = c_{i_t} + a_{i_t} \varepsilon_{t-1}^2$$

We denote the most general form of our RS model as RS(2)-AR(1)-ARCH(1), where we have[4]

- RS(2): Two different regimes ($i_t = 0$ or 1) of the process
- AR(1): A lag-one autoregressive process of the mean equation
- ARCH(1): An ARCH(1) process for the conditional standard deviation

The switching of regimes is assumed to follow a Markov chain with constant transition probabilities.

$$\begin{aligned} \Pr[i_t = 0 \mid i_{t-1} = 0] &= P \\ \Pr[i_t = 1 \mid i_{t-1} = 0] &= 1 - P \\ \Pr[i_t = 1 \mid i_{t-1} = 1] &= Q \\ \Pr[i_t = 0 \mid i_{t-1} = 1] &= 1 - Q \end{aligned} \tag{3}$$

By fixing $a_{i_t} = 0$, we consider a restricted version of our model where we do not allow for any ARCH effects. This RS model considered by Bazdresch and Werner (2005) therefore is nested within our general model without the ARCH(1) and will be referred to as RS(2)-AR(1).

A filtering technique similar to that in Gray (1996) and Hamilton (1989) is used to conduct the maximum likelihood estimation of the parameters. This approach also is adopted by Ramchand and Susmel (1998) and Ang and Bekaert (2002). As a

[4]We only consider an ARCH model rather than the more general GARCH version. As pointed out by Hamilton and Susmel (1994), GARCH is not nested within the commonly used Markov switching model.

byproduct of the maximum likelihood estimation, the endogenously determined probability of realizing a particular regime also can be extracted at any point in time. For example, the filter probability, $p(i_t = 0|S_{t-1}, S_{t-2}, S_{t-3}, \ldots, S_0)$, represents the conditional probability that the process is in regime 0 at t given the observed time series of exchange rates up to the beginning of that period. Alternatively, we can compute the smooth probability, $p(i_t = 0|S_{T-1}, S_{T-2}, S_{T-3}, \ldots, S_0)$, in which the inference about the regime is now based on exchange rate data up to some future time T (where T is larger than t).

Table 3 reports the results of fitting the RS models with and without the ARCH effects. In Panel A, the estimated parameters and standard errors obtained for the non-ARCH model for the Mexican peso are similar to those reported in Table 2 of Bazdresch and Werner (2005). No statistical tests were performed in their study to ascertain if the two regimes are statistically different. We perform additional tests on the statistical significance of regime switching and on the residuals for possible volatility clustering. Panels B and C report these results. In the literatures on regime switching in the currency market such as Bazdresch and Werner (2005), Engel and Hamilton (1990), and Engel (1994), a regime is characterized by its distinct mean and volatility.[5] We perform two types of tests on regime switching. One type is characterized by regimes with distinct mean returns. The other type is characterized by regimes with distinct variances. Panel B contains the test results. In the case of RS(2)-AR(1) for Mexican peso, both the Wald and likelihood ratio tests indicate statistically distinct means and variances. This provides the tests of statistical significance of Bazdresch and Werner's results. The ARCH tests reported in Panel C indicate a weak first-order effect for regime 0 and a weak fourth-order for regime 1. We then estimate the RS(2)-AR(1)-ARCH(1) for the Mexican peso. While the conclusions in Bazdresch and Werner remain unaffected, the ARCH tests on the residuals in Panel C indicate no sign of volatility clustering.

The results on the other two currencies are interesting. In the case of the Chilean peso, the Wald and likelihood ratio tests in Panel B point to two regimes with weakly distinct means at the 10 percent level and distinct variances when volatility clustering is ignored. Furthermore, the ARCH tests on the residuals point to strong first order effects. With the RS(2)-AR(1)-ARCH(1) model, the two regimes no longer have distinct means. The ARCH tests on the residuals indicate no significant ARCH effects.

The Japanese yen presents a compelling case for the importance of controlling for volatility clustering. Based on the RS(2)-AR(1) model, the yen demonstrates two

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[5]When regime switching is applied to other assets, a regime is sometime defined in terms of its distinct volatility. See, for example, Edwards and Susmel (2001).

Table 3—Regime Switching Models of the Daily Changes in Exchange Rate from January 1996 to December 2001

	Mexican Peso		Chilean Peso		Japanese Yen	
	RS(2)-AR(1)	RS(2)-AR(1)-ARCH(1)	RS(2)-AR(1)	RS(2)-AR(1)-ARCH(1)	RS(2)-AR(1)	RS(2)-AR(1)-ARCH(1)
Panel A: Estimated Parameters and Standard Errors						
μ_0 ($\times 10^{-3}$)	-0.2026^{+}	-0.2557*	0.0580	0.0594	-3.0657^{+}	-1.4054
	(0.1111)	(0.1129)	(0.06067)	(0.0626)	(1.5984)	(1.0876)
μ_1 ($\times 10^{-3}$)	1.6862*	1.3691*	0.5259**	0.2578^{+}	0.4466**	0.4387*
	(0.7049)	(0.6122)	(0.2067)	(0.1476)	(0.1707)	(0.1737)
ρ_0	-0.0246	-0.0373	0.0916**	0.0854^{+}	-0.1009^{+}	-0.0086
	(0.0293)	(0.0341)	(0.0351)	(0.0492)	(0.0562)	(0.1015)
ρ_1	0.0007	0.0491	0.0929**	0.1819**	0.0166	0.0129
	(0.0606)	(0.0727)	(0.0258)	(0.0303)	(0.0297)	(0.0303)
c_0 ($\times 10^{-4}$)	0.1317**	0.1147**	0.0245**	0.0172**	2.9158**	1.7726**
	(0.0065)	(0.0074)	(0.0015)	(0.0014)	(0.2628)	(0.2835)
c_1 ($\times 10^{-4}$)	1.0760**	0.6994**	0.2821**	0.1675**	0.3605**	0.3471**
	(0.0702)	(0.1022)	(0.0092)	(0.0072)	(0.0146)	(0.0155)
a_0	-	0.1116*	-	0.2109*	-	0.2392*
		(0.0527)		(0.0853)		(0.1110)
a_1	-	0.3565**	-	0.3653**	-	-0.0124*
		(0.0992)		(0.0486)		(0.0063)
Panel B: Hypothesis Tests						
Wald Tests						
Equal Mean	7.764*	8.781*	4.803^{+}	4.427	6.875*	2.763
$\mu_0 = \mu_1$, $\rho_0 = \rho_1$	(0.021)	(0.012)	(0.091)	(0.109)	(0.032)	(0.251)
Equal Variance						
$c_0 = c_1$	181.346**	33.0659**	773.492**	422.224**	95.041**	25.529**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$c_0 = c_1$, $a_0 = a_1$	-	107.080**	-	515.182**	-	102.734**
		(0.000)		(0.000)		(0.000)
Likelihood Ratio Tests						
Equal Mean	7.782*	8.236*	4.864^{+}	3.985	6.129*	2.585
$\mu_0 = \mu_1$, $\rho_0 = \rho_1$	(0.020)	(0.016)	(0.088)	(0.136)	(0.047)	(0.274)
Equal Variance						
$c_0 = c_1$	94.148**	79.610**	499.335**	196.260**	358.660**	60.914**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$c_0 = c_1$, $a_0 = a_1$	-	143.079**	-	240.055**	-	104.669**
		(0.000)		(0.000)		(0.000)

Table 3 (cont.)—Regime Switching Models of the Daily Changes in Exchange Rate from January 1996 to December 2001

	Mexican Peso		Chilean Peso		Japanese Yen	
	RS(2)-AR(1)	RS(2)-AR(1)-ARCH(1)	RS(2)-AR(1)	RS(2)-AR(1)-ARCH(1)	RS(2)-AR(1)	RS(2)-AR(1)-ARCH(1)
Panel C: Autocorrelation and ARCH tests on Standardized Fitted Residuals						
Autocorrelation tests						
DW						
(regime 0)	1.9265	1.8754	1.9680	1.8836	2.0680	1.9072
(regime 1)	1.8335	1.9014	1.9705	2.0169	1.5753	1.9017
BG: p-value						
(regime 0)	0.9629	0.9624	0.9517	0.9415	0.9780	0.9887
(regime 1)	0.9739	0.9894	0.9519	0.9457	0.9097	0.9939
ARCH Tests						
ARCH1: p-value						
(regime 0)	0.0954	0.6751	0.0084	0.7469	0.0002	0.3166
(regime 1)	0.1238	0.6175	0.0081	0.7457	0.0005	0.9729
ARCH4: p-value						
(regime 0)	0.1037	0.3171	0.0857	0.6780	0.0021	0.2950
(regime 1)	0.0893	0.2113	0.0843	0.5770	0.0080	1.0000

DW: the standard Durbin-Watson statistics on serial correlation. BG: p-values corresponding to the Breusch (1978) and Godfrey (1978) LM test statistics for higher-order serial correlation. ARCH1 and ARCH4: p-values of tests for first- and fourth-order autoregressive conditional heteroskedasticity (ARCH). Note: $^{+}$, * and ** denote 10 percent, 5 percent, and 1 percent significance levels, respectively

distinct regimes with means and variances that are statistically significantly different. But the ARCH tests on the residuals suggest the presence of the volatility clustering. When this issue is addressed in the RS(2)-AR(1)-ARCH(1) model, the two regimes with distinct means disappear. What is being detected as regime switching is nothing more than volatility clustering.

Simulations

What has been demonstrated so far is the possibility that volatility clustering can be disguised as regime switching. To gain further insights into this issue, we simulate 100 different time series of daily changes in exchange rates respectively from each of the four different processes for each of the three currencies. The four different processes are described in more detail below. In each of the simulation exercises, we assume the set of parameters used in the simulations are the true parameters of the particular process being studied. Our objectives here are to create simulated environments in which various hypothesis tests can be conducted and the likelihoods of reaching false statistical conclusions can be ascertained. Tables 4 to 6 report the p-values of the Wald tests (similar to those used in Panel B in Table 3) of various simulation exercises.

Table 4 contains the case for the Japanese yen. In Panel A of Table 4, the true environment is based on the RS(2)-AR(1)-ARCH(1) model of equation (2). Specifically, the simulations are based on the assumption that the estimated parameters reported in Panel A in Table 3 associated with the RS(2)-AR(1)-ARCH(1) model for the Japanese yen are the true parameters. We conduct the hypothesis tests by fitting the simulated data with RS models with and without the ARCH effect. They are the same tests conducted in Panel B of Table 3 but now on each simulated time series of returns. Let us first consider the test results obtained allowing the ARCH effect (i.e., a_i are unrestricted), which are reported in the first four columns of Panel A. The three possible null hypotheses are the two regimes having equal means, equal volatilities, and both equal means and volatilities, respectively. Panel A in Table 4 contains the distribution of the p-values. The first column of figures report the p-values for the case of equal means between the regimes, the next two columns provide those for the tests of equal volatilities, and the fourth column tests for both equal means and volatilities. With the exception of equal means, we can usually correctly conclude the existence of two distinct regimes at the usual 5 percent level (i.e., rejecting the null of no regime switching). The more interesting question is how the statistical conclusions will be affected if a simple regime switching model without ARCH is used instead when the simulated data are based on the RS(2)-AR(1)-ARCH(1) process. This corresponds to the RS model considered by Bazdresch and Werner (2005) when the restriction $a_{i_t} = 0$ is imposed. The last three columns of Panel A provide the p-values when the model being tested is RS(2)-AR(1). The percentage of p-values rejecting equal means rises from 18 percent to 28 percent. This should come as no surprise as the ARCH effect not explicitly modeled is being picked up as regime switching.

What if the true process is an AR(1)-ARCH(1) model without regime switching and a researcher tests for regime switching without accounting for the ARCH effect? To entertain this scenario, the raw data reported in Table 1 are first fit to an AR(1)-ARCH(1) process. Simulated daily changes in the exchange rate based on the resulting estimated parameters then are generated. Similar to Panel A, we conduct hypothesis tests on regime switching by fitting the simulated data with RS models with and without the ARCH effect. Panel B in Table 4 reports the distribution of p-values when the two models are tested on the simulated data. In general, the percentage of the p-value below the 5 percent level is much higher in the last three

Table 4—Summary Statistics of p-values of Wald Tests on Regime Switching of Returns on the Japanese Yen

The p-values are obtained from 100 simulations of the respective true processes. Hypothesis tests are conducted by fitting the simulated returns with RS models with and without the ARCH effect

	Hyp. Test: Fitting w/ RS(2)-AR(1)-ARCH(1)				Hyp. Test: Fitting w/ RS(2)-AR(1)		
	Equal Mean $\mu_0 = \mu_1$, $\rho_0 = \rho_1$	Equal ARCH $c_0 = c_1$	Equal ARCH $c_0 = c_1$, $a_0 = a_1$	All Equal $\mu_0 = \mu_1$, $\rho_0 = \rho_1$, $c_0 = c_1$, $a_0 = a_1$	Equal Mean $\mu_0 = \mu_1$, $\rho_0 = \rho_1$	Equal Variance $c_0 = c_1$	All Equal $\mu_0 = \mu_1$, $\rho_0 = \rho_1$, $c_0 = c_1$
Panel A: Simulation from the Estimated Process of RS(2)-AR(1)-ARCH(1) as the True Process							
Mean	0.310	0.003	0.000	0.000	0.281	0.000	0.000
Median	0.218	0.000	0.000	0.000	0.222	0.000	0.000
5th Percentile	0.006	0.000	0.000	0.000	0.004	0.000	0.000
95th Percentile	0.842	0.013	0.000	0.000	0.784	0.000	0.000
% of $p < 0.05$	18%	99%	100%	100%	28%	99%	100%
Panel B: Simulation from the Estimated Process of AR(1)-ARCH(1) as the True Process							
Mean	0.193	0.398	0.311	0.112	0.322	0.091	0.019
Median	0.018	0.392	0.135	0.000	0.187	0.000	0.000
5th Percentile	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95th Percentile	0.989	0.934	0.960	0.897	0.910	0.746	0.070
% of $p < 0.05$	59%	23%	40%	74%	30%	83%	93%
Panel C: Simulation from the Process where RS and ARCH effects are Increased 50 Percent from the Estimated Process of RS(2)-AR(1)-ARCH(1)							
Mean	0.229	0.002	0.000	0.000	0.203	0.000	0.000
Median	0.101	0.000	0.000	0.000	0.096	0.000	0.000
5th Percentile	0.002	0.000	0.000	0.000	0.001	0.000	0.000
95th Percentile	0.802	0.003	0.000	0.000	0.679	0.000	0.000
% of $p < 0.05$	31%	99%	100%	100%	40%	100%	100%
Panel D: Simulation from the Process where ARCH Effect is only One-Third that of the Estimated Process of AR(1)-ARCH(1)							
Mean	0.214	0.353	0.339	0.139	0.117	0.297	0.033
Median	0.019	0.274	0.195	0.002	0.001	0.147	0.000
5th Percentile	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95th Percentile	0.982	0.965	0.982	0.863	0.566	0.895	0.152
% of $p < 0.05$	56%	22%	37%	68%	71%	41%	85%

columns when the RS(1)-AR(1) model is tested. Note that these last three columns with the RS(1)-AR(1) correspond to the model considered by Bazdresch and Werner (2005). In other words, if the true process is simply ARCH(1) without regime switching, the false conclusion of regime switching is more likely to be accepted when the ARCH effect is ignored in the estimation and the hypothesis testing. When volatility clustering is not explicitly accounted for in the estimation, its effect would be (incorrectly) captured as regime switching. When the ARCH effect is explicitly modeled, the likelihood of accepting regime switching when there is none in the data is much lower. The first four columns in Panel B confirm. The results here reinforce what is reported in the previous section for the Japanese yen.

It is important to note that volatility clustering is common in high frequency financial data and our AR(1)-ARCH(1) is a very general model. It therefore can be argued that the results in Panel B with its underling true process of AR(1)-ARCH(1) is far more common and relevant than those in Panel A.

As a robustness check, we consider two more (third and fourth) plausible true processes to further study the sensitivity of the interaction of volatility clustering and regime switching under different modeling and parametric assumptions. In the third process, the estimated parameters of the RS(2)-AR(1)-ARCH(1) process of equation (2) are varied to intensify the effects of regime switching and ARCH. The across-regime differences in the estimated values of $\hat{\mu}_i$, $\hat{c}_i$, and $\hat{a}_i$ are magnified by 50 percent, which are then assumed to be the true parameters. Specifically, the true parameters μ_i^*, ρ_i^*, c_i^*, and a_i^* of the third process are defined as follows (without loss of generality, assuming $\hat{\mu}_1 \geq \hat{\mu}_0$, $\hat{c}_1 \geq \hat{c}_0$, and $\hat{a}_1 \geq \hat{a}_0$):

$$\mu_0^* = \hat{\mu}_0 \text{ and } \mu_1^* = \hat{\mu}_1 + 0.5 \times (\hat{\mu}_1 - \hat{\mu}_0)$$

$$\rho_0^* = \hat{\rho}_0 \text{ and } \rho_1^* = \hat{\rho}_1$$

$$c_0^* = \hat{c}_0 \text{ and } c_1^* = \hat{c}_1 + 0.5 \times (\hat{c}_1 - \hat{c}_0)$$

$$a_0^* = \hat{a}_0 \text{ and } a_1^* = \hat{a}_1 + 0.5 \times (\hat{a}_1 - \hat{a}_0)$$

The hypothesis test results of the simulations based on the magnified parameters are reported in Panel C. The results are similar to those reported in Panel A in that ignoring the ARCH effect in the hypothesis testing improves the likelihood of correctly rejecting no regime switching when the true process is characterized by intensified regime switching and ARCH. This should come as no surprise, as the intensified ARCH effect is again being perceived as an even stronger regime switching effect as in the case of Panel A.

Finally, we consider a true process (the fourth process) in which the ARCH effect is only one-third that of the estimated AR(1)-ARCH(1) process of Panel B. The objective is to measure the sensitivity of the results reported in Panel B to changes in the intensity of ARCH effect when the true process is without any regime switching effects. One would expect a reduction of the ARCH effect in the true process to lower the chance of wrongfully accepting the existence of regime switching when ARCH effect is being ignored in the estimation and the hypothesis testing. There is simply less volatility clustering effect to be spilled over and thus wrongfully captured as regime switching in the estimation process. Specifically, we consider a

Table 5—Summary Statistics of p-values of Wald Tests on Regimes Switching of the Returns on the Mexican Peso

The p-values are obtained from 100 simulations of the respective true processes. Hypothesis tests are conducted by fitting the simulated returns with RS models with and without the ARCH effect

	Hyp. Test: Fitting w/ RS(2)-AR(1)-ARCH(1)				Hyp. Test: Fitting w/ RS(2)-AR(1)		
	Equal Mean	Equal ARCH		All Equal	Equal Mean	Equal Variance	All Equal
	$\mu_0 = \mu_1$, $\rho_0 = \rho_1$	$c_0 = c_1$	$c_0 = c_1$, $a_0 = a_1$	$\mu_0 = \mu_1$, $\rho_0 = \rho_1$, $c_0 = c_1$, $a_0 = a_1$	$\mu_0 = \mu_1$, $\rho_0 = \rho_1$	$c_0 = c_1$	$\mu_0 = \mu_1$, $\rho_0 = \rho_1$, $c_0 = c_1$
Panel A: Simulation from the Estimated Process of RS(2)-AR(1)-ARCH(1) as the True Process							
Mean	0.069	0.000	0.000	0.000	0.077	0.000	0.000
Median	0.006	0.000	0.000	0.000	0.004	0.000	0.000
5th Percentile	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95th Percentile	0.340	0.000	0.000	0.000	0.397	0.000	0.000
% of $p < 0.05$	70%	100%	100%	100%	71%	100%	100%
Panel B: Simulation from the Estimated Process of AR(1)-ARCH(1) as the True Process							
Mean	0.265	0.444	0.359	0.185	0.324	0.000	0.000
Median	0.045	0.414	0.255	0.010	0.223	0.000	0.000
5th Percentile	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95th Percentile	0.998	0.974	0.988	0.975	0.948	0.000	0.000
% of $p < 0.05$	51%	18%	27%	64%	33%	100%	100%
Panel C: Simulation from the Process where RS and ARCH Effects are Increased 50 Percent from the Estimated Process of RS(2)-AR(1)-ARCH(1)							
Mean	0.018	0.000	0.000	0.000	0.035	0.000	0.000
Median	0.001	0.000	0.000	0.000	0.001	0.000	0.000
5th Percentile	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95th Percentile	0.074	0.000	0.000	0.000	0.153	0.000	0.000
% of $p < 0.05$	91%	100%	100%	100%	87%	100%	100%
Panel D: Simulation from the process where ARCH effect is only one-third that of the estimated process of AR(1)-ARCH(1)							
Mean	0.235	0.379	0.306	0.125	0.215	0.194	0.021
Median	0.040	0.267	0.163	0.002	0.028	0.024	0.000
5th Percentile	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95th Percentile	0.983	0.959	0.953	0.682	0.866	0.871	0.123
% of $p < 0.05$	52%	26%	34%	68%	53%	56%	89%

process of which the true parameters μ^*, ρ^*, c^*, and a^* are defined as $\mu^* = \hat{\mu}$, $\rho^* = \hat{\rho}$, $c^* = \hat{c}$, and $a^* = \hat{a}/3$, where $\hat{\mu}$, $\hat{\rho}$, $\hat{c}$, and $\hat{a}$ are the estimated parametric values of the AR(1)-ARCH(1) process used in the generation of the simulations for Panel B. The distributions of the p-values of the two types of hypothesis tests conducted on the simulated data of this fourth process are reported in Panel D. Comparing with the results in Panel B, reducing the ARCH effect in the true process lowers the chances of wrongfully accepting the existence of regime switching in most of the hypothesis tests. For example, in testing for any regime-switching in

Table 6—Summary Statistics of p-values of Wald Tests on Regime Switching of the Returns on Chilean Peso

The p-values are obtained from 100 simulations of the respective true processes. Hypothesis tests are conducted by fitting the simulated returns with RS models with and without the ARCH effect

	Hyp. Test: Fitting w/ RS(2)-AR(1)-ARCH(1)				Hyp. Test: Fitting w/ RS(2)-AR(1)		
	Equal Mean	Equal ARCH		All Equal	Equal Mean	Equal Variance	All Equal
	$\mu_0 = \mu_1$, $\rho_0 = \rho_1$	$c_0 = c_1$	$c_0 = c_1$, $a_0 = a_1$	$\mu_0 = \mu_1$, $\rho_0 = \rho_1$, $c_0 = c_1$, $a_0 = a_1$	$\mu_0 = \mu_1$, $\rho_0 = \rho_1$	$c_0 = c_1$	$\mu_0 = \mu_1$, $\rho_0 = \rho_1$, $c_0 = c_1$
Panel A: Simulation from the Estimated Process of RS(2)-AR(1)-ARCH(1) as the True Process							
Mean	0.174	0.000	0.000	0.000	0.129	0.000	0.000
Median	0.045	0.000	0.000	0.000	0.030	0.000	0.000
5th Percentile	0.001	0.000	0.000	0.000	0.000	0.000	0.000
95th Percentile	0.699	0.000	0.000	0.000	0.772	0.000	0.000
% of $p < 0.05$	51%	100%	100%	100%	58%	100%	100%
Panel B: Simulation from the Estimated Process of AR(1)-ARCH(1) as the True Process							
Mean	0.297	0.397	0.393	0.236	0.230	0.000	0.000
Median	0.061	0.373	0.360	0.011	0.063	0.000	0.000
5th Percentile	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95th Percentile	0.999	0.986	0.987	0.987	0.850	0.000	0.000
% of $p < 0.05$	49%	19%	25%	55%	47%	100%	100%
Panel C: Simulation from the Process where RS and ARCH Effects are Increased 50 Percent from the Estimated Process of RS(2)-AR(1)-ARCH(1)							
Mean	0.132	0.000	0.000	0.000	0.111	0.000	0.000
Median	0.035	0.000	0.000	0.000	0.017	0.000	0.000
5th Percentile	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95th Percentile	0.656	0.000	0.000	0.000	0.628	0.000	0.000
% of $p < 0.05$	56%	100%	100%	100%	67%	100%	100%
Panel D: Simulation from the Process where ARCH Effect is only One-Third that of the Estimated Process of AR(1)-ARCH(1)							
Mean	0.335	0.511	0.484	0.274	0.391	0.065	0.015
Median	0.074	0.589	0.510	0.011	0.343	0.000	0.000
5th Percentile	0.000	0.009	0.000	0.000	0.000	0.000	0.000
95th Percentile	1.000	0.960	0.985	1.000	0.908	0.473	0.058
% of $p < 0.05$	47%	11%	18%	60%	24%	88%	91%

variance, the chance of wrongfully rejecting the hypothesis of equal variance is reduced by more than half (from 83 percent in Panel B to 41 percent in Panel D) when the ARCH effect is ignored in conducting these tests.

Table 5 and 6 contain the results for the other two currencies which are similar to those reported in Table 4. The last three columns in Panels B in Tables 5 and 6 show a more dramatic increase in the percentage in the p-value below the 5 percentage level. In other words, if the true process is ARCH(1) without regime switching, the false conclusion of regime switching is far more likely to be accepted when the ARCH effect is ignored in the estimation and hypothesis tests.

Conclusions

Instability in the currency markets and other financial crises has been an important issue in the academic literature and among policymakers. The regime-switching models appear to be a promising technique to capture instability empirically. This paper shows the importance of addressing the volatility clustering effects at the same time in estimating regime-switching models. One can falsely pick up regime-switching effects when a volatility clustering problem is the reality. We demonstrate this importance in the case of the Japanese yen. The simulation in our study confirms the higher likelihood of falsely accepting regime switching when the ARCH effect is relatively pronounced. Given that volatility clustering is common in high frequency financial data, the explicit accounting for the effect should be an important issue.

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