# When Political Uncertainty Mimics Efficiency under the Adaptive Markets Hypothesis: Peru as a Rare Case Today, a Precedent for Tomorrow? *

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**Abstract**

This paper examines how extreme domestic political uncertainty disrupts expectation formation in the Peruvian stock market, causing market dynamics to appear as statistical efficiency —lower return predictability— rather than the temporary inefficiency predicted by the standard Adaptive Markets Hypothesis. Using weekly data from 1990 to 2026, the study applies parametric and nonparametric rolling variance ratio tests to compare global shocks and domestic political events, supported by fractional logit regressions for the latter. The evidence reveals a sharp asymmetry. Global crises, such as the Great Recession and the COVID-19 pandemic, generate temporary return predictability, consistent with investors relying on imperfect heuristics before adapting. By contrast, domestic political shocks produce the opposite pattern. Elections involving radical or outsider candidates and episodes of institutional crisis reduce return predictability, moving the market toward statistical efficiency. This does not indicate better information processing, but a breakdown in expectation formation under extreme regime uncertainty. Comparative evidence from Latin America suggests that Peru's party-system collapse and weak institutionalization explain this distinctive response. The paper shows that institutional fragility can reshape, and even invert, standard adaptive-market dynamics.
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# 1 Introduction

Political events affect financial markets because they change investors' conjectures about the future. Elections, institutional crises, and threats to political continuity may alter expectations about economic policy, corporate cash flows, discount rates, and risk premia (see Pastor and Veronesi, 2012, 2013). Yet the market impact of these events depends on whether political outcomes can be mapped into credible expectations about future policy regimes. In well-institutionalized systems, parties, platforms, and legislative coalitions provide anchors for this mapping; in weakly institutionalized systems, by contrast, investors face a deeper form of uncertainty: not only who will govern, but whether any coherent and credible policy path can be anticipated (see Downs, 1957; Ghalke et al., 2023). This raises the question of how political uncertainty affects the process through which information and expectations are incorporated into asset prices.

This question is closely related to the Efficient Market Hypothesis (EMH), according to which asset prices reflect available information and returns should not be systematically predictable from past price information (Fama, 1965, 1970). However, both theory and evidence suggest that market efficiency need not be absolute or constant over time. Theoretically, Grossman (1976) and Grossman and Stiglitz (1980) argue that perfectly efficient markets are impossible, since the absence of profit opportunities would eliminate incentives to acquire and process information. Empirically, the evidence is mixed: while some studies find behavior consistent with random walks (e.g. Malkiel, 1999), others reject the hypothesis or find that efficiency holds only in specific periods, markets, or institutional settings (see Niederhoffer and Osborne, 1966; Boya, 2019; Dias et al., 2020). This suggests that market efficiency may vary over time and across contexts, particularly when shocks alter the environment in which investors process information.

Behavioral finance provides a further reason to question a static view of efficiency. Under uncertainty, investors may rely on heuristics and exhibit systematic biases in judgment and decision-making, including framing effects, loss aversion, overreaction, and overconfidence (see Tversky and Kahneman, 1974; Kahneman and Tversky, 1979; Tversky and Kahneman, 1981; De Bondt and Thaler, 1985; Barber and Odean, 2001). Such behavioral responses can generate temporary mispricing and return predictability when investors adapt imperfectly to new environments. However, the direction and nature of these departures from efficiency may depend on the type of shock and on the institutional context in which expectations are formed.

In response to these challenges, Lo (2004, 2005) proposed the Adaptive Market Hypothesis (AMH), which integrates insights from behavioral finance and evolutionary theory. The AMH suggests that market efficiency is not static but evolves over time, influenced by factors such as competition, the availability of investment opportunities, and the ability of market participants to adapt to changing environments. This framework reconciles the EMH with behavioral biases, arguing that markets fluctuate between periods of efficiency and inefficiency as investors learn and adapt. Previous studies have tested the AMH in the context of various shocks, such as financial crises, technological advancements, and regulatory changes, showing that market efficiency changes when investors face new economic, financial, or institutional environments (see Hiremath and Narayan, 2016; Kim and Singal, 2000; Dos Santos et al., 2024)[1]. In the AMH mechanism, shocks alter the environment in which investors operate. Because market participants cannot immediately determine which rules, signals, or strategies

[1]For a more complete bibliographic review, see Appendix A.4.

remain useful under the new conditions, they may rely on heuristics that lead to errors in decision-making. These errors can generate return predictability and temporary inefficiency until investors learn through experience and adjust to the new environment. However, when uncertainty originates in domestic political shocks in weakly institutionalized markets, the problem is not only that investors must adapt to a new environment, but that the future policy regime itself may become difficult to map into stable expectations. In such settings, predictability-based tests may classify the market as efficient because returns become harder to predict, even though this unpredictability may reflect extreme political uncertainty rather than the adaptive learning process emphasized by the AMH.

This paper examines the AMH in the context of the Peruvian stock market, focusing on the impact of both domestic political events and global shocks. Using parametric and non-parametric rolling variance ratio tests, I analyze the evolution of market efficiency from 1990 to 2026. The results reveal a sharp contrast between the two types of shocks. Global shocks, consistent with the standard adaptive-market mechanism, tend to induce temporary market inefficiency by increasing return predictability. Domestic political shocks, by contrast, move the Peruvian market toward statistical efficiency, as presidential elections and episodes of institutional crisis associated with regime uncertainty reduce rather than increase return predictability. This should not be interpreted as improved information processing, but as evidence that extreme political uncertainty can make returns unpredictable when investors are unable to form coherent expectations about future fundamentals. To provide a broader perspective, the study also examines the effects of political events in other Latin American countries, including Argentina, Brazil, Chile, Colombia, Mexico, and Panama. The findings suggest that Peru's institutional and political context, characterized by weak party structures and low institutionalization, plays a critical role in shaping this distinctive market response.

This study contributes to the literature in three ways. First, it extends the AMH literature by showing that the effect of uncertainty on market efficiency depends on the nature of the shock. While global shocks are associated with temporary inefficiency, domestic political shocks in Peru reduce return predictability, leading traditional variance-ratio tests to classify the market as efficient. This result highlights a conceptual limitation of equating efficiency with the absence of predictability: when political shocks generate extreme uncertainty about future fundamentals, they may disrupt the formation of expectations in ways that make returns harder to predict without necessarily implying a better-functioning market. Second, the paper contributes to the political finance literature by shifting the focus from the price-level effects of political uncertainty, such as changes in asset prices, volatility, and risk premia, to its role in shaping the process through which investors form expectations and incorporate political information into prices. Third, by comparing Peru with other Latin American markets, the study shows that this pattern is not a generic emerging-market response, but is closely related to the country's weak party structures and low political institutionalization.

I organize the paper as follows: besides this introduction, section 2 develops a review of the literature on the relationship between politics and financial markets. Section 3 discusses the methodology, section 4 presents variable definitions and the data, section 5 discusses results, and section 6 offers concluding remarks.

# 2 Political Uncertainty, Expectation Formation, and Market Adaptation

Numerous studies show that political events affect financial markets by changing investors' expectations about future policy and by altering the pricing of political risk. Elections, changes in government orientation, and policy-related uncertainty can affect asset prices, volatility, risk premia, and correlations across assets (see Goodell and Vahamaa, 2013; Pastor and Veronesi, 2012, 2013; Nguyen et al., 2023). Evidence from emerging markets also shows that government interventions can significantly affect stock market performance (see Aharon and Siev, 2021). These effects are particularly relevant around elections and other periods in which investors revise their beliefs about the future direction of economic policy. However, the market impact of political uncertainty depends not only on the event itself, but also on whether investors can translate political outcomes into credible expectations about future policy regimes.

A common distinction in this literature is between electoral uncertainty and policy uncertainty. Electoral uncertainty refers to uncertainty about who will win an election and how markets should price the probability of alternative political outcomes. This type of uncertainty is particularly relevant around elections, when investors revise their expectations as new information about candidates, electoral competitiveness, and likely changes in government orientation becomes available (see Jens, 2017; Goodell and Vahamaa, 2013; Białkowski et al., 2008; Nguyen et al., 2023). Policy uncertainty, by contrast, refers to uncertainty about the economic consequences of the policies that may follow, including their effects on corporate cash flows, discount rates, risk premia, volatility, and correlations across assets (see Pastor and Veronesi, 2012, 2013; Ghalke et al., 2023). In practice, however, these two dimensions are closely connected. Elections matter for markets because they change the perceived likelihood of future policy regimes, while policy uncertainty matters because investors must evaluate whether those regimes are economically relevant, politically feasible, and likely to persist. The key issue, therefore, is not only whether an election is uncertain, but whether the political outcome can be translated into a stable assessment of future economic policy.

Political uncertainty is shaped by several interrelated factors that affect the ability of investors to translate political outcomes into expectations about future policy. The first is the economic orientation of candidates or parties. Political alternatives may imply different macroeconomic priorities, different attitudes toward market-oriented policies, and different implications for fiscal, regulatory, and investment conditions. Partisan differences have long been associated with distinct macroeconomic policy preferences (see Hibbs Jr, 1977). In financial markets, these differences become especially relevant during electoral periods, when changes in political support can increase uncertainty about future policy and affect stock market volatility (see Nguyen et al., 2023). The second factor is governing capacity. Even when the economic orientation of an incoming government is observable, investors must assess whether it has the legislative support and coalition strength required to implement its program. Weak or fragmented coalitions can make policy implementation less predictable, increasing uncertainty about the economic consequences of political decisions (see Ghalke et al., 2023). This uncertainty is especially relevant when economic conditions are fragile, since political risk premia and market volatility tend to rise under weaker macroeconomic conditions (see Pastor and Veronesi, 2013). The third factor is the institutionalization of the party system. Stable parties, platforms, and coalitions provide anchors that help investors map electoral outcomes into future policy paths (see Downs, 1957; Powell et al., 2015). When

party systems are weak or fragmented, these anchors become less reliable, making policy regimes harder to anticipate. This is particularly relevant in Peru, which has been described as one of the most extreme cases of party-system collapse in Latin America (see Levitsky and Cameron, 2003; Levitsky and Zavaleta, 2019; Zavaleta, 2022). Recent comparative research further characterizes Peru as a case of self-reproducing partylessness, in which personalistic electoral vehicles and weak party organizations limit the consolidation of stable programmatic alternatives (see Sánchez-Sibony, 2024). In such a context, political actors often rely on temporary electoral vehicles and coalitions of independents, weakening programmatic continuity and deepening the deinstitutionalization of democratic competition.

Taken together, these factors suggest that political shocks can alter the environment in which market participants form expectations and make investment decisions. When political outcomes provide relatively clear signals about future policy, investors can update their beliefs and asset prices may adjust as uncertainty is resolved. However, when political uncertainty is amplified by weak governing capacity, fragmented coalitions, or party-system collapse, the adjustment process becomes more complex. In such contexts, investors may have difficulty assessing not only the likely content of future policies, but also their feasibility, credibility, and persistence. This is precisely the type of changing environment emphasized by the AMH, in which market participants rely on heuristics, make errors, and gradually adapt. Yet in weakly institutionalized political systems, extreme uncertainty may also reduce return predictability by making future fundamentals harder to map into stable scenarios. This provides the basis for examining whether domestic political shocks affect market efficiency in the same way as global shocks.

# 3 Methodology

The empirical analysis operationalizes the AMH through time variation in return predictability. Denote $P_t$ as the price of a stock in period $t$, define $p_t \equiv log(P_t)$ as a log price process and $r_t \equiv p_t - p_{t-1}$ as the returns. If the AMH holds, then markets should fluctuate between periods of efficiency where $p_t$ follows a random walk and consequently $r_t$ are unpredictable, and periods of inefficiency where it is possible to predict $r_t$. These fluctuations would be caused by events that affect the economic environment and may lead to errors in agents' decision making.

There are many strategies for testing the random walk hypothesis, but the Variance Ratio (VR) test is considered the most appropriate and powerful (see Poterba and Summers, 1988; Lo and MacKinlay, 1989; Campbell et al., 1998). In addition, this test has the advantage over others, such as Box-Pierce statistics, of providing information about the direction of the departure from the null hypothesis. This has a relevant interpretation in economic terms as it gives information about the behavior of returns (momentum vs mean reversion). Thus, the VR test has become the primary tool for testing whether stock return series are serially uncorrelated (see Lim and Brooks, 2011)[2].

[2]The use of unit root is possible but its nature is different, see detailed discussion in Campbell et al. (1998, pp. 64-65) and Lo and MacKinlay (1989, pp. 204-205)

## 3.1 A Parametric Test

Proposed by Lo and MacKinlay (1988), the VR test is based on the statistical property that if $p_t$ follows a random walk, then the variance of the $k$-period return is equal to $k$ times the variance of the one-period return. For a time series of asset returns $(r_t)$ with a sample of size $T$, the VR statistic can be written as:

$$VR(k) = \frac{Var[r_t(k)]}{kVar[r_t]} = 1 + 2\sum_{j=1}^{k-1}\left(1 - \frac{j}{k}\right)\rho(j) \tag{1}$$

Where $k$ is the holding period of returns $r_t(k) \equiv r_t + r_{t-1} + ... + r_{t-k+1}$ and $\rho(j)$ is the $jth$ order autocorrelation coefficient of $(r_t)$

The variance ratio z-statistics is:

$$z_s(k) = (VR(k) - 1)\left[\widehat{s}_s(k)^2\right]^{-1/2} \tag{2}$$

$z_s(k)$ is asymptotically $N(0,1)$ for appropriate choice of estimator $\widehat{s}_s(k)^2$. If $r_t$ is $iid$ and under the assumption of homoscedasticity, for $k > 2$, then:

$$\widehat{s_1}(k)^2 = \frac{2(2k-1)(k-1)}{3kT} \tag{3}$$

While, in the presence of heteroscedasticity:

$$\widehat{s}_2(k)^2 = \sum_{j=1}^{k-1}\left(\frac{2(k-j)}{k}\right)^2 \delta_j \tag{4}$$

where:

$$\delta_j = \frac{\left\{\sum_{t=j+1}^{T}(r_{t-j} - \bar{u})^2\left(r_t - \bar{u})^2\right)\right\}}{\left\{\sum_{t=j+1}^{T}(r_{t-j} - \bar{u})^2\right)\right\}^2} \tag{5}$$

Where $\bar{u}$ is the mean of returns. In order to evaluate the AMH, it is common to test the VRs for several holding periods $(k)$ and the random walk hypothesis is rejected when the estimated VR statistic is significantly different from unity. However, this multiple comparison across all pre-selected holding periods can lead to over-rejection of the null hypothesis. To control for the overall test size I use the joint test procedure proposed by Chow and Denning (1993). These authors propose to use the maximum absolute value among a set of Lo and MacKinlay (1988) variance ratio statistics, each estimated at a different holding period $k_i$ for $i = 1, 2, ...m$. The statistics for the homoscedasticity and heteroscedasticity case are defined as follows:

$$z_1^m(k) = \max_{1 \leqslant i \leqslant m} |z_1(k_i)|, \tag{6}$$

$$z_2^m(k) = \max_{1 \leqslant i \leqslant m} |z_2(k_i)|. \tag{7}$$

In this case, the multiple variance ratio test statistic is bounded from above by the probability for the Studentized Maximum Modulus (SMM) distribution with parameter $m$ and $T$ degrees of freedom.

As an additional parametric robustness check, I use the variance ratio framework proposed by Hong, Linton and Zhang (Hong et al., 2017, hereafter HLZ). Although their main contribution is multivariate, their approach is also useful in the univariate case because it provides an alternative inference procedure that is robust to heteroscedasticity and leverage effects. In this paper, the HLZ approach is implemented using the same variance-scaling restriction described in Equation (1), but with a different parametric treatment of the statistic. It is therefore used to assess whether the evidence from the conventional Lo and MacKinlay (1988) variance ratio test is robust to an alternative inference procedure.

A related concern is that, even when heteroscedasticity-robust variance ratio tests are used, their finite-sample performance may still be affected in small samples. To address this issue, Kim (2006) proposes a wild bootstrap procedure for the individual and joint VR tests in order to improve their small-sample properties. The author finds that the wild bootstrap method for VR tests has desirable size properties and exhibits greater power than conventional versions of the test.

The procedure for $z_i^m(k)$, for $i = 1, 2$, is implemented in three stages:

i Form a bootstrap sample of $T$ observations $r_t^* = \eta_t r_t$ $(t = 1, ..., T)$ where $\eta_t$ is a random sequence with zero mean and unit variance.

ii Calculate $z_i^{m*} \equiv z_i^m(r_t^*, k)$, the $z^m$ statistic obtained from the bootstrap sample $\{r_t^*\}_{t=1}^T$.

iii Repeat (i) and (ii) $m$ times to form a bootstrap distribution of the test statistic $\{z_i^m(r_t^*, k_j; j)\}_{j=1}^m$

## 3.2 Non-Parametric Test

Wright (2000) proposed using VR tests based on the rank and signs of returns. This non-parametric approach has two advantages with respect to the conventional VR test. First, it is possible to compute their exact distribution. By not having to rely on asymptotic distributions, the researcher does not have to worry about size distortions when using the test. Second, the test will be more powerful than the conventional test if the data have a highly non-normal distribution.

Let $Rank(r_t)$ be the rank of $r_t$ among $r_1 ... r_T$, and define the standardized ranks $Rank_{1t}$ and $Rank_{2t}$:

$$Rank_{1t} = \left( Rank(r_t) - \frac{T+1}{2} \right) / \sqrt{\frac{(T-1)(T-1)}{12}}, \tag{8}$$

$$Rank_{2t} = \Phi^{-1}(Rank(r_t)/(T+1)). \tag{9}$$

Where $\Phi^{-1}$ is the inverse of the standard normal cumulative distribution function. Wright (2000) proposed the $R_i(k)$ statistics for $i = 1, 2$, defined as:

$$R_i(k) = \left[ \frac{\sum_{t=k+1}^T (Rank_{it} + ... + Rank_{it-k})^2}{k \sum_{t=1}^T Rank_{it}} - 1 \right] \left[ \frac{2(2k-1)(k-1)}{3kT} \right]^{-1/2}, \tag{10}$$

Similarly, the sign-based tests are given by:

$$S_1(k) = \left[ \frac{\sum_{t=k+1}^{T} (s_t + ... + s_{t-k})^2}{k \sum_{t=1}^{T} s_t^2} - 1 \right] \left[ \frac{2(2k-1)(k-1)}{3kT} \right]^{-1/2}, \tag{11}$$

$$S_2(k) = \left[ \frac{\sum_{t=k+1}^{T} (s_t(\bar{\mu}) + ... + s_{t-k}(\bar{\mu}))^2}{k \sum_{t=1}^{T} s_t(\bar{\mu})^2} - 1 \right] \left[ \frac{2(2k-1)(k-1)}{3kT} \right]^{-1/2}, \tag{12}$$

Where $s_t = 2u(r_t, 0) = 2u(\varepsilon_t, 0)$, $s_t(\bar{\mu}) = 2u(r_t, \mu)$, $\mu$ is the nuisance parameter associated to the drift in the $p_t$ process and $u(r_t, q) = \begin{cases} 0.5 \text{ if } r_t > q \\ \text{-}0.5 \textit{ otherwise} \end{cases}$. Critical values can be calculated by simulating their exact distribution. Wright (2000) shows that the sign-based VR tests have generally less power than the rank-based VR test.

Finally, as in the parametric case, when there are several values of $k$ there is a tendency to over-reject the null hypothesis. Therefore, a generalization of Chow and Denning (1993) applicable to sign and rank tests proposed by Belaire-Franch and Contreras (2004) will be used. For $k_i \mid i = 1, 2, ..., m$ the statistics are:

$$CD_{(R_1)} = \max_{1 \leqslant i \leqslant m} |R_1(k_1)|, \tag{13}$$

$$CD_{(R_2)} = \max_{1 \leqslant i \leqslant m} |R_2(k_1)|, \tag{14}$$

$$CD_{(S_1)} = \max_{1 \leqslant i \leqslant m} |S_1(k_1)|, \tag{15}$$

$$CD_{(S_2)} = \max_{1 \leqslant i \leqslant m} |S_2(k_1)|, \tag{16}$$

## 3.3 Quantifying the Effect of Political Events

To complement the visual analysis of the rolling variance ratio tests, I estimate a regression that quantifies the conditional association between political events and the time-varying p-values of the VR tests. The dependent variable is the rolling p-value ($p_t^{BVL} \in [0, 1]$) of a given variance ratio test (HLZ, Kim or Wright), defined on a two-year rolling window. To accommodate this bounded support, I employ the fractional logit specification of Papke and Wooldridge (1996), which models the conditional mean through a logistic link:

$$\Lambda(z) = \frac{\exp(z)}{1 + \exp(z)} \tag{17}$$

where $\Lambda(\cdot)$ denotes the logistic Cumulative Distribution Function. I estimate two specifications of this model, which differ only in how political events enter the linear index. In the first specification, all local political events enter through a single aggregate dummy $D_t$, so that:

$$E\left[p_t^{BVL} \,\middle|\, \mathbf{X}_t\right] = \Lambda\left(\beta_0 + \beta_1 P_t^{EM} + \beta_2 D_t\right).$$

In the second, the aggregate dummy is replaced by three mutually exclusive event-type dummies: Elections with a Radical Candidate ($D_t^{ERC}$), Pro-Market Elections ($D_t^{PME}$), and Institutional Crises ($D_t^{IC}$):

$$E\big[p_t^{BVL} \,\big|\, \mathbf{X}_t\big] = \Lambda(\beta_0 + \beta_1 p_t^{EM} + \beta_{ERC} D_t^{ERC} + \beta_{PME} D_t^{PME} + \beta_{IC} D_t^{IC})$$

In both specifications, $p_t^{EM}$ denotes the rolling p-value of the same variance ratio test computed on the MSCI Emerging Markets Index, which controls for the contribution of global return-predictability dynamics to the level of the BVL p-value. The base category consists of weeks with no local political event. As a robustness check, I also estimate an augmented version of each specification that includes the conditional volatility from a GARCH(1,1) process on the Peruvian return series as an additional control, in order to absorb the residual contribution of background market turbulence to the level of $p_t^{BVL}$.

Coefficients are estimated by quasi-maximum likelihood using the Bernoulli log-likelihood, which delivers consistent estimates of $\beta$ under arbitrary distributional assumptions about the underlying p-value process. The quantity of interest is the average marginal effect (AME) of each event dummy on the Peruvian p-value. Since all event regressors are binary, the AME is computed as a discrete difference rather than a derivative:

$$AME = \frac{1}{T}\sum_{t=1}^{T}\left[\Lambda\Big(\hat{\beta}' X_t \,\Big|\, D_t^j = 1\Big) - \Lambda\Big(\hat{\beta}' X_t \,\Big|\, D_t^j = 0\Big)\right],$$

Inference is based on a parametric bootstrap with $B = 2{,}000$ replications, where coefficient draws are taken from $\mathcal{N}(\hat{\beta}, \hat{V}_{HAC})$ and $\hat{V}_{HAC}$ is a Newey–West HAC covariance matrix with $L = 103$ lags, chosen to accommodate the serial overlap induced by the two-year rolling window used to compute the variance ratio statistics.

# 4 Data

This study uses weekly closing prices for the Peruvian stock exchange measured by the MSCI NUAM Peru General Index [3]. This Index has minimum float-adjusted market capitalization and liquidity criteria. It uses a modified market capitalization weighting scheme to reduce stock concentration. Additionally, for comparative purposes, the S&P500 and MSCI Emerging Markets indices are included. Data span from January 12, 1990 to June 12, 2026, namely 1901 observations.

Summary statistics of the variables are detailed in Table 1. As can be seen, during the study period, the return of the Peruvian index has been higher than those of the emerging-market and U.S. indices, whether measured as mean or median, as a result of the Peruvian market taking off in line with the export commodity boom during the 2000s and the demand from pension funds and foreign investors. However, it can be seen that this higher return was accompanied by higher risk, measured as a higher standard deviation, a lower minimum

[3]Using daily data would allow to enlarge the sample size. However, with daily observations the biases resulting from non-trading days, bid-ask spreads, trading fees, price asynchronism, among other factors would have increased significantly (Lo and MacKinlay, 1988). This bias is more relevant in underdeveloped markets like the Peruvian Stock Market.

return and distribution tails (kurtosis) twice as wide as those of the emerging-market and U.S. indices. It should be noted that the Jarque-Bera test rejects in all cases the assumption of normality of the series, as is common for financial asset returns.

Table 1: Summary Statistics: Index Weekly Returns

| | Lima Stock Exchange | MSCI EM | S&P500 |
|---|---|---|---|
| Mean | 0.006 | 0.001 | 0.002 |
| Median | 0.004 | 0.003 | 0.003 |
| Maximum | 0.420 | 0.185 | 0.114 |
| Minimum | -0.346 | -0.226 | -0.201 |
| Std. Dev. | 0.042 | 0.029 | 0.023 |
| Skewness | 1.871 | -0.768 | -0.785 |
| Kurtosis | 21.43 | 8.73 | 9.92 |
| Jarque-Bera | 27874 | 2771 | 3966 |
| Probability | 0 | 0 | 0 |
| Observations | 1901 | 1901 | 1901 |

Source: Bloomberg

# 5 Empirical Results

## 5.1 Testing the Weak Form of Efficiency

Table 2 reports the results of the parametric and non-parametric VR tests. In all cases, the hypothesis that the Peruvian index price follows a random walk is strongly rejected[4]. Additionally, the variance ratios are above one, indicating that the process followed by the Peruvian stock market index has been dominated by momentum.

Table 2: Results of multiple VR Tests - Peruvian Stock Exchange

| Holding Period (k) | Traditional Parametric Test (Lo MacKinlay, 1988) | Leverage-Robust (HLZ, 2017) | Wild Bootstrap (Kim, 2006) | Non Parametric Test (Wright, 2000) | | |
|---|---|---|---|---|---|---|
| | | | | Sign 1 | Rank 1 | Rank 2 |
| Variance Ratio | | | | | | |
| 2 | 1.3 | 1.3 | 1.3 | 1.1 | 1.2 | 1.2 |
| 4 | 1.9 | 1.9 | 1.9 | 1.4 | 1.5 | 1.6 |
| 8 | 2.7 | 2.7 | 2.7 | 1.6 | 1.9 | 2.1 |
| 16 | 4.0 | 4.0 | 4.0 | 2.0 | 2.4 | 2.7 |
| Tests Statistics | | | | | | |
| Joint Test | $11.91^a$ | $5.23^a$ | $0.00^a$ | $10.29^a$ | $13.54^a$ | $17.03^a$ |
| 2 | $4.53^a$ | $4.53^a$ | $0.00^a$ | $6.08^a$ | $9.08^a$ | $10.08^a$ |
| 4 | $6.86^a$ | $5.23^a$ | $0.00^a$ | $8.21^a$ | $12.10^a$ | $13.96^a$ |
| 8 | $9.50^a$ | $5.10^a$ | $0.00^a$ | $9.28^a$ | $13.15^a$ | $15.91^a$ |
| 16 | $11.91^a$ | $4.66^a$ | $0.00^a$ | $10.29^a$ | $13.54^a$ | $17.03^a$ |

Notes: a, b and c denote statistical significance at the 1, 5 and 10% level, respectively. P-values are given for the Wild Bootstrap test of Kim (2006), whereas the VR test is reported for the other tests.

There are four possible factors that could explain these results. The first factor is that liquidity is structurally very low. On the supply side, only 36% of the market capitalization

[4]The result does not change if the tests are performed with daily series (see Appendix A.1)

of main local stocks remains as free float. On the demand side, private pension funds keep about 60% of that float (see Segura and Villavicencio, 2019). The second factor is the absence of a developed derivatives market. This makes it difficult to exploit arbitrage opportunities through long and short positions. The third factor is that corporate governance and the flow of information are still far from what is available in other markets, including emerging markets. This discourages additional investor participation. Finally, the cost of participation of investors, especially individual investors (who are normally liquidity providers) can be as much as eleven times what an institutional investor pays. This has continually discouraged participation by these investors (see Villavicencio, 2022).

## 5.2 Testing the Adaptive Market Hypothesis

The results of the previous section show a strong rejection of the weak form of the EMH. However, it is possible that it hides short-term dynamics resulting from different events that impact the local stock market environment, causing it to fluctuate between different levels of efficiency (unpredictability) and inefficiency (predictability), as conjectured by the AMH. Therefore, following the literature, in this section I will test the AMH for Peru by studying the evolution of the VR tests over time in the face of international and local events, considering different rolling windows. For the rolling-window analysis I focus on the leverage-robust test of Hong et al. (2017), since by relaxing the no-leverage (H4) assumption of Lo and MacKinlay (1988) through cross-lag covariance terms it provides the most conservative inference and therefore the most defensible rejections in the presence of asymmetric volatility. Results obtained using the wild bootstrap test of Kim (2006), which improves the small-sample properties of the conventional VR test, are reported in Appendix A.3 as a robustness check. In the non-parametric case, I use the Rank indicator because, according to Wright (2000) and Belaire-Franch and Contreras (2004), it has more power than the sign test.

### Global Events

Table 3 describes the international events that may have affected the efficiency of the domestic equity market. Figure 1 shows the returns and volatility of the Peruvian stock market index. In the same figure, the gray areas mark each of the international events considered in Table 3.

Table 3: International Events

| | International Events: International Crisis |
|---|---|
| December 20, 1994 to November 11, 1995 | Mexican Crisis |
| July 2, 1997 to March 31, 1999 | Asian Financial Crisis/Russian Financial Crisis |
| March 19, 2000 to November 16, 2001 | Crisis Dot-com |
| December 31, 2007 to June 30, 2009 | Subprime Crisis and Great Recession |
| June 20, 2013 to January 7, 2016 | China Hard Landing (Ahmed et al., 2019) |
| January 30, 2020 to July 24, 2020 | COVID-19 pandemic |

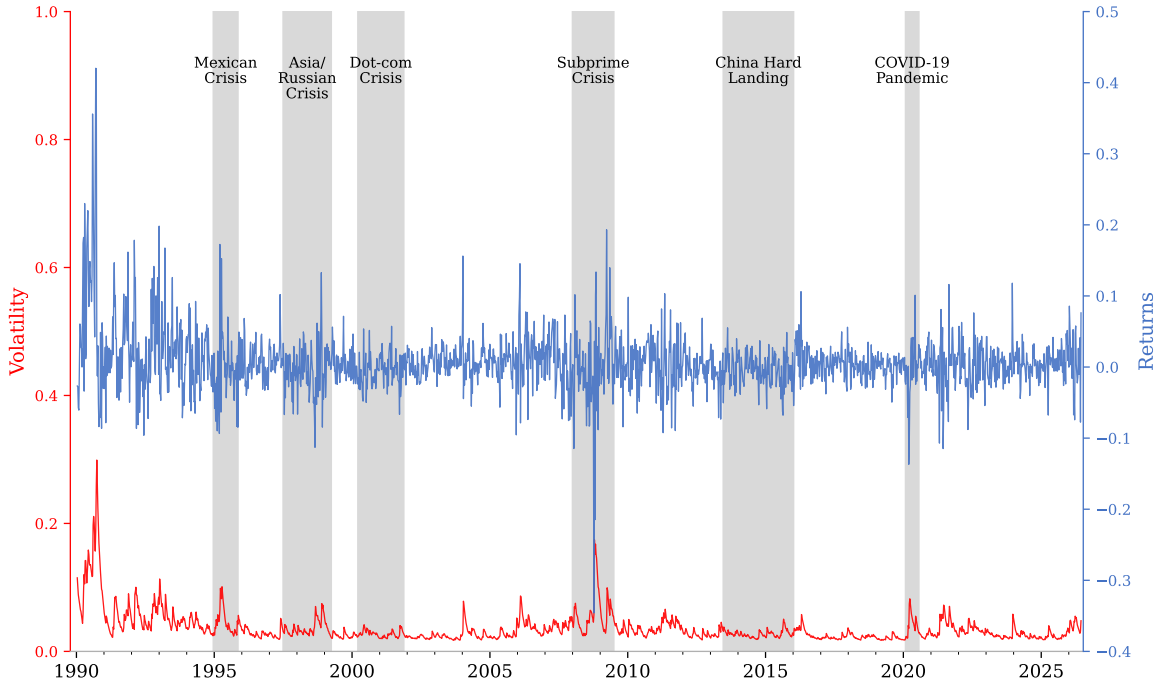



Figure 1: MSCI NUAM Peru General Index returns and Volatility. Source: Bloomberg. Volatility is described by a GARCH(1,1) process.

The following figures present the results of the overlapping rolling-window analysis based on the p-values of Hong et al. (2017) leverage-robust test and the Wright (2000) rank test, using the MSCI NUAM Peru General Index. Figures 2 and 3 show windows of 104 and 260 weeks, which are approximately equivalent to two and five years, respectively. In both cases, a gray area is added to mark the periods where negative global events occurred. Additionally, two lines are included in the graphs to mark the 5% and 10% p-value. Thus, if, for example, the p-value of a test falls below the 5% threshold, the null hypothesis that the stock market index follows a random walk is rejected at the 5% significance level.

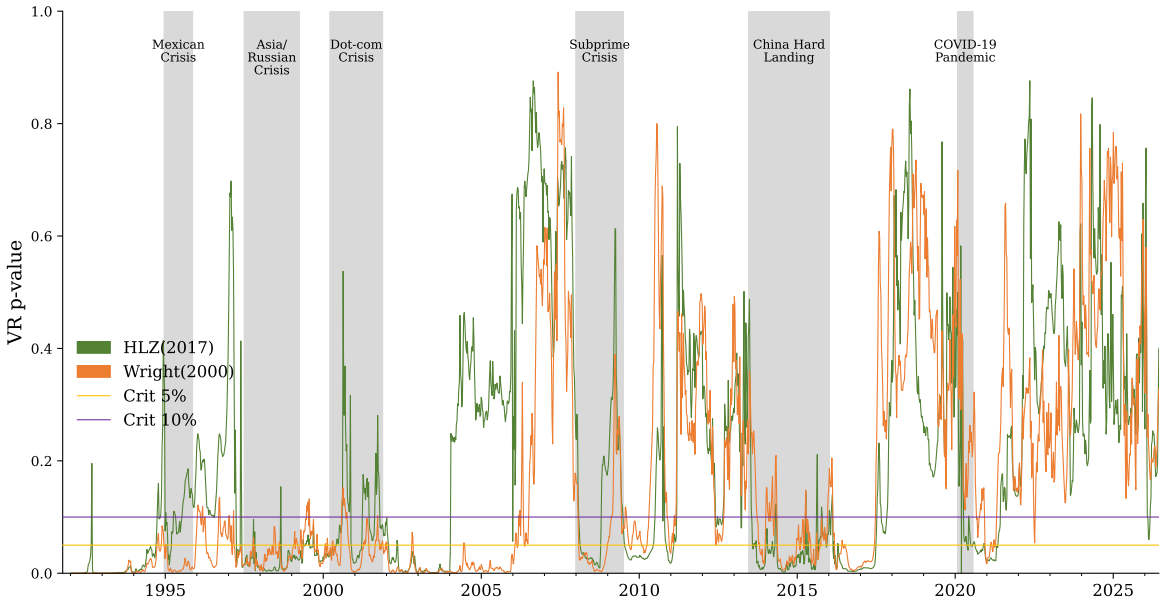



Figure 2: Leverage-Robust (HLZ, 2017) and Rank Test (Wright, 2000). Rolling window T= 104 weeks

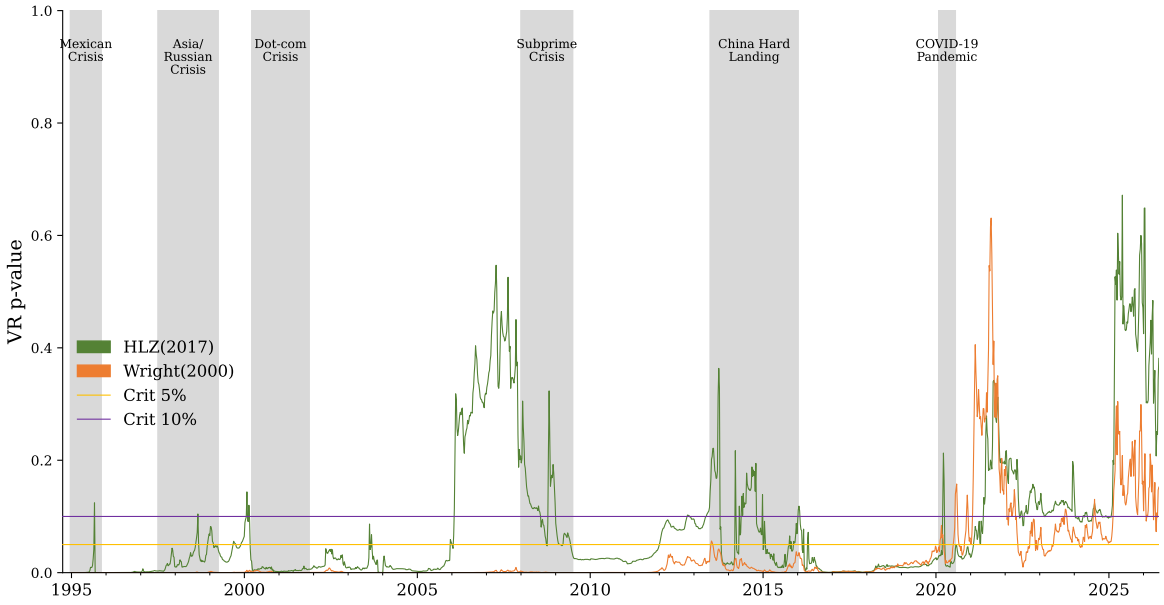



Figure 3: Leverage-Robust (HLZ, 2017) and Rank Test (Wright, 2000). Rolling window T= 260 weeks

Beyond the results of the Table 2, Figures 2 and 3 show that there are periods where it is not possible to predict the asset returns, which implies that the null hypothesis of random walk is not rejected. However, these periods are more clearly identifiable when using the two-year window than when using the five-year window. This suggests that the events that generate the switches between efficiency and inefficiency occur for short periods. It is

important to note that the parametric and non-parametric test results in the 2-year window case coincide in magnitude and direction more frequently after 2005.

In terms of the impact of international events, Figure 2 shows that the Asian/Russian crises of 1997/1998, the Dot-com crisis of 2000-2001, the 2008 Subprime Crisis, the China "Hard Landing", as well as the COVID-19 Pandemic have negative, albeit temporary, effects on efficiency [5]. In line with Lo (2004, 2005), in the face of a negative shock that changes the environment, agents adapt using heuristic approaches that lead them to make mistakes (inefficient market), from which they learn, at which point efficiency returns. This result is different from that obtained by Hoque et al. (2007) and Kim and Shamsuddin (2008) in their research on the impact of the 1997 Asian Crisis on the countries of that region. Unlike my analysis, they use a non-overlapping sub-sample analysis. It is possible that such an analysis strategy makes short-run fluctuations in efficiency/inefficiency difficult to detect[6]. However, my result is in line with other research that follow overlapping sub-sample analysis for developed and developing countries (see Boya, 2019; Hiremath and Narayan, 2016; Cheong et al., 2007; Lim et al., 2008).

## Local Political Events

A different pattern emerges when the analysis turns to local political events. Table 4 reports the eleven most important Peruvian political episodes between 2001 and 2026, classifying each according to the type of uncertainty it introduced into the market: Elections with a Radical Candidate (ERC), in which a contender proposing a sharp departure from the prevailing market-oriented policy framework reached a competitive position; Pro-Market Elections (PME), in which both runoff candidates held broadly market-oriented platforms and the contest posed no perceived threat to local financial assets; and Institutional Crises (IC), non-electoral episodes in which democratic stability was directly compromised, such as presidential removal. Across the electoral episodes in the sample, candidates perceived as radical or non-market-friendly were a recurrent source of uncertainty, reaching the runoff in all cases except 2016, the only PME episode, when the second round was ultimately contested by two broadly market-oriented candidates. Among the radical or non-market-friendly candidates, only those in 2011 and 2021 ultimately secured the presidency. Overall, the selected political episodes were associated with heightened volatility and deteriorating local asset prices, reflecting recurrent uncertainty about the future direction of economic policy.

Table 4: Local Political Events in Peru (2001-2026)

| Event | Start | End | Classification | | | Summary |
|---|---|---|---|---|---|---|
| | | | ERC | PME | IC | |
| 2001 Election: Toledo vs. García | 08/04/2001 | 03/06/2001 | ✓ | | | Fear of a possible victory by Alan García due to memories of his first administration. Uncertainty dissipated after his defeat to Toledo in the runoff election. |

[5] In the case of the Mexican Crisis, the market was statistically inefficient before the event.

[6] When using non-overlapping subsamples, a date is determined based on some rationale and the sample is split in two. This does not allow for the identification of events that may have occurred within those sub-samples or the fact that the event itself may have been anticipated prior to the date chosen

| Event | Start | End | Classification | | | Summary |
|---|---|---|---|---|---|---|
| | | | ERC | PME | IC | |
| 2006 Election: García vs. Humala | 09/04/2006 | 04/06/2006 | ✓ | | | The emergence of Ollanta Humala with radical proposals, including nationalizations, generated concern among investors. Uncertainty ended when Humala lost the runoff election. |
| 2011 Election: Humala vs. Fujimori | 10/04/2011 | 05/06/2011 | ✓ | | | Humala ran again and won, initially generating substantial uncertainty, reflected in declining stock prices and exchange-rate depreciation. Once elected, he moderated his economic policies. |
| 2016 Election: Kuczynski vs. Fujimori | 10/04/2016 | 05/06/2016 | | ✓ | | Although the two candidates that advanced to the runoff held pro-market platforms, the left-wing candidate came very close to second place after months of rising support, generating uncertainty during the first-round campaign that dissipated with her defeat. |
| Resignation of Kuczynski | 15/12/2017 | 23/03/2018 | | | ✓ | The second impeachment attempt against President Pedro Pablo Kuczynski culminated in his resignation from office. |
| Impeachment of Vizcarra | 18/09/2020 | 09/11/2020 | | | ✓ | President Martín Vizcarra was removed from office by Congress. |
| 2021 Election: Castillo vs. Fujimori | 11/04/2021 | 06/06/2021 | ✓ | | | Pedro Castillo's victory, accompanied by radical proposals including constitutional change, triggered a decline in stock prices and a depreciation of the domestic currency to historical lows. |
| Castillo's Self-Coup Attempt | 08/03/2022 | 07/12/2022 | | | ✓ | Period between the approval of the second impeachment motion against Castillo and his self-coup attempt on December 7. Characterized by successive episodes of institutional uncertainty. |
| Peruvian Protests (2022–2023) | 07/12/2022 | 09/12/2023 | | | ✓ | Wave of protests following Castillo's self-coup attempt and Boluarte's succession. |
| Impeachment of Boluarte | 26/09/2025 | 10/10/2025 | | | ✓ | Fourth interruption of a presidential term since 2018, occurring only months before an election that was already a source of uncertainty. |
| 2026 Election: Sánchez vs. Fujimori | 12/04/2026 | 07/06/2026 | ✓ | | | Roberto Sánchez advanced economic proposals comparable in radicalism to those of previous left-wing candidates, alarming investors about the prospect of a radical victory. |

*Notes:* ERC = Election with a Radical Candidate; PME = Pro-Market Election; IC = Institutional Crisis. A check mark indicates the classification assigned to each event for the event-window analysis.

Figures 4, 5, and 6 show the evolution of the p-value of the Hong et al. (2017), Wright (2000) and Kim (2006) variance ratio test, respectively, in each of the local political events

described. The circles mark the dates surrounding domestic political events. Additionally, the volatility of the Peruvian stock market and the p-value of the emerging markets test are included. The latter is included to detect if there is an external influence on the result.

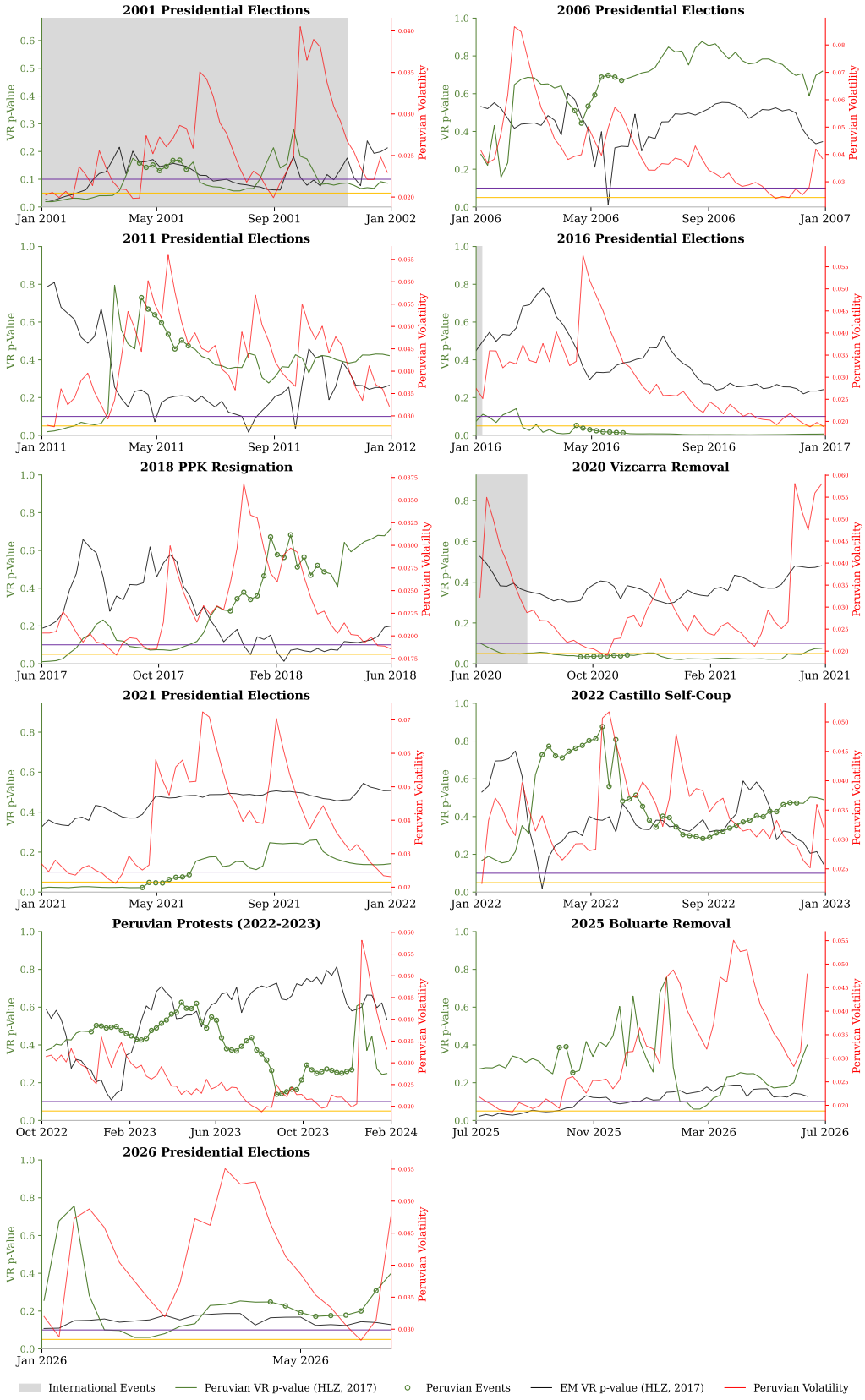



Figure 4: Peruvian Political Event - Leverage Robust HLZ (2017). Note: Rolling window T=104 weeks.Volatility is described by a GARCH(1,1) process.

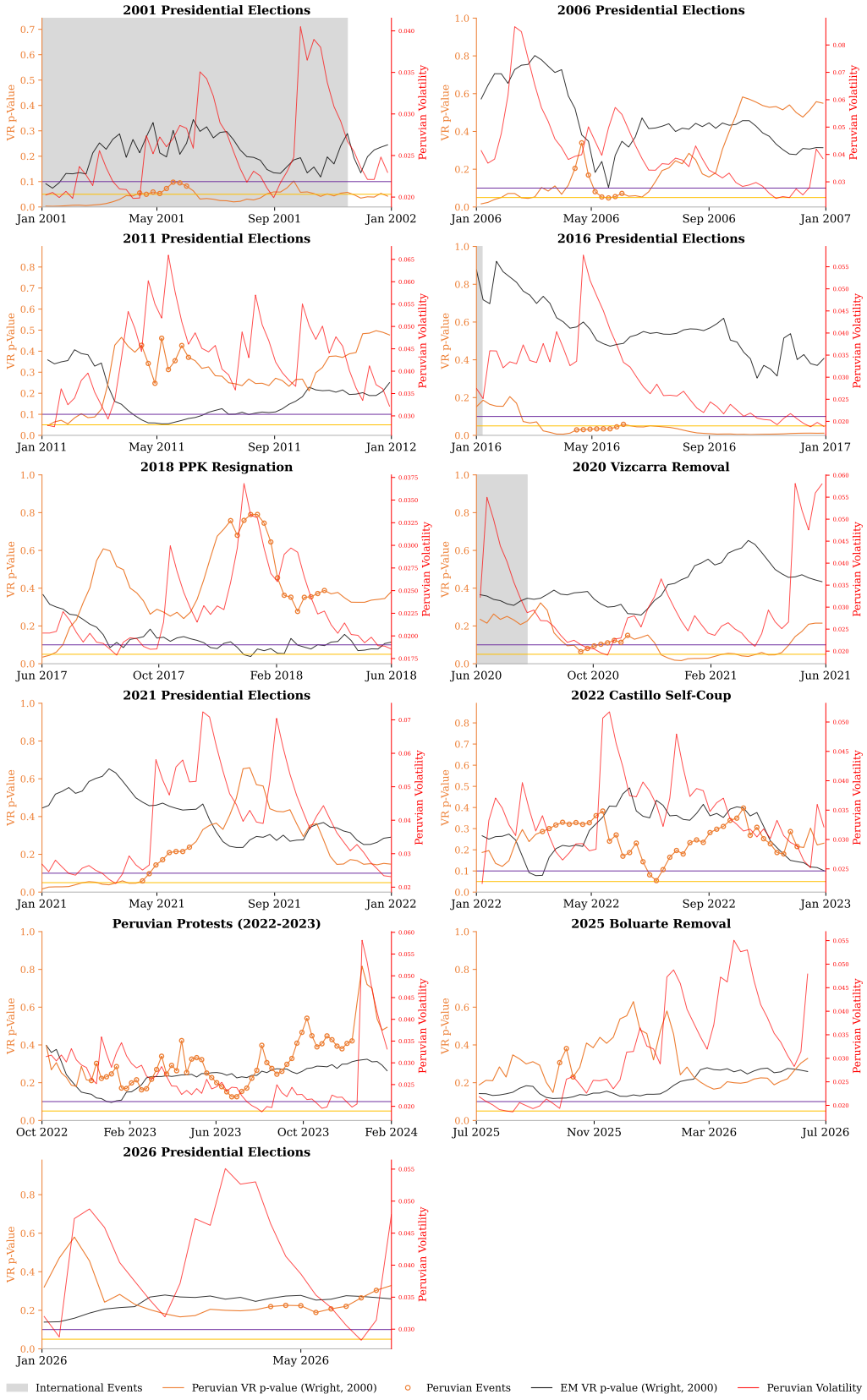



Figure 5: Peruvian Political Event - VR Wright(2000). Note: Rolling window T=104 weeks. Volatility is described by a GARCH(1,1) process.

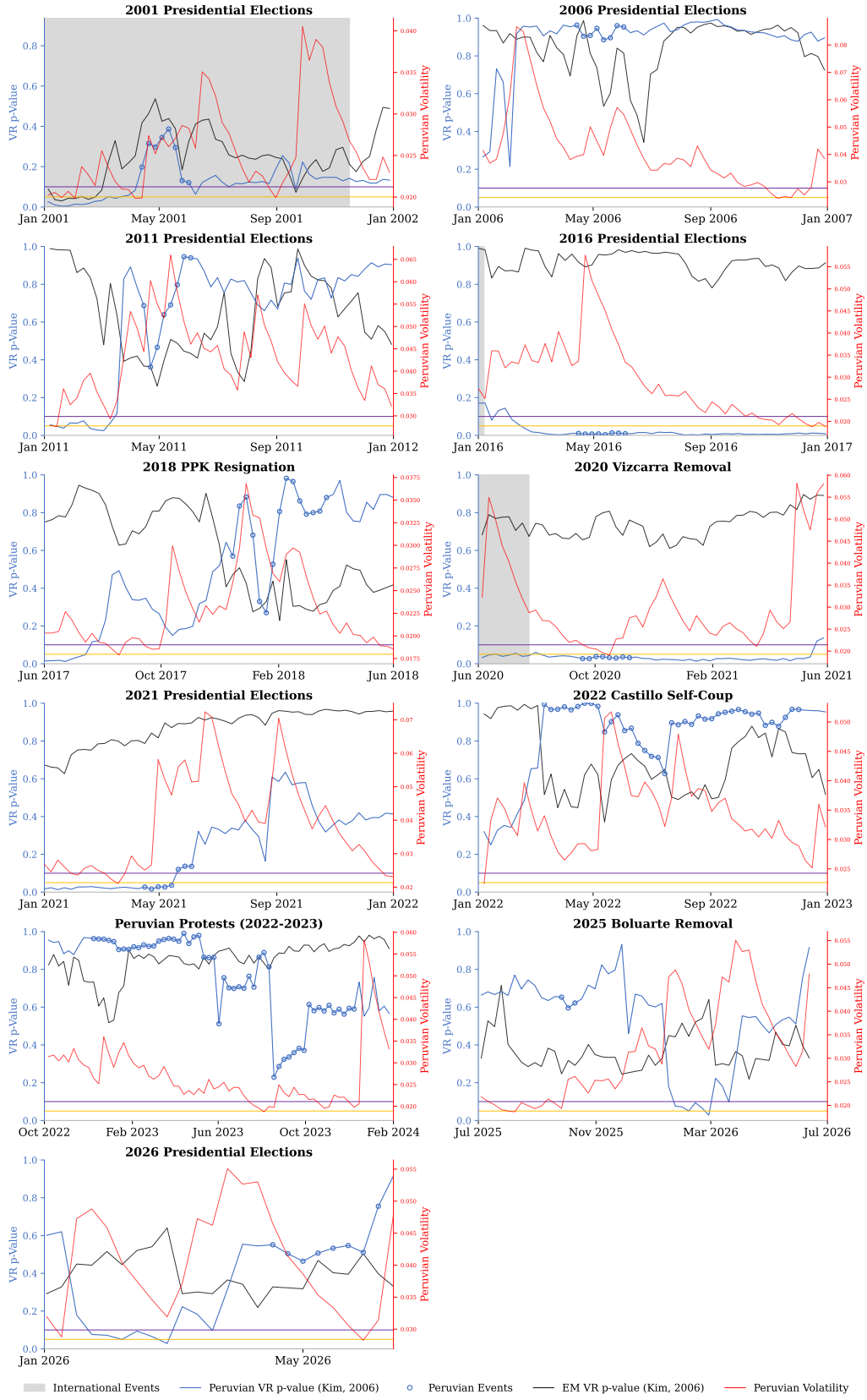



Figure 6: Peruvian Political Event - VR Kim (2006). Note: Rolling window T=104 weeks. Volatility is described by a GARCH(1,1) process.

For Elections with a Radical Candidate (ERC), the three variance ratio tests reveal a movement toward statistical efficiency during the event window, in contrast to both the standard AMH prediction and the pattern observed around global shocks. Rather than increasing return predictability, ERC episodes are associated with rising p-values that move away from the rejection zone of the random walk null. Under HLZ and Kim, the p-value shifts from rejection to non-rejection in 2001, 2011, 2021, and 2026, while under Wright this transition occurs in 2001, 2006, and 2021 at the 5% level. In the remaining ERC episodes, the p-value already starts in the non-rejection region and moves further away from the critical thresholds during the event window.

Institutional Crises (IC) display the same broad movement toward statistical efficiency, although with more heterogeneous within-event dynamics than electoral episodes. The 2018 Kuczynski resignation provides the clearest case, with all three tests moving from rejection to non-rejection during the event window. By contrast, the 2020 Vizcarra removal moves in the opposite direction, most likely reflecting the fading of the COVID-19 shock rather than an idiosyncratic response to the political event itself.

The 2016 election, the only Pro-Market Election (PME) in the sample, remains entirely within the rejection region across HLZ, Kim, and Wright, consistent with the perception that a runoff between two pro-market candidates posed no meaningful threat to local financial assets.

These results are supported by the fractional logit regression analysis reported in Table 5. For the electoral events (ERC and PME), the event dummies run from the first-round election through December 31 of the same year, rather than ending at the runoff. This choice reflects the fact that the incoming administration takes office only on July 28 and that uncertainty about its policy orientation is resolved gradually rather than immediately after the election. The event windows for institutional crises follow the dates reported in Table 4.

Table 5: Average Marginal Effects (AME) of the Event Dummies by VR Test

| | HLZ | | Kim | | Wright | |
|---|---|---|---|---|---|---|
| | Base | Extended | Base | Extended | Base | Extended |
| *Specification 1: Single dummy* | | | | | | |
| $D_t$ | $0.1475^{***}$ | $0.1479^{***}$ | $0.2128^{**}$ | $0.2188^{**}$ | $0.0879^{**}$ | $0.0925^{**}$ |
| | (0.0550) | (0.0538) | (0.0901) | (0.0898) | (0.0407) | (0.0419) |
| *Specification 2: Dummy by event class* | | | | | | |
| $D_t^{ERC}$ | $0.1748^{*}$ | $0.1796^{**}$ | $0.2038^{*}$ | $0.2253^{**}$ | $0.0974^{*}$ | $0.1193^{*}$ |
| | (0.0908) | (0.0883) | (0.1089) | (0.1086) | (0.0573) | (0.0666) |
| $D_t^{PME}$ | $-0.1873^{***}$ | $-0.1876^{***}$ | $-0.3382^{***}$ | $-0.3387^{***}$ | $-0.1430^{***}$ | $-0.1435^{***}$ |
| | (0.0319) | (0.0320) | (0.0499) | (0.0490) | (0.0370) | (0.0358) |
| $D_t^{IC}$ | $0.2101^{***}$ | $0.2064^{***}$ | $0.3841^{***}$ | $0.3727^{***}$ | $0.1500^{***}$ | $0.1355^{***}$ |
| | (0.0680) | (0.0686) | (0.0990) | (0.1060) | (0.0519) | (0.0518) |

*Notes:* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses. Base refers to the basic model specification. Extended includes GARCH(1,1) as an additional control variable. Only events AMEs are shown.

The fractional logit results reinforce the visual evidence. In the baseline aggregate specifi-

cation, local political events have positive and significant Average Marginal Effects (AMEs) across the three tests (HLZ: +0.15, Kim: +0.22, Wright: +0.09), indicating that these episodes are associated with higher rolling p-values and, therefore, with a movement toward the non-rejection region. The disaggregated specification shows that this result is driven by both ERC and IC events. ERC episodes display positive AMEs across all tests (HLZ: +0.17, Kim: +0.20, Wright: +0.10), while IC episodes exhibit larger and highly significant effects (HLZ: +0.21, Kim: +0.38, Wright: +0.15), consistent with stronger displacements toward statistical efficiency during institutional crises. By contrast, the PME dummy is negative and significant across the three tests (HLZ: -0.19, Kim: -0.34, Wright: -0.14). These patterns remain unchanged when GARCH volatility is included as an additional control.

The negative PME coefficient should therefore be interpreted with caution. In 2016, the event window begins at the first round, when a radical candidate narrowly failed to reach the runoff. The regression therefore captures the resolution of this near-radical outcome rather than the runoff itself, which was ultimately contested by two pro-market candidates. Consistent with this interpretation, the HLZ p-value reaches a small local maximum around the first round and declines thereafter, while remaining below the critical thresholds throughout the episode. Thus, the PME coefficient reflects movement within the rejection region, not evidence against the broader result that radical electoral shocks and institutional crises move the market toward statistical efficiency.

These findings suggest that the Peruvian result is not simply a mechanical response to political events, but an institutionally conditioned form of expectation disruption. Elections matter for financial markets because they provide information about future fiscal, monetary, and regulatory policy, leading investors to revise their expectations about the economy (see Pantzalis et al., 2000). However, the evidence reported above indicates that, in Peru, the effect of political events depends on whether investors can translate electoral or institutional outcomes into credible expectations about future policy regimes. When parties and coalitions are weak, this mapping becomes more difficult: political platforms are less stable, governing agendas are harder to anticipate, and policy implementation becomes less predictable (see Downs, 1957; Powell et al., 2015). In this context, political uncertainty may reduce return predictability not because information is processed more efficiently, but because investors face greater difficulty assigning stable probabilities to future economic scenarios.

The recurrent emergence of radical or outsider candidates in Peru is closely related to the country's low level of political institutionalization. Peru has been described as one of the most extreme cases of party-system collapse in Latin America (see Zavaleta, 2022; Levitsky and Zavaleta, 2019; Levitsky and Cameron, 2003). Recent comparative research further characterizes Peru as a case of self-reproducing partylessness, where personalistic electoral vehicles, weak internal cohesion, and limited institutional memory undermine the consolidation of stable programmatic parties (see Sánchez-Sibony, 2024). Consistent with this diagnosis, identification with political parties declined from 30% in 2006, already a low level, to 10.8% in 2018 and 9% in 2023, the most recent available measurement and the lowest level recorded since the Americas Barometer series began[7]. Figure 7 shows the same institutional deterioration from the electoral side. The number of political parties increased from 8 in the 2001 election to 18 in 2021 and 36 in 2026, the highest level recorded since Peru's return to democracy in 1980. At the same time, the representativeness of the first- and second-place candidates, measured by their combined vote share in the first round of presidential elections, fell from 83% in the 2000 election to only 24% in the most recent election. This combination

[7]See The Americas Barometer by the LAPOP Lab, `http://www.vanderbilt.edu/lapop`.

of fragmentation and declining representativeness helps explain why political events in Peru can generate regime uncertainty severe enough to make future policy paths harder to map into stable expectations.

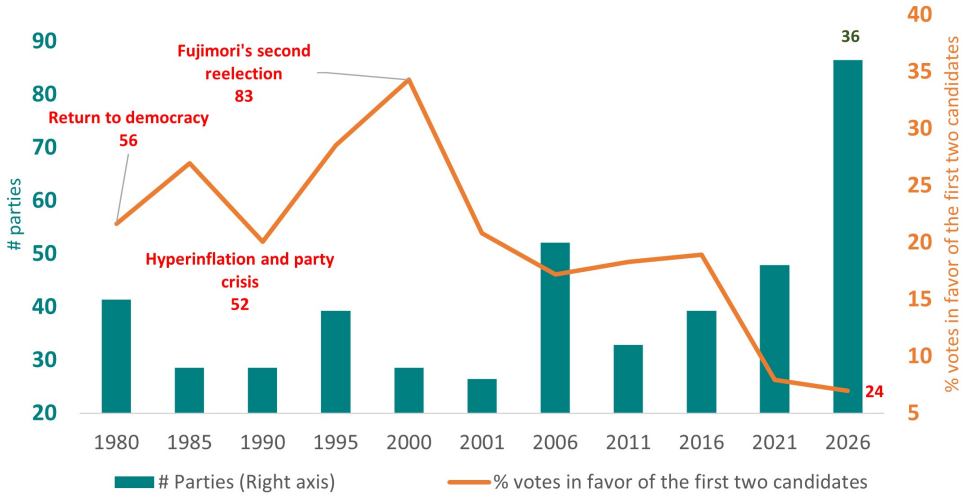



Figure 7: Evolution of the number of political parties and their representativeness in elections. Source: ONPE

### Political events in other countries of the Latin American region

As discussed in the previous section, Peruvian political events impact the local stock market in a way that contradicts the standard AMH. Rather than political shocks acting as uncertainty events that cause decision-making errors among agents and generate predictable returns, my results show that the statistical tests move further away from rejecting market efficiency.

This raises the question of whether the same phenomenon occurs in other Latin American countries, such as Argentina, Brazil, Chile, Colombia, Mexico, and Panama. Table 6 reports the fractional logit regression results for each country. A single election event dummy is used, as only electoral episodes are considered for the comparator countries. Figures 8 to 13, in Appendix A.2, complement these results by plotting the rolling p-values of the Hong et al. (2017) and Wright (2000) tests around each electoral event.

The central conclusion from Table 6 is that the Peruvian pattern is not systematically present across the rest of the region. Argentina and Mexico are the only other countries displaying positive and significant Average Marginal Effects (AMEs), but only under the parametric tests; the Wright Rank test fails to confirm the effect in both cases. Conversely, Colombia and Panama show negative AMEs —which aligns with the standard AMH prediction that political uncertainty pushes markets toward inefficiency— though these results are not significant across all three variance ratio (VR) tests. Brazil shows no significant effect under any test, while Chile displays weak or negligible effects. All results are robust to the inclusion of GARCH(1,1) volatility as an additional control. Thus, Peru remains the only country where political events produce a positive and significant effect on rolling p-values across all three inference procedures simultaneously.

We attribute this anomaly to Peru's exceptionally weak party structure. The frequent emergence of political outliers during elections and the recent, recurrent interruptions of presidential terms make it exceedingly difficult to anticipate the country's future direction,

thereby generating unpredictability in Peruvian asset returns. This aligns with the characterization of Peru as one of Latin America's most extreme cases of party-system collapse and self-reproducing partylessness (see Levitsky and Cameron, 2003; Levitsky and Zavaleta, 2019; Sánchez-Sibony, 2024). In countries with more robust political institutions and party structures, such as Brazil, Chile, and Panama, this Peruvian effect is not observed. However, this does not preclude the possibility of similar patterns emerging elsewhere in the region as political landscapes evolve,[8] and the framework presented in this paper may help shed light on future market evolutions in those contexts.

Table 6: Average Marginal Effects (AME) of the Event Dummies by VR Test for Latin American Countries

| | HLZ | | Kim | | Wright | |
|---|---|---|---|---|---|---|
| | Base | Extended | Base | Extended | Base | Extended |
| *Argentina* | | | | | | |
| $D_t$ | $0.0834^{*}$ | $0.0817^{*}$ | $0.2088^{***}$ | $0.2049^{***}$ | 0.0543 | 0.0563 |
| | (0.0445) | (0.0438) | (0.0468) | (0.0442) | (0.0739) | (0.0720) |
| *Brazil* | | | | | | |
| $D_t$ | 0.0408 | 0.0453 | 0.0225 | 0.0400 | $-0.0154$ | $-0.0110$ |
| | (0.0501) | (0.0499) | (0.0698) | (0.0696) | (0.0474) | (0.0483) |
| *Chile* | | | | | | |
| $D_t$ | 0.0060 | 0.0042 | 0.0142 | 0.0100 | $-0.0769^{*}$ | $-0.0852^{**}$ |
| | (0.0433) | (0.0422) | (0.0675) | (0.0675) | (0.0416) | (0.0391) |
| *Colombia* | | | | | | |
| $D_t$ | $-0.0877^{*}$ | $-0.0896^{*}$ | $-0.1631^{**}$ | $-0.1639^{**}$ | $-0.0460$ | $-0.0447$ |
| | (0.0497) | (0.0483) | (0.0757) | (0.0753) | (0.0475) | (0.0472) |
| *Mexico* | | | | | | |
| $D_t$ | $0.1428^{**}$ | $0.1431^{**}$ | $0.1862^{***}$ | $0.1891^{***}$ | 0.0795 | 0.0825 |
| | (0.0580) | (0.0569) | (0.0709) | (0.0716) | (0.0787) | (0.0791) |
| *Panama* | | | | | | |
| $D_t$ | $-0.0578^{*}$ | $-0.0580^{**}$ | $-0.0857$ | $-0.0857$ | $-0.0803^{*}$ | $-0.0805^{*}$ |
| | (0.0298) | (0.0289) | (0.0798) | (0.0780) | (0.0473) | (0.0467) |

*Notes:* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses. Base refers to the basic model specification. Extended includes GARCH(1,1) as an additional control variable. Only event AMEs are shown. Since only election events are considered for the Latin American countries, a single event dummy ($D_t$) is included for each country.

[8] According to the Americas Barometer, the proportion of people in the aforementioned regional countries who do not believe democracy is the best form of government increased from 19.9% in 2008 to 39.2% in 2021. Over the same period, this figure in Peru surged from 27% to 64.9%.

# 6 Conclusions

This paper shows that the empirical interpretation of AMH tests depends critically on the source of uncertainty. Under the standard AMH mechanism, shocks that alter the market environment may generate temporary inefficiencies as investors rely on heuristics, make errors, and gradually adapt to new conditions. The evidence from Peru confirms this mechanism in the case of global systemic shocks. International financial crises and the COVID-19 pandemic are associated with temporary increases in return predictability, followed by a gradual return toward statistical efficiency.

Domestic political shocks, however, generate a markedly different response. Presidential elections characterized by radical or outsider candidates, as well as episodes of institutional crisis, do not increase return predictability. Instead, they are associated with higher rolling p-values and movements toward non-rejection of the random walk hypothesis. The fractional logit results confirm that this pattern is not only visual: Elections with a Radical Candidate and Institutional Crises display positive and significant average marginal effects across the parametric and non-parametric variance-ratio tests. These findings suggest that domestic political uncertainty in Peru can mimic statistical efficiency by making returns harder to predict.

This result should not be interpreted as improved information processing. Rather, it reflects a disruption in expectation formation under extreme regime uncertainty. In weakly institutionalized political systems, investors may face difficulty assigning stable probabilities to future policy scenarios because parties, platforms, and governing coalitions provide weak anchors for anticipating the direction, feasibility, and persistence of economic policy. In such a setting, political shocks may reduce predictability not because markets adapt more efficiently, but because future fundamentals become harder to map into stable expectations.

The Peruvian case highlights the importance of political institutions for market adaptation. Peru's party-system collapse, high electoral fragmentation, declining party identification, and recurrent emergence of radical or outsider candidates provide an institutional context in which political events can affect the statistical properties of asset returns in a distinctive way. Comparative evidence from Argentina, Brazil, Chile, Colombia, Mexico, and Panama suggests that this pattern is not a generic emerging-market response, but is more closely associated with weak party-system institutionalization and severe regime uncertainty.

The contribution of this study therefore extends beyond testing the AMH in an emerging market. It suggests that institutional fragility can reshape the observed dynamics of market efficiency by altering the way investors form expectations about future policy regimes. Market adaptability depends not only on competition, learning, and behavioral biases, but also on the institutional anchors that allow agents to translate political outcomes into credible economic scenarios.

Peru thus provides a rare contemporary case and potentially an early signal for other democracies experiencing rising fragmentation and declining party identification. Future research should further examine how institutional quality, party-system stability, and regime uncertainty interact with market adaptability across countries and over time.

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# A Appendix

## A.1 Evaluating the efficiency of the Peruvian market with daily data

In this research I used weekly data, given that with daily data the biases resulting from non-trading days, bid-ask spreads, trading fees, price asynchronism, among other factors would have increased significantly (Lo and MacKinlay, 1988). This is more relevant in underdeveloped markets like the Peruvian Stock Markets.

This appendix reviews the consistency of the test results compared to those obtained using daily data. As can be seen in the Table 7, the statistics remain in the rejection zone for the whole sample as is the case when using weekly data, although showing higher statistics for the case of daily data.

Table 7: Results of multiple VR Tests - Peruvian Stock Exchange - Daily Data

| Holding | Traditional Parametric Test | Leverage-Robust | Wild Bootstrap | Non Parametric Test (Wright, 2000) | | |
|---|---|---|---|---|---|---|
| Period (k) | (Lo MacKinlay, 1988) | (HLZ, 2017) | (Kim, 2006) | Sign 1 | Rank 1 | Rank 2 |
| | | | Tests Statistics | | | |
| Joint Test | $18.11^a$ | $11.20^a$ | $0.00^a$ | $14.71^a$ | $24.73^a$ | $29.67^a$ |
| 2 | $11.20^a$ | $11.20^a$ | $0.00^a$ | $13.84^a$ | $21.24^a$ | $24.29^a$ |
| 4 | $12.69^a$ | $9.81^a$ | $0.00^a$ | $14.51^a$ | $22.70^a$ | $26.04^a$ |
| 8 | $14.94^a$ | $8.84^a$ | $0.00^a$ | $14.60^a$ | $23.30^a$ | $27.19^a$ |
| 16 | $18.11^a$ | $8.74^a$ | $0.00^a$ | $14.71^a$ | $24.73^a$ | $29.67^a$ |

Notes: a, b and c denote statistical significance at the 1, 5 and 10% level, respectively. P-value are given for the Wild Bootstrap test (Kim, 2006), whereas the VR test is reported for the other tests

## A.2 AMH political events in Latam Region

This section presents the evolution of the statistical tests for the following countries in the Latin American region: Argentina, Brazil, Chile, Colombia, Mexico and Panama. Table 8 reports the main descriptive statistics from January 08, 1993 to June 12, 2026. Peru is included in the table for comparative purposes.

The table shows that in all Latin American countries the normality of returns is rejected (Jarque-Bera test probability below 0.01). This result is corroborated when negative skewness and kurtosis above 3 (number corresponding to normal distributions) are observed. This fact indicates that the stock market returns of the Latin American countries studied suffer from extreme negative events.

Table 8: Summary Statistics: Weekly returns of Latin American indexes

| Country | Argentina | Brasil | Chile | Colombia | Mexico | Panama | Peru |
|---|---|---|---|---|---|---|---|
| Index | MSCI | MSCI | MSCI | MSCI | MSCI | General | MSCI General |
| Mean | 0.0014 | 0.0011 | 0.0007 | 0.0013 | 0.0010 | 0.0023 | 0.0029 |
| Median | 0.0028 | 0.0041 | 0.0020 | 0.0020 | 0.0028 | 0.0001 | 0.0025 |
| Maximum | 0.3477 | 0.2562 | 0.1913 | 0.2777 | 0.2255 | 0.1692 | 0.1931 |
| Minimum | -0.4908 | -0.3306 | -0.3466 | -0.3913 | -0.3168 | -0.1087 | -0.3460 |
| Std. Dev. | 0.0558 | 0.0515 | 0.0350 | 0.0423 | 0.0404 | 0.0142 | 0.0334 |
| Skewness | -0.7384 | -0.4814 | -0.8448 | -0.9431 | -0.7576 | 3.8510 | -0.4143 |
| Kurtosis | 11 | 7 | 11 | 13 | 10 | 44 | 13 |
| Jarque-Bera | 4521 | 1002 | 4650 | 7112 | 3616 | 125537 | 7899 |
| Probability | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Observations | 1745 | 1745 | 1745 | 1745 | 1745 | 1745 | 1745 |

Source: Bloomberg

The following figures show the results of the evaluation of adaptive markets for the Latin American countries considered in the presence of political events [9]. It should be noted that the title of each sub-figure is the last name of the winning candidate in the election, with the exception of the 2025 Congress Election in Argentina.

[9]Finally, it is worth noting that the impacts of global events on market evolution in Latin American countries are similar to those in Peru. Therefore, in this appendix I focus on political events.

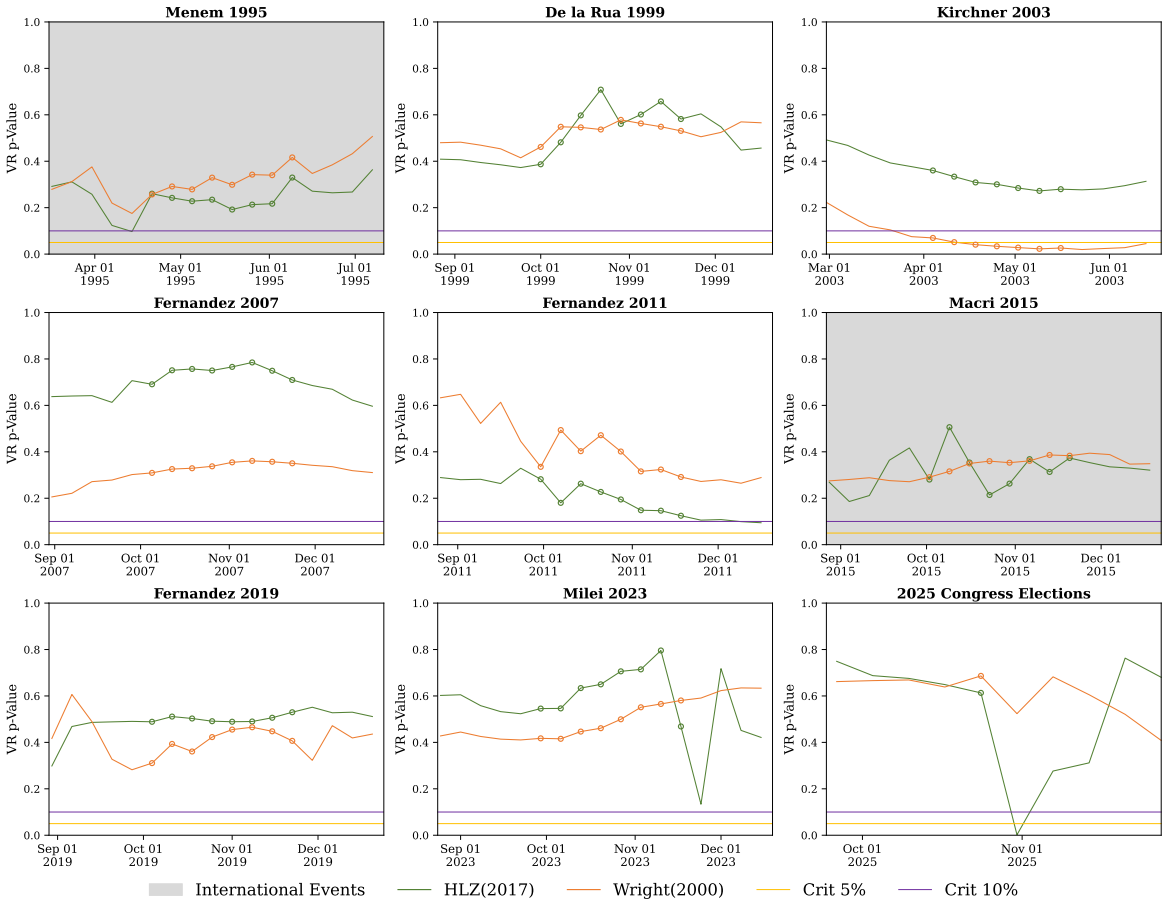



Figure 8: Argentine Political Events. Leverage-Robust (HLZ, 201T) and Rank Test (Wright, 2000). Rolling window T= 104 weeks. The gray areas represent external events.

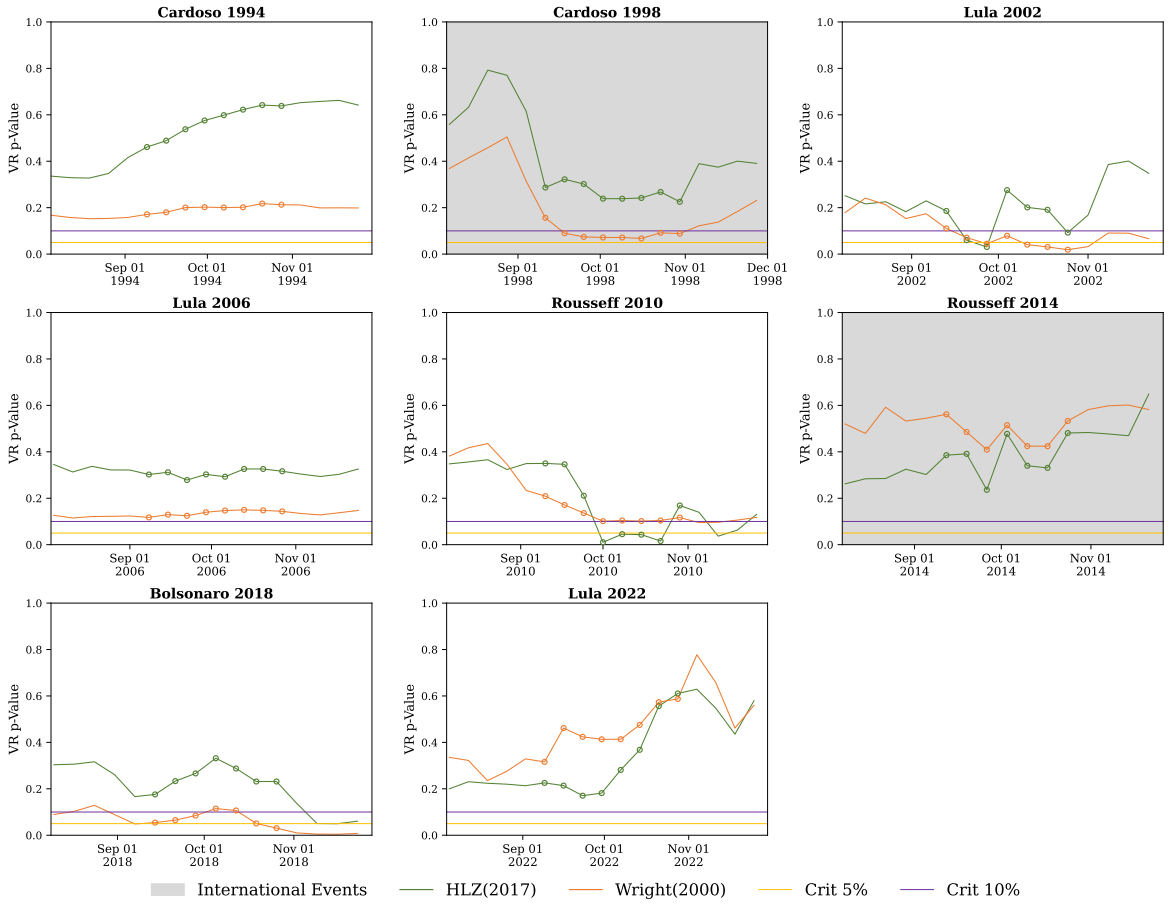



Figure 9: Brazilian Political Events. Leverage-Robust (HLZ, 2017) and Rank Test (Wright, 2000). Rolling window T= 104 weeks. The gray areas represent external events.

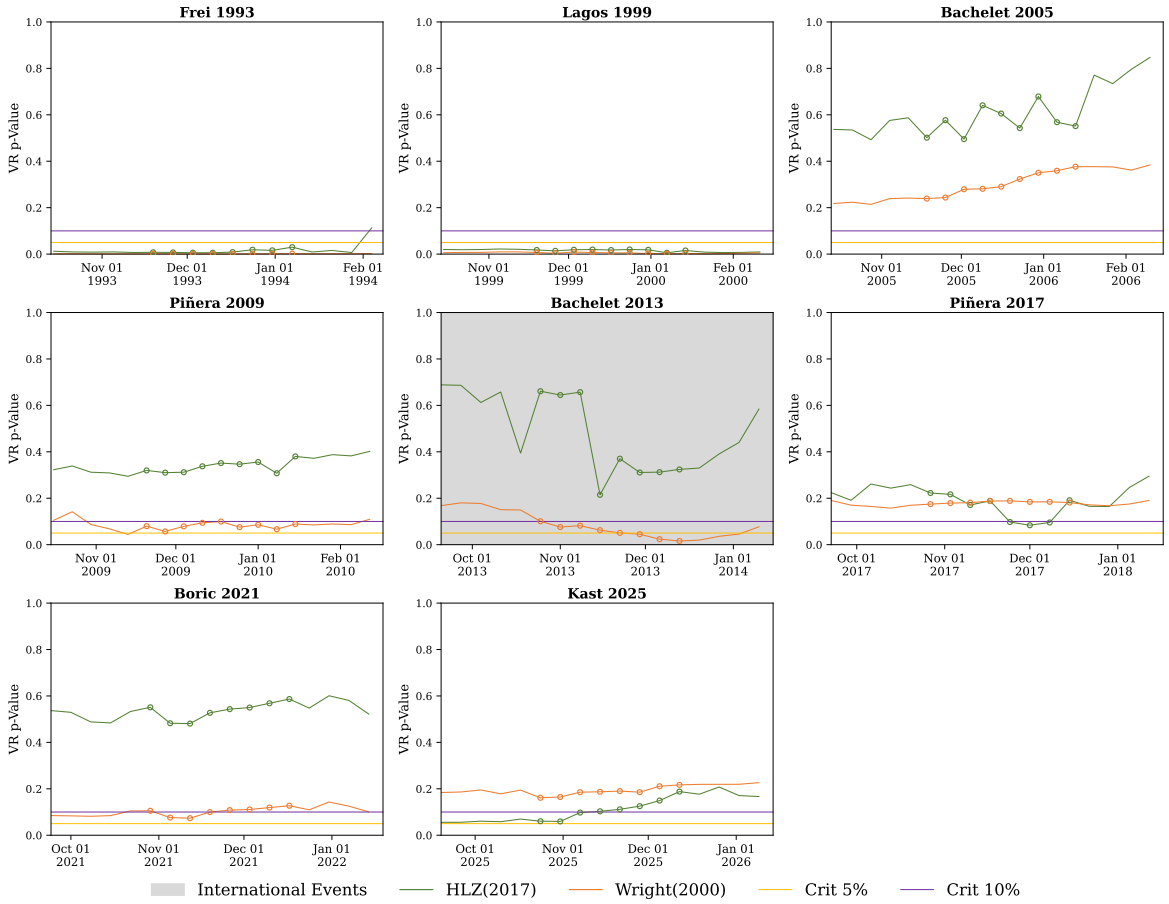



Figure 10: Chilean Political Events. Leverage-Robust (HLZ, 2017) and Rank Test (Wright, 2000). Rolling window T= 104 weeks. The gray areas represent external events.

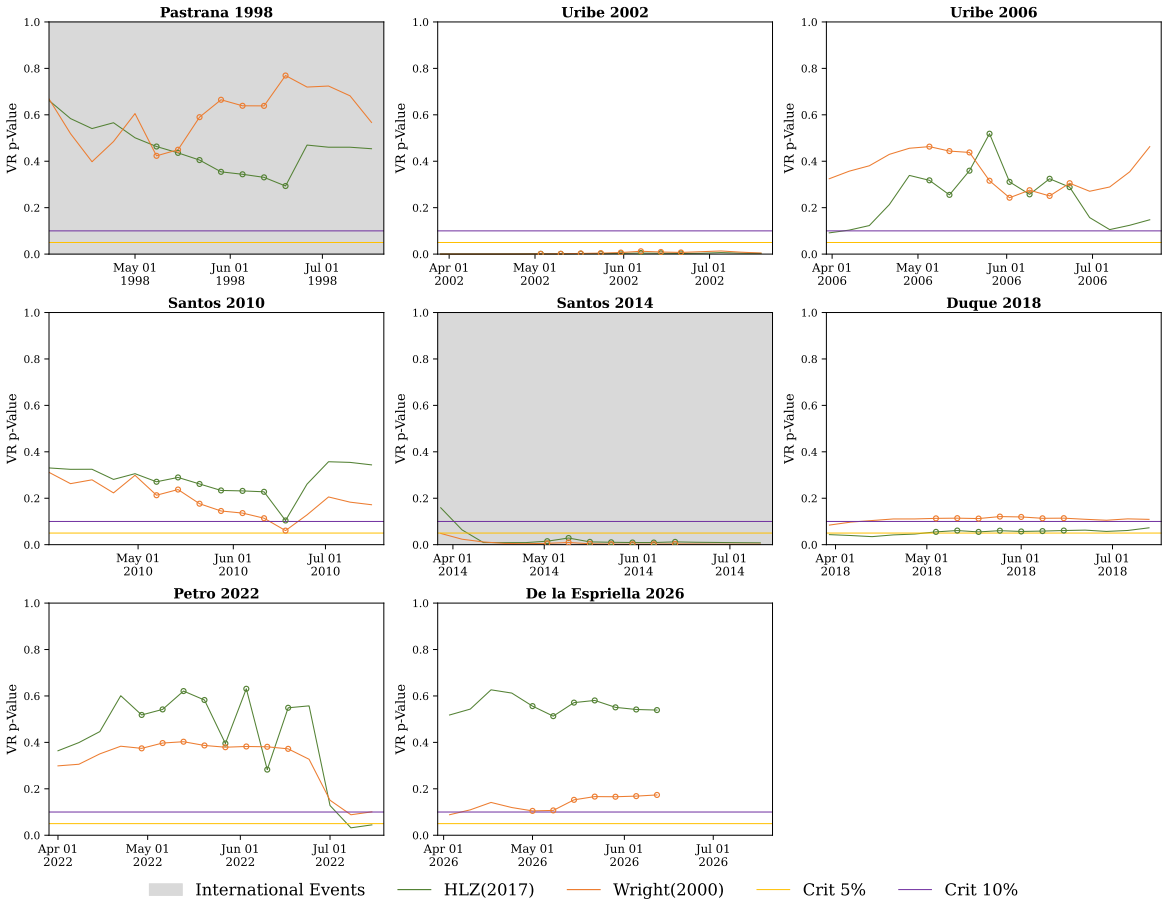



Figure 11: Colombian Political Events. Leverage-Robust (HLZ, 2017) and Rank Test (Wright, 2000). Rolling window T= 104 weeks. The gray areas represent external events.

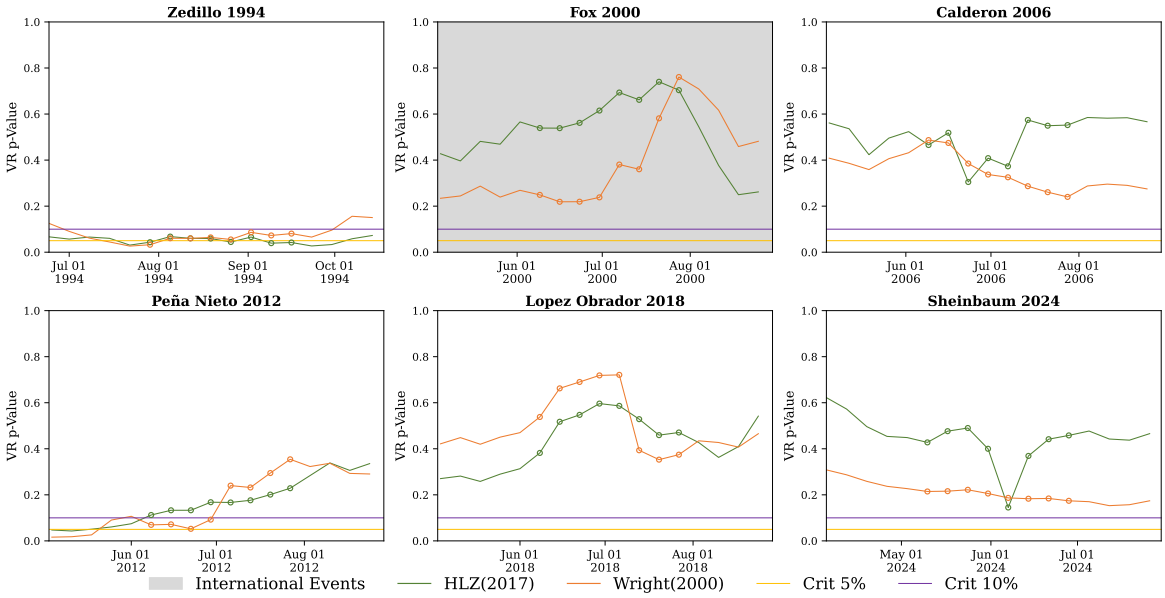



Figure 12: Mexican Political Events. Leverage-Robust (HLZ, 2017) and Rank Test (Wright, 2000). Rolling window T= 104 weeks. The gray areas represent external events.

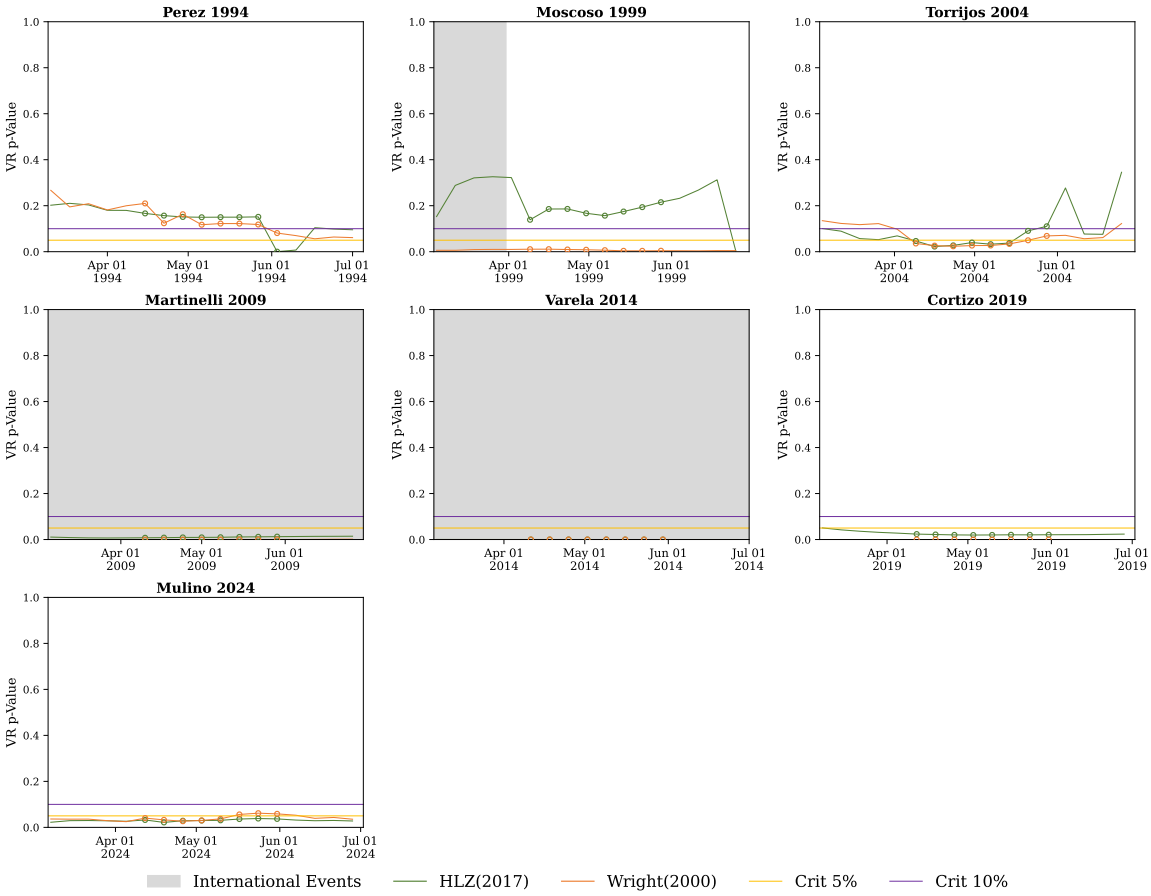



Figure 13: Panamanian Political Events. Leverage-Robust (HLZ, 2017) and Rank Test (Wright, 2000). Rolling window T= 104 weeks. The gray areas represent external events.

## A.3 Wild Bootstrap Results

The rolling analysis in Section 5 relies on the Hong et al. (2017) leverage-robust test as the parametric measure of efficiency. This choice is motivated by HLZ's more conservative inference. By allowing for cross-lag covariance terms in the variance estimator, it relaxes the no-leverage assumption underlying Lo and MacKinlay (1988). It produces rejections of the random walk hypothesis that are robust to volatility asymmetry.

A natural concern, however, is whether the qualitative conclusions of the paper are an artifact of this specific parametric choice. To address this, I replicate Figures 2, 3 and 4 using the wild bootstrap test of Kim (2006), which serves as an alternative parametric benchmark. The Kim (2006) test improves the small-sample properties of the conventional VR test through a wild bootstrap procedure; however, it does not incorporate the leverage-robust correction of HLZ.

Figures 14 and 15 reproduce the overlapping rolling window analysis of the MSCI NUAM Peru General Index for 104-week and 260-week windows, respectively, using the Kim (2006) wild bootstrap test alongside the Wright (2000) rank test. Figure 16 reproduces the panel of local political events shown in Figure 4 of the main text, again using Kim (2006) for the parametric series.

The qualitative conclusions are unchanged. For global events, the 104-week window continues to show temporary decreases in p-values around the Asian/Russian crises, the Dot-com crisis, the Subprime crisis, the China Hard Landing and the COVID-19 pandemic, consistent with the AMH and with the discussion in Section 5.2. The 260-week window again smooths out these short-run fluctuations.

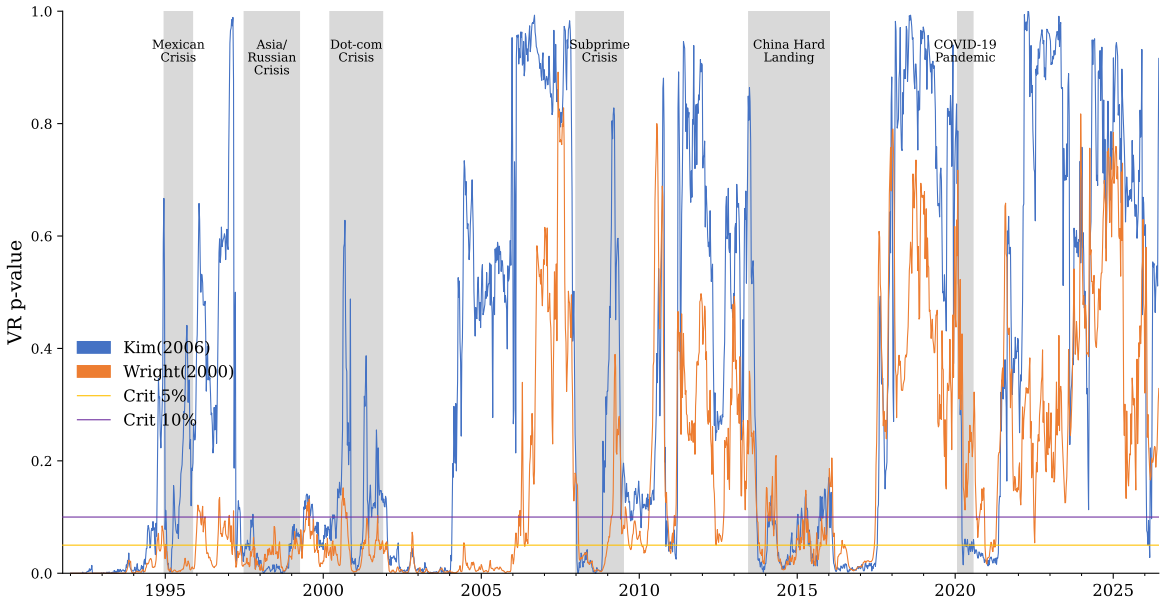



Figure 14: Wild Bootstrap (Kim, 2006) and Rank Test (Wright, 2000). Rolling window T= 104 weeks

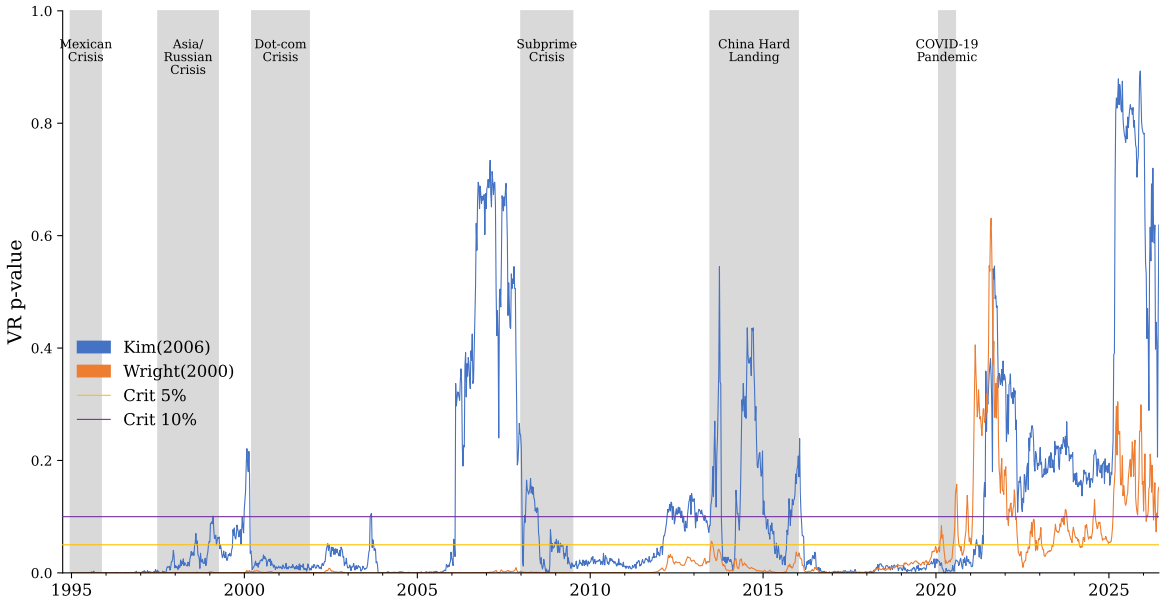



Figure 15: Wild Bootstrap (Kim, 2006) and Rank Test (Wright, 2000). Rolling window T= 260 weeks

For local political events, the asymmetry highlighted in the main text also holds under Kim (2006). The 2001, 2006, 2011, 2021 and 2026 presidential elections, as well as the 2018 Kuczynski resignation, are accompanied by movements of the parametric p-value away from the rejection zone, whereas the 2016 election, with two pro-market

candidates in the runoff, does not show this displacement. As expected, the Kim (2006) p-values are somewhat less conservative than those of Hong et al. (2017), occasionally crossing the rejection thresholds where HLZ does not. However, the direction and timing of the efficiency/inefficiency switches around political events are essentially the same.

These results confirm that the central empirical finding —that local political shocks in Peru push the market toward statistical efficiency rather than away from it— is not driven by the specific choice of parametric inference procedure.

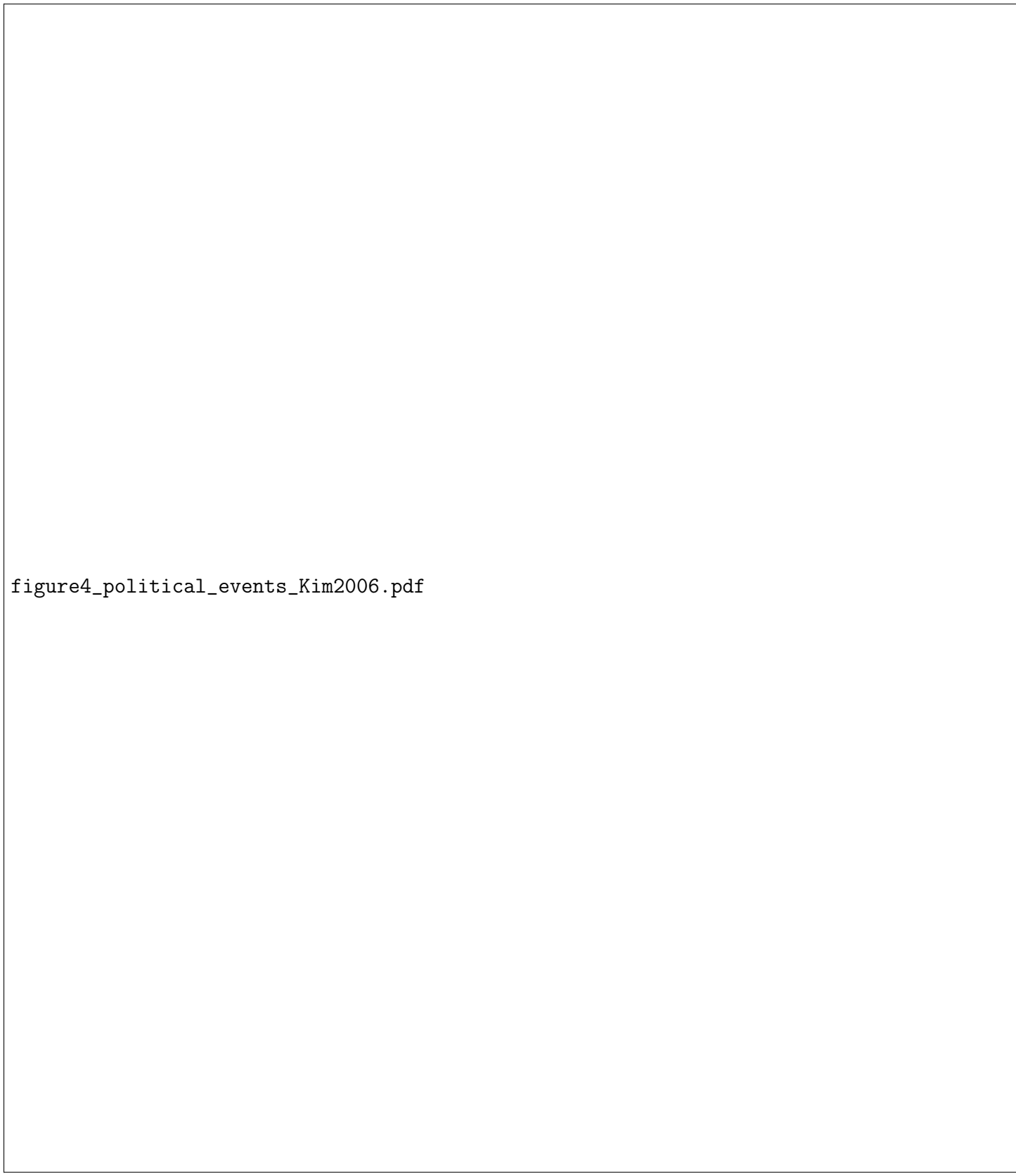



Figure 16: Peruvian Political Event - Wild Bootstrap - Kim (2006). Note: Rolling window T=104 weeks. Volatility is described by a GARCH(1,1) process.

## A.4 AMH: a literature review

The AMH has been receiving increasing attention in academia. Lo (2004, 2005) finds that between 1871 and 2003 the degree of efficiency of the U.S. stock market has varied over time, making the AMH a more plausible description of returns behavior. This result is confirmed by Ito and Sugiyama (2009) for the period 1955 to 2006. These findings have been extended to other countries (see Wan et al., 2024; Dos Santos et al., 2024; Boya, 2019; Urquhart and Hudson, 2013) .

Nevertheless, a significant strand of the literature has focused on identifying the factors associated with the evolution of the degree of market efficiency. Identifying these factors is particularly relevant for emerging markets, as they face numerous frictions that can push them away from efficiency. Hiremath and Narayan (2016) find that in the Indian Stock Exchange periods of inefficiency coincide with important macroeconomic events. Kim and Singal (2000) for twenty emerging markets and Fuss (2005) for seven emerging Asian countries find that markets become more efficient when foreign investors are allowed to participate, although, Omet and Maghyereh (2002) find no effect for the Amman stock exchange. Antoniou et al. (1997) and Fifield and Jetty (2008) find that changes in regulatory framework have a significant effect on the efficiency of the underlying stock market. Gu and Finnerty (2002) find that technological progress and the increasing ability of investors to rationally identify and use information has a significant impact on market efficiency. Lee et al. (2019) using a panel regression for 71 countries find that the advance of information and communication technology contributes to market efficiency because it increases transparency, rather than crowding the market with misinformation. Dos Santos et al. (2024) find, in a panel of 50 countries between 1990 and 2022, that macroeconomic and institutional fundamentals affect the efficiency of capital markets. These authors find that market inefficiency increases in periods of expansion. They also find that the greater the legal certainty, the lower the inefficiency.

Financial crises are another factor that the literature tests as a contributor to market inefficiency. This is because in a context of chaos and panic, investors' ability to correctly value assets is impaired. Surprisingly, Hoque et al. (2007) find that the 1997 Asian crisis had no significant effect on the level of efficiency of the stock markets of Hong Kong, Indonesia, Malaysia, Philippines, Singapore and Thailand, which remained inefficient even after the crisis, while the opposite occurred for South Korea. Kim and Shamsuddin (2008) show that the stock markets of Hong Kong, Japan and Taiwan remain efficient after the Asian financial crisis. Nevertheless, due to the differences in the results of the various tests used, the authors cannot reach a consensus on the

impact of the financial crisis on the efficiency of Korea, India, Malaysia, Philippines, Indonesia, and Thailand.

## A.5 Rolling Window VR tests results per event

Section 5.2 discusses the results shown in Figures 4, 5, and 6, aggregated by event type. This appendix details the results for each event separately. It can be observed, contrary to expectations, that efficiency increases rather than decreases in cases where the political event implies uncertainty about the future orientation of the economy. This behavior occurred in the 2001, 2006, 2011, 2021 and 2026 elections, as well as in the Kuczynski resignation in 2018. It should be noted that in the case of the Hong et al. (2017) test, the market moves from inefficiency to efficiency in the 2001, 2011, 2021, and 2026 elections. In the rest of the cases, the stock market starts from a situation of efficiency; therefore, during the negative political event, the test moves away from the efficiency rejection area. In the case of Wright (2000), the shift from inefficiency to efficiency occurs in the 2001 (at 5% significance level), 2006 and 2021 elections. In the context of the remaining negative political events, the p-value of the test moves away from the rejection zone. A possible explanation for these results is that the high uncertainty about the future of the country also makes the future of the returns of asset prices unpredictable, causing their prices to behave as random walks. In contrast, during the 2016 election, where both candidates running in the runoff were pro-market, the test remains unchanged in the inefficiency zone at 5% and 10% for both the Hong et al. (2017) and Wright (2000) tests.

A similar pattern emerges when examining the non-electoral political events. Although these events differ from presidential elections in nature, they share a defining feature with the radical-candidate elections discussed above: they also involve acute uncertainty about the future direction of the political and institutional regime. Under the Hong et al. (2017) test, the period running from the approval of the second impeachment motion against Castillo to the self-coup itself displays two distinct episodes in which the p-value moves away from the rejection zone —first immediately after the impeachment vote and again in the months preceding the self-coup— with a temporary calming in between. It is worth noting that the p-value remains above the critical values throughout the entire span of the episode, so the dynamics reflect movements within the efficient zone rather than a transition into it. The same dynamic continues into the protests episode. Efficiency increases sharply in the aftermath of the self-coup and remains elevated until approximately May 2023, fading thereafter as the intensity of the protests diminishes during the second half of the year. The Boluarte removal episode begins from a position of efficiency and culminates with an increasing, although highly volatile, p-value. The fact that the response is volatile rather than a single sustained displacement may itself be informative. By 2025, this was the fourth interruption of a

presidential term since 2018, and it took place only a few months before a presidential election that was itself already a source of regime uncertainty. It is plausible that investor expectations had partially habituated to this class of institutional shock, and that the Boluarte removal was absorbed into the broader uncertainty associated with the upcoming election rather than producing a separate response of its own.

In comparison to the Hong et al. (2017) approach, the Wright (2000) test yields qualitatively similar conclusions, with two notable differences. First, the decline in the p-value following the post-impeachment peak is more pronounced than under HLZ, and is in fact strong enough to push the statistic below the 10% rejection threshold. Second, while the Boluarte removal also coincides with a movement toward higher efficiency, the trajectory of the Wright p-value is markedly smoother than that of HLZ. Taken together, these additional episodes reinforce the central interpretation of this section: regime uncertainty, whether triggered by radical electoral outcomes or by acute institutional crises, displaces the parametric and non-parametric tests away from the rejection zone, consistent with a breakdown in the formation of coherent expectations rather than with improved information processing.

The impact of these negative political events is short-term. In the case of elections, the radical candidates who generated high uncertainty for investors either lost the election or moderated their policies once elected president. In the case of institutional crises in the form of interruptions of the presidential term, the resolution mechanism is analogous. For this reason, the 5-year window test is not reported, as the longer window smooths over the short-run fluctuations that are the object of interest and therefore offers little additional insight relative to the 2-year window. The only episode the 5-year window does pick up is the 2021 election, where uncertainty was one of the highest in history and persisted throughout Castillo's entire term.

## A.6 Alternative Calculation of the Average Marginal Effects

The Average Marginal Effects (AMEs) reported in the main text average the discrete difference $\Lambda(\hat{\boldsymbol{\beta}}'\mathbf{X}_t \mid D_t = 1) - \Lambda(\hat{\boldsymbol{\beta}}'\mathbf{X}_t \mid D_t = 0)$ over the full sample of $T$ observations. This appendix reports an alternative calculation in which the same discrete difference is averaged only over the subset of weeks during which the corresponding event dummy is active. Formally, for each event dummy $D_t$, the alternative AME is defined as

$$\widetilde{\text{AME}} = \frac{1}{T_D} \sum_{t\,:\,D_t=1} \left[ \Lambda\Big(\hat{\boldsymbol{\beta}}'\mathbf{X}_t \,\Big|\, D_t = 1\Big) - \Lambda\Big(\hat{\boldsymbol{\beta}}'\mathbf{X}_t \,\Big|\, D_t = 0\Big) \right], \tag{21}$$

where $T_D = \sum_{t=1}^{T} D_t$ is the number of weeks in which the event dummy is active. The difference with respect to the main AME calculation lies solely in the averaging sample. The main AME averages over the full sample of $T$ weeks, whereas $\widetilde{\text{AME}}$ averages over the $T_D$ treated weeks only. The latter is therefore closer in spirit to an average treatment effect on the treated, in the sense that it reports the average effect over the actual covariate distribution observed during the event windows rather than over the unconditional distribution of the sample. Standard errors are computed by the same parametric bootstrap procedure described in Section 3.3, with the average in each replication taken over the $T_D$ treated weeks.

Table 9 reports the alternative AME estimates for the three variance ratio tests and the two specifications described in Section 3.3. The qualitative conclusions of the main text are preserved across all cases. The aggregate dummy $D_t$ delivers positive and significant effects across the three tests, with magnitudes between 0.09 and 0.22. In the disaggregated specification, ERC events display positive effects significant at the 10% level in the baseline, reaching the 5% level under Kim once the GARCH volatility control is added. IC events display positive and highly significant effects at the 1% level in all six cases, with magnitudes that are largest under Kim and smallest under Wright, mirroring the ordering observed in the main text. PME events deliver negative effects significant at the 1% level across all cases. Magnitudes are also broadly consistent with those reported in the main text, with the most notable departure being a larger absolute value for the PME effect under Kim ($-0.40$ here versus $-0.34$ in the main calculation). Overall, the results in Table 9 confirm that the central findings of the paper do not depend on the specific sample over which the discrete difference is averaged.

Table 9: Average Marginal Effects (AME) of the Event Dummies by VR Test (Alternative Calculation) - Peru

| | HLZ | | Kim | | Wright | |
|---|---|---|---|---|---|---|
| | Base | GARCH | Base | GARCH | Base | GARCH |
| *Specification 1: Single dummy* | | | | | | |
| $D_t$ | 0.1540*** | 0.1542*** | 0.2220** | 0.2288** | 0.0884** | 0.0920** |
| | (0.0571) | (0.0558) | (0.0910) | (0.0914) | (0.0413) | (0.0421) |
| *Specification 2: Dummy by event class* | | | | | | |
| $D_t^{ERC}$ | 0.1784* | 0.1817** | 0.2223* | 0.2460** | 0.0966* | 0.1112* |
| | (0.0950) | (0.0925) | (0.1162) | (0.1169) | (0.0569) | (0.0628) |
| $D_t^{PME}$ | −0.1630*** | −0.1659*** | −0.3952*** | −0.4050*** | −0.1410*** | −0.1442*** |
| | (0.0334) | (0.0349) | (0.0795) | (0.0818) | (0.0444) | (0.0434) |
| $D_t^{IC}$ | 0.2239*** | 0.2212*** | 0.4048*** | 0.3947*** | 0.1483*** | 0.1397*** |
| | (0.0692) | (0.0700) | (0.1011) | (0.1078) | (0.0509) | (0.0523) |

*Notes:* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses. Base and GARCH refer to the two model specifications. Results are based on the alternative calculation of the average marginal effects. Only event AMEs are shown.