# Political Shocks and Asset Prices

Supplementary Online Appendix

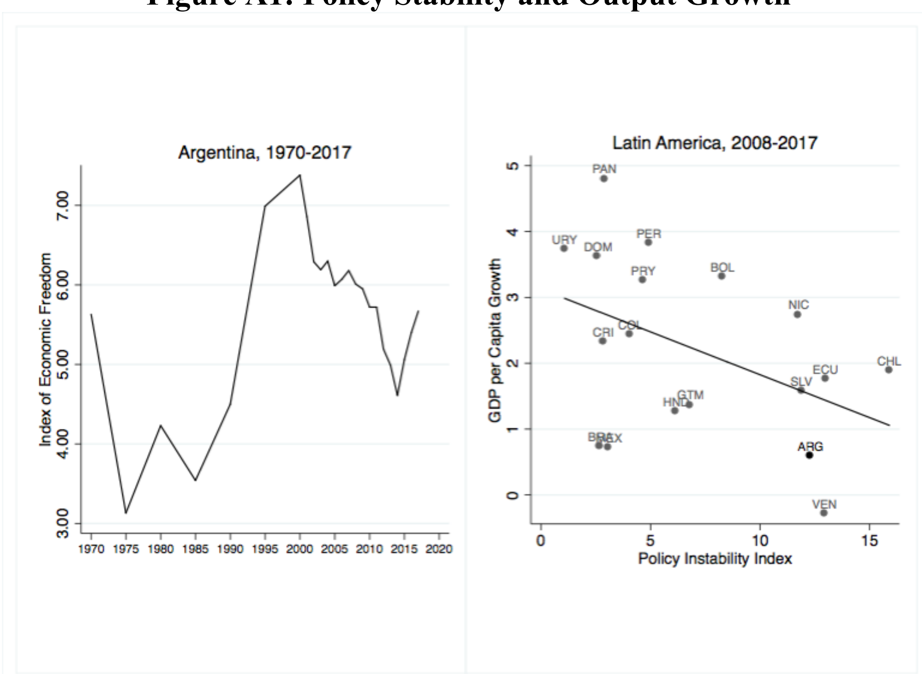
Contents

## A. The Argentine Case

According to Spiller and Tommasi (2007), the most noticeable characteristic of public policies in Argentina is their instability. In their view, Argentine policies are unstable in ways that "… weaken their credibility in the eyes of economic actors, rendering them far less effective in bringing about desired economic behavior, such as investment, savings, and job creation, and hence desired economic outcomes, such as sustainable growth and employment …" (Spiller and Tommasi 2007: 183).

The left panel in Figure A1 shows the value of Argentina's Fraser Index of Economic Freedom for the period between 1970 and 2017. The indicator grades the country's overall economic policy according to its market friendliness. An examination of the evolution of the Fraser Index over time reveals the ebb and flow of economic policies in Argentina. The right panel of Figure A1 presents a scatter plot relating the average of GDP per capita growth and of the Global Competitiveness Report' Index of Policy Stability in Latin America between 2008 and 2017. The data reveal that countries where businesspeople view policy instability as very costly for the operation of their businesses experienced lower rates of output growth (correlation coefficient, r=-0.44).

**Figure A1: Policy Stability and Output Growth**



Taken together, the data presented in Figure A1 combined with the discussion of the relationship between policy uncertainty and economic activity underscore why volatility is an interesting measure of interest. They also highlight why, in the Argentine case, the performance of the country's stock exchange provides an important insight to understand the social welfare impacts of market volatility.

**Reference**

Spiller, Pablo and Mariano Tommasi. 2007. *The Institutional Foundations of Public Policy in Argentina.* New York: Cambridge University Press.

## B. Variance Risk in Event vs. Non-event Days

The empirical findings presented in Section 3 of the paper make clear that return volatility rises in the day immediately following an unexpected, major policy-shifting event. Further inquiry into the nature of these volatility shocks begs the following questions: how do the event days in our sample stack up against non-event days in terms of variance risk? Second, how large are the volatility bouts spurred by the political events in our sample?

Before we answer these questions, two important facts need to be considered. First, variance risk can be ascribed to a variety of market-related news released on days when none of the events examined in this study took place. For example, some of the largest volatility ratios in our sample correspond to global plunges in equity markets, as well as days immediately following the launching of macroeconomic stabilization plans.[1] Second, many large daily price changes in the Argentine stock market cannot be associated with the public disclosure of any discernible events.[2]

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[1] Stabilization plans were sometimes released simultaneously with the appointment of a new economic minister; but in most cases, the news did not overlap with the news that an economic minster was no longer at the helm. The so-called *Rodrigazo*, the announcement of major economic reforms, including a 100% devaluation of the Argentine peso, is a case in point. The plan's details, named after economic minister Celestino Rodrigo, did not became public until the evening of Monday June 2nd, 1975. His predecessor's resignation, though, was announced the day before, on Sunday June 1st. In addition, Wednesday June 4th was the first day the Argentine stock market could respond to the *Rodrigazo* shock, as markets were closed on Tuesday June 3rd. According to our coding rules, the post-event volatility, reflecting the response to previous minister's resignation, corresponds to Monday June 2nd, before any major economic announcements were publicly made. A sharp rise in volatility, however, took place on the following trading day, Wednesday June 4th. This date, however, is coded as a non-event day in our sample.

[2] The weak linkage between public information and US stock market volatility has been documented by Cutler, Poterba, and Summers (1989), Mitchell and Mulherin (1994), and Andersen, Bollerslev, and Cai (2000).

The visual representation in Figure B1 allows us to make a meaningful comparison between the variance risk of event and non-event days. It shows a probability–probability (P-P) plot comparing the empirical cumulative distribution functions (Ecdfs) of our volatility ratios in event versus non-event days against each other.[3] The latter is represented by the horizontal axis, and the former by the vertical axis. Both distributions were calculated using returns expressed in US consumption units. Measuring returns in local consumption units in either nominal or real terms yields similar results.

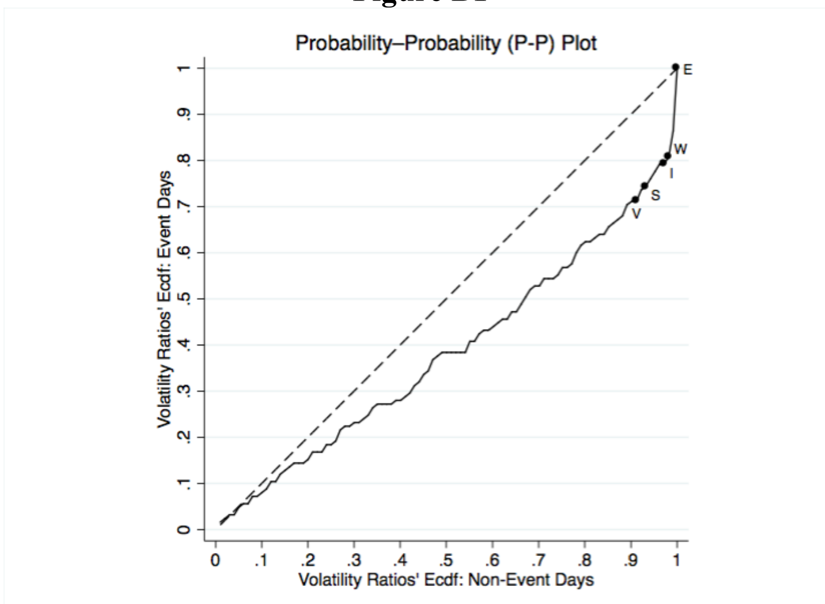
For any percentile value $z$, Figure B1 shows what percentage of observations lies at or below $z$ in each distribution. Two distributions are equal if and only if the plot falls on the 45° line from (0,0) to (1,1). It is clear from the graph that the market movements associated with the events under study do not just reflect other sources of variation in the Buenos Aires exchange's stock prices. Take, for example, the 50$^{th}$ percentile. While half of the observations for volatility ratios corresponding to non-event days lie at or above the median, roughly 62 percent of the observations for volatility ratios corresponding to event days lie at or above the 50$^{th}$ percentile. A comparison of the 100$^{th}$ percentile is even more illustrative. Of the 129 observations in that percentile, 17 observations correspond to volatility ratios from days in which an event identified in Table 1 took place.

Using Figure B1, we can now place the average post-event volatility ratios from Table 2 (in the paper), in context. For comparability, we focus on the results presented on Panel C. The average post-event volatility ratio across all the events (marked with a V) is 0.372. This value is greater than 91% of the volatility ratios corresponding to days when none of the events considered in this study took place. In the case of changes in a country's economic stewardship, the average post-event volatility ratio (marked with an S) is at the 93$^{rd}$ percentile of non-event days' volatility ratios. The effect of elections on variance risk is quite similar. Irregular government turnovers (coup d'états, presidential death, resignations), however, are associated

[3] For non-event days, we restrict our attention to observations corresponding to days in which the events listed in Table 1 did not take place. Therefore, we do not consider the volatility ratios of the days immediately following days when the events listed in Table 1 became publicly known. The sample is non-event days is thus composed of 12,851 days; and the one for event days contains 125 observations.

with even more extreme deviations from typically observed price changes. Only 3% of the observations for non-event days have a higher volatility ratio than their average post-event volatility ratio of 0.737 (marked with an I).

**Figure B1**




Finally, we can also use the P-P plot to compare the magnitude of the changes in the variance risk observed after specific events with the overall distribution of the volatility ratios in non-event days. Consider the Falklands/Malvinas war between Argentina and the United Kingdom. The news of the Argentine invasion broke early in the morning of Friday April 2nd, 1982. The stock market remained calm throughout the trading day. A sharp drop in prices, though, took place after the weekend. On Monday April 5th, following the Argentine military's reluctance to comply with a UN resolution urging them to withdraw their troops from the islands, the British fleet set sail. At that point, it became clear to the public that a full-fledged war would ensue. The end of the war was more abrupt and took the markets by surprise. On Friday June 11th, the exchange was closed due to Pope John Paul II's visit to the country. When it opened again, on Monday June 14th, most traders were still oblivious to what was happening in the islands. By mid-day, however, news of the Argentine forces' surrender became publicly known. The stock market index fell by 10% by the end of the trading day. As Figure B1 shows, with a volatility ratio of 0.849 (marked with a W), this was clearly an exceptional day. To put things in perspective, only 2% of the volatility ratios corresponding to non-event days in our sample exceed this value.

An even more extreme market reaction to one of the events in our sample took place on Monday August 12th, 2019. Argentine assets suffered an unprecedented decline, and the stock market index fell by 48 percent. The sell-off was an immediate response to incumbent President Mauricio Macri's loss to Peronist Alberto Fernández in a primary election, which occurred the day before. Hailed by Macri as a landmark election, the country's peculiar brand of primaries was widely seen as a preview of the country's forthcoming presidential contest. Just a day prior to the election, five different polling firms showed Fernandez in a statistical dead heat with Macri.[4] The biggest unanswered question was whether either of the candidates could garner 45 percent of the vote and make a second-round runoff election less likely. On election day, Macri lost by a far greater margin than expected. He received only 32.1 percent of the vote, compared to Fernandez's 47.7 percent. The volatility ratio for Monday August 12th, 2019 (3.96) is marked with an E in Figure B1. The probability of observing such a high probability ratio, based on the empirical distribution of all volatility ratios, is 0.04 per cent. As such, this was truly an exceptional event, even for a country as tumultuous as Argentina.

**References**

Andersen, Torben G., Bollerslev Tim, and Jun Cai. 2000. "Intraday and interday volatility in the Japanese stock market," *Journal of International Financial Markets, Institutions and Money*, Vol. 10: 107-130.

Cutler, David M., Jim M. Poterba, and Lawrence H. Summers. 1989. "What moves stock prices?," *Journal of Portfolio Management*, Vol. 15: 4-12.

Mitchell, Mark L., and J. Harold Mulherin. 1994. "The impact of public information on the stock market", *Journal of Finance*, Vol. 49: 923-950.

[4] See https://www.clarin.com/economia/ultima-rueda-paso-bolsa-sube-5-riesgo-pais-cae-874_0_fiYbQbTR6.html, and https://www.clarin.com/opinion/intrigas-casa-rosada-pases-factura-city-lunes-negro_0_jnggAIsh5.html

## C. State Dependency

The analysis in the main body of the paper indicates that distinct types of policy-shifting events have different effects on asset prices. One should also consider if market actors' expectations are state dependent. For example, investors may accustom themselves to changes in the country's economic stewardship. In addition, given the tremendous swings in Argentina's political economy, market participants may have behaved differently in the 2010s -- when they had already experienced hyperinflation, devaluations, regime changes, etc.-- than in the 1970s, before some of these things happened. Finally, the economic context might condition investors' responses to political events. For instance, according to Pastor and Veronesi (2013), political uncertainty commands a larger risk premium when the economy is weak. Hence, a political event that occurs during a bout of hyperinflation may have a different impact than one occurring in a low inflation environment.[5]

Figure C1 shows the average post-event volatility ratios of the returns expressed in US consumption units for all the events listed in the paper's Table 1 (excluding terrorist acts) in each of the five decades included in this study.[6] The number of events included in each decade are listed in parentheses. The error bars indicate 95% confidence intervals, calculated using the empirical distribution of the test statistics. The vertical dashed line indicates the average post-event volatility ratio across all decades for all the events listed in Table 1 (excluding terrorist acts).

The findings suggest that investors did not behave differently in the 2010s than in the 1970s. It seems, though, that market responses to political events were somewhat state dependent. Specifically, the evidence indicates that the average post-event volatility ratio in the 1990s was significantly lower than that of the entire sample period (i.e. 1970-2019).[7] As Spiller and Tommasi point out, "… the macroeconomic performance of Argentina for much of the

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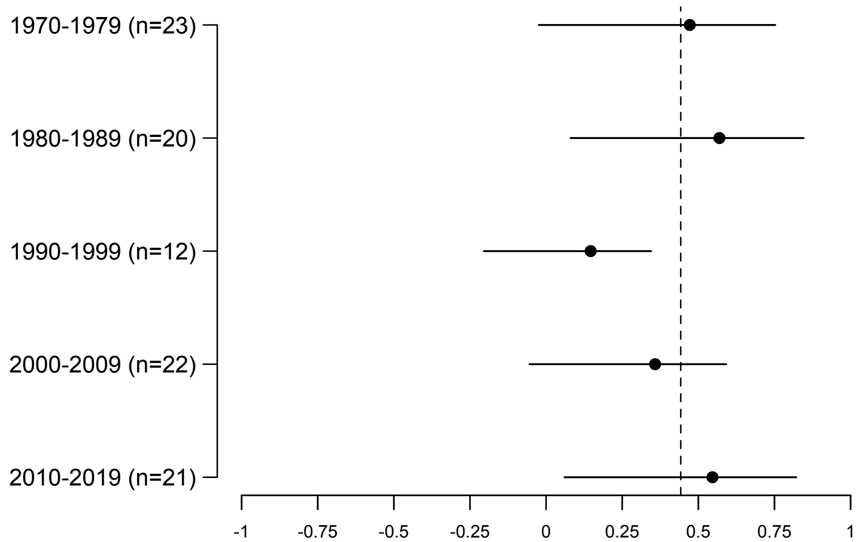
[5] We thank an anonymous referee for pointing this out.

[6] We exclude terrorist acts from this analysis because 24 out of the 27 events of this type included in our sample (89%) occurred in the 1970-1979 decade. are shown. We obtain very similar findings when returns are measured in local consumption units both in nominal as well as in real terms.

[7] Notice that the number of events is also smaller.

1990s was very strong, with GDP growth switching from negative in the 1980s to an increase of over 50 percent in the 1991-7 period and inflation coming down from hyperinflation levels (23,104 percent) in 1990 to around zero in 1997…" (2007: 183). This pattern thus conforms to the theoretical expectations in Pastor and Veronesi (2013). As they note, when the economy is strong, governments are less likely to change their policies, and voters are less likely to replace governments. Therefore, the influence of political uncertainty on financial markets should be smaller when economic conditions – like those in Argentina during the 1990s – are better.

**Figure C1. Post-Event Volatility Ratios by Decade**




## References


Pastor, Lubos and Pietro Veronesi. 2013. "Political uncertainty and risk premia," *Journal of Financial Economics*, Vol. 110: 520-545.

Spiller, Pablo and Mariano Tommasi. 2007. *The Institutional Foundations of Public Policy in Argentina.* New York: Cambridge University Press.

## D. Long Memory

We conduct a series of tests to diagnose long memory, or fractional integration, in our stock returns time series. First, we fit an ARFIMA model to the data to recover the fractional integration parameter estimate. Next, we use three different approaches to test for fractional integration: (1) the Geweke/Porter-Hudak (GPH) semiparametric log periodogram regression; (2) Phillips' modification of the GPH estimator; and (3) Robinson's univariate log-periodogram regression estimator. We also test for long-range dependence in our time series using the modified rescaled range statistic proposed by Lo. Finally, we consider the possibility that the recovered long memory estimates may be an artifact of the state dependency uncovered in Appendix C.

### D1. Maximum Likelihood Estimates.

We examine the existence of long memory, or fractional integration, in the series of daily cumulative returns of the Buenos Aires Stock Exchange's General Index for the period between January 2nd, 1967 and March 30th, 2020. The returns are measured in: (1) local consumption units in nominal terms; (2) local consumption units in real terms; and (3) real returns expressed in US consumption units. For each series, we estimate the parameters of an ARFIMA model with the fractional difference parameter and a constant. Both the Akaike information criterion and the Bayesian information criterion select a specification with one autoregressive term and one moving-average term.

Table D1 shows the recovered estimates of the fractional-difference parameter in each series, along with their standard deviation and 95% confidence intervals. In each series, the fractional difference parameter is different from zero and statistically significant at the 5% level. Therefore, we can reject the null d=0 in all three series. In each one of them, though, the confidence intervals of the fractional integration parameter do not include estimates greater than 0.5, suggesting a long-memory, mean-reverting, process with finite variance.

Table D1. Fractional Difference Parameter (ARFIMA model)

| Series | Coef. | Std. Err. | 95% Conf. Interval | |
|---|---|---|---|---|
| Nominal Returns | 0.262 | 0.027 | 0.210 | 0.314 |
| Inflation Adjusted Returns | -0.045 | 0.010 | -0.065 | -0.024 |
| Real Returns in USD | 0.163 | 0.029 | 0.107 | 0.220 |

D2. Semi-Parametric Estimates.

In the MLE approach discussed above, the estimation of the full ARFIMA model is conditional on choosing an appropriate specification. Therefore, the recovered values of the fractional difference parameter depend on the specification of the p and q values. We now turn our attention to an alternative set of semiparametric approaches that allow us to estimate the long memory parameter d without fully specifying the data-generating process. Specifically, we consider : (1) the Geweke/Porter-Hudak (GPH) semiparametric log periodogram regression; (2) Phillips' modification of the GPH estimator; and (3) Robinson's univariate log-periodogram regression estimator. Table D2 presents the results of these tests when stock returns are measured in nominal terms, in real terms, and in US dollars. We evaluate the robustness of our fractional integration parameter estimates using power values ranging from 0.40 to 0.6.

The results presented in Table D2 indicate that when the returns series is expressed in nominal local consumption units, the GPH test generates estimates of the long memory parameter that can reject the null of d=0 for all powers tested. The Phillips' modified estimator finds that both d = 0 and d==1 can be rejected for all powers tested. Applying Robinson's approach to the series finds an estimated value and standard error of the long memory (fractional integration) parameter d = 0.25 (0.06) for power 0.5.

Regarding stock returns expressed in real local consumption units, the results presented in Table D2 are somewhat mixed. When we apply the GPH test to this series, we find that d = 0 can only be rejected at the 95% level for powers 0.4, 0.45, and 0.5. In the case of the Phillips' estimator, both d = 0 and d==1 can be rejected at conventional levels for all powers tested. According to Robinson's semiparametric test, the estimated value and standard error of d = -0.17 (0.06) for power 0.5.

When we measure stock returns in US dollars, the GPH test indicates that we cannot reject the null of d=0 for all powers tested. The Philips' estimator, however, suggests that both d==0 and d==1 can be rejected for all powers tested. The estimated value and standard error of the long memory parameter according to Robinson's semiparametric test is d=-0.05 (0.07) for power 0.5.

## Table D2. Semi-Parametric Tests

| Power | Ords | Est d | StdErr | t(H0: d=0) | P>t | Assym. SE | z(H0: d=0) | P>z |
|---|---|---|---|---|---|---|---|---|
| **Nominal Returns** | | | | | | | | |
| **Geweke/Porter-Hudak** | | | | | | | | |
| Power | Ords | Est d | StdErr | t(H0: d=0) | P>t | Assym. SE | z(H0: d=0) | P>z |
| 0.4 | 45 | 0.300 | 0.082 | 3.657 | 0.001 | 0.111 | 2.698 | 0.007 |
| 0.45 | 72 | 0.210 | 0.080 | 2.611 | 0.011 | 0.084 | 2.492 | 0.013 |
| 0.5 | 115 | 0.247 | 0.061 | 4.063 | 0.000 | 0.065 | 3.818 | 0.000 |
| 0.55 | 184 | 0.252 | 0.048 | 5.284 | 0.000 | 0.050 | 5.039 | 0.000 |
| 0.6 | 296 | 0.204 | 0.039 | 5.201 | 0.000 | 0.039 | 5.263 | 0.000 |
| **Philips** | | | | | | | | |
| Power | Ords | Est d | Std Err | t(H0: d=0) | P>t | | z(H0: d=1) | P>z |
| 0.4 | 44 | 0.338 | 0.077 | 4.411 | 0.000 | | -6.852 | 0.000 |
| 0.45 | 71 | 0.247 | 0.081 | 3.062 | 0.003 | | -9.900 | 0.000 |
| 0.5 | 114 | 0.275 | 0.061 | 4.491 | 0.000 | | -12.073 | 0.000 |
| 0.55 | 183 | 0.272 | 0.048 | 5.661 | 0.000 | | -15.353 | 0.000 |
| 0.6 | 295 | 0.218 | 0.039 | 5.551 | 0.000 | | -20.938 | 0.000 |
| **Robinson** | | | | | | | | |
| Power | Ords | Est d | Std Err | t(H0: d=0) | P>t | | | |
| 0.4 | 45 | 0.299 | 0.080 | 3.741 | 0.001 | | | |
| 0.45 | 71 | 0.210 | 0.080 | 2.611 | 0.011 | | | |
| 0.5 | 115 | 0.247 | 0.060 | 4.104 | 0.000 | | | |
| 0.55 | 183 | 0.252 | 0.048 | 5.284 | 0.000 | | | |
| 0.6 | 295 | 0.204 | 0.039 | 5.200 | 0.000 | | | |
| **Inflation Adjusted Returns** | | | | | | | | |
| **Geweke/Porter-Hudak** | | | | | | | | |
| Power | Ords | Est d | StdErr | t(H0: d=0) | P>t | Assym. StdI | z(H0: d=0) | P>z |
| 0.4 | 45 | 0.281 | 0.119 | -2.367 | 0.023 | 0.111 | -2.529 | 0.011 |
| 0.45 | 72 | -0.256 | 0.083 | -3.076 | 0.003 | 0.084 | -3.047 | 0.002 |
| 0.5 | 115 | -0.173 | 0.063 | -2.730 | 0.007 | 0.065 | -2.672 | 0.008 |
| 0.55 | 184 | -0.066 | 0.049 | -1.339 | 0.182 | 0.050 | -1.326 | 0.185 |
| 0.6 | 296 | -0.024 | 0.041 | -0.597 | 0.551 | 0.039 | -0.627 | 0.530 |
| **Phillips** | | | | | | | | |
| Power | Ords | Est d | Std Err | t(H0: d=0) | P>t | | z(H0: d=1) | P>z |
| 0.4 | 44 | 0.303 | 0.094 | 3.230 | 0.002 | | -7.211 | 0.000 |
| 0.45 | 71 | 0.195 | 0.072 | 2.698 | 0.009 | | -10.572 | 0.000 |
| 0.5 | 114 | 0.165 | 0.057 | 2.878 | 0.005 | | -13.905 | 0.000 |
| 0.55 | 183 | 0.177 | 0.045 | 3.899 | 0.000 | | -17.359 | 0.000 |
| 0.6 | 295 | 0.148 | 0.038 | 3.904 | 0.000 | | -22.807 | 0.000 |
| **Robinson** | | | | | | | | |
| Power | Ords | Est d | Std Err | t(H0: d=0) | P>t | | | |
| 0.4 | 45 | -0.283 | 0.116 | -2.441 | 0.019 | | | |
| 0.45 | 71 | -0.256 | 0.083 | -3.076 | 0.003 | | | |
| 0.5 | 115 | -0.175 | 0.063 | -2.789 | 0.006 | | | |
| 0.55 | 183 | -0.066 | 0.049 | -1.339 | 0.182 | | | |
| 0.6 | 295 | -0.024 | 0.041 | -0.597 | 0.551 | | | |
| **Real Returns in US Dollars** | | | | | | | | |
| **Geweke/Porter-Hudak** | | | | | | | | |
| Power | Ords | Est d | StdErr | t(H0: d=0) | P>t | Assym. StdI | z(H0: d=0) | P>z |
| 0.4 | 45 | 0.181 | 0.110 | -1.639 | 0.109 | 0.111 | -1.627 | 0.104 |
| 0.45 | 72 | -0.097 | 0.082 | -1.187 | 0.239 | 0.084 | -1.155 | 0.248 |
| 0.5 | 115 | -0.048 | 0.068 | -0.703 | 0.483 | 0.065 | -0.738 | 0.460 |
| 0.55 | 184 | 0.010 | 0.056 | 0.188 | 0.851 | 0.050 | 0.210 | 0.834 |
| 0.6 | 296 | -0.017 | 0.040 | -0.429 | 0.668 | 0.039 | -0.444 | 0.657 |
| **Phillips** | | | | | | | | |
| Power | Ords | Est d | Std Err | t(H0: d=0) | P>t | | z(H0: d=1) | P>z |
| 0.4 | 44 | 0.176 | 0.114 | 1.542 | 0.130 | | -8.526 | 0.000 |
| 0.45 | 71 | 0.161 | 0.081 | 2.002 | 0.049 | | -11.019 | 0.000 |
| 0.5 | 114 | 0.140 | 0.066 | 2.116 | 0.037 | | -14.317 | 0.000 |
| 0.55 | 183 | 0.143 | 0.054 | 2.642 | 0.009 | | -18.083 | 0.000 |
| 0.6 | 295 | 0.078 | 0.040 | 1.977 | 0.049 | | -24.691 | 0.000 |
| **Robinson** | | | | | | | | |
| Power | Ords | Est d | Std Err | t(H0: d=0) | P>t | | | |
| 0.4 | 45 | -0.157 | 0.110 | -1.430 | 0.159 | | | |
| 0.45 | 71 | -0.097 | 0.082 | -1.187 | 0.239 | | | |
| 0.5 | 115 | -0.051 | 0.067 | -0.764 | 0.446 | | | |
| 0.55 | 183 | 0.011 | 0.056 | 0.189 | 0.851 | | | |
| 0.6 | 295 | -0.017 | 0.040 | -0.429 | 0.668 | | | |

We also conducted tests for long-range dependence in our time series using the modified rescaled range statistic proposed by Lo. In the case of nominal returns, the test rejects the null hypothesis of no long-range dependence at the 99% level. The test, however, cannot reject the null hypothesis of no long-range dependence at any level of significance when the returns series is expressed in real local consumption units. Likewise, the null hypothesis of no long-range dependence can be rejected all levels of significance according to this test, when returns are measured in US Dollars.

D3. State Dependency.

A stationary process with structural breaks and/or occasional regime switches has some properties that are similar to those of a long-memory process (Diebold and Inoue, 2001; Granger and Hyung, 2004). Therefore, we need to examine if the stock returns series show the "long memory" property because of the presence of structural changes in the series rather than an I(d) process. We simply divide our sample of returns into five decades and estimate the fractional integration parameter using Robinson's approach for power 0.5. Table D3 presents the results.

Table D3. State Dependency

| Nominal Returns | | | | |
|---|---|---|---|---|
| Decade | Est d | Std Err | t(H0: d=0) | P>t |
| **1970-1979** | **0.326** | **0.103** | **3.156** | **0.003** |
| 1980-1989 | 0.191 | 0.104 | 1.828 | 0.074 |
| 1990-1999 | 0.116 | 0.068 | 1.706 | 0.094 |
| 2000-2009 | 0.055 | 0.103 | 0.528 | 0.600 |
| 2010-2019 | -0.202 | 0.104 | -1.933 | 0.059 |
| **Inflation Adjusted Returns** | | | | |
| Decade | Est d | Std Err | t(H0: d=0) | P>t |
| **1970-1979** | 0.146 | 0.102 | 1.432 | 0.158 |
| 1980-1989 | -0.066 | 0.115 | -0.571 | 0.570 |
| 1990-1999 | -0.104 | 0.093 | -1.116 | 0.270 |
| 2000-2009 | 0.072 | 0.105 | 0.685 | 0.497 |
| 2010-2019 | -0.165 | 0.098 | -1.674 | 0.100 |
| **Real Returns in US Dollars** | | | | |
| Decade | Est d | Std Err | t(H0: d=0) | P>t |
| 1970-1979 | 0.047 | 0.127 | 0.370 | 0.713 |
| 1980-1989 | -0.061 | 0.104 | -0.594 | 0.556 |
| 1990-1999 | 0.138 | 0.104 | 1.333 | 0.189 |
| **2000-2009** | **0.242** | **0.087** | **2.775** | **0.008** |
| 2010-2019 | -0.140 | 0.089 | -1.584 | 0.120 |

The evidence indicates that, with a few exceptions, we cannot reject the null of d=0. Therefore, these findings suggest that the appearance of long memory may be due to the existence of structural breaks and/or regime switches in the series. We examine this issue in more detail in Appendix E and F below.

## E. Parameter Instability

We use a series of diagnostics to test for parameter instability. First, we use the sup-Wald (i.e., the supremum of a set of Wald statistics) test. We examine the conditional as well as the unconditional mean and variance of our stock returns series. Next, we use the cumulative sum of recursive residuals (CUSUM) test to detect potential structural changes in our series' unconditional mean and variance, as well as identifying the times of any such changes.

### E1. CM/CV Stability Tests.

To test for structural breaks in the conditional mean (CM), we estimate a first order AR model for each of our series. Following the analysis in our paper, we also control for global conditions using the S&P 500 as our benchmark index. In the case of the conditional variance (CV), for each series we compute:

$$e' = \frac{1}{2}(e_t - e_{t-1})^2,$$

where $e$ are the residuals from the first order AR models with the S&P 500 index as controls. We then test for a mean break in the transformed residuals. After we fit these models, we use the estimated regression coefficients and check if they are stable over time. The top panel of Table E1 shows the results for the supremum Wald test with symmetric trimming of 15%.

Table E1. Structural Break Tests

| Conditional Mean | | | |
|---|---|---|---|
| Series | Statistic | p-value | Break Date |
| Nominal Returns | 46.902 | 0.000 | October 15, 1991 |
| Inflation Adjusted Returns | 1.481 | 0.912 | September 3, 1975 |
| Real Returns in US Dollars | 2.184 | 0.740 | August 26, 1975 |
| **Conditional Variance** | | | |
| Series | Statistic | p-value | Break Date |
| Nominal Returns | 39.176 | 0.000 | December 12, 1991 |
| Inflation Adjusted Returns | 47.206 | 0.000 | April 24, 1991 |
| Real Returns in US Dollars | 52.761 | 0.000 | April 24, 1991 |
| **Unconditional Mean** | | | |
| Series | Statistic | p-value | Break Date |
| Nominal Returns | 55.994 | 0.000 | October 17, 1991 |
| Inflation Adjusted Returns | 2.263 | 0.721 | September 3, 1975 |
| Real Returns in US Dollars | 3.187 | 0.516 | September 17, 1975 |
| **Unconditional Variance** | | | |
| Series | Statistic | p-value | Break Date |
| Nominal Returns | 34.481 | 0.000 | December 11, 1991 |
| Inflation Adjusted Returns | 44.849 | 0.000 | April 2, 1991 |
| Real Returns in US Dollars | 47.100 | 0.000 | April 16, 1990 |

With respect to the CM, the findings indicate that we can only reject the null of no break for nominal returns. The break corresponds to the implementation in 1991 of the structural macroeconomic stabilization plan, based on the convertibility of the Argentine peso. For the other two series, no evidence for breaks exists. The CV tests, in turn, show a structural break in the conditional variance of all three series in 1991, associated with the *Convertibility* plan.

E2. UM/UV Break Tests.

Structural break tests for regression models are sensitive to model misspecification. Therefore, we also check for breaks in the unconditional mean (UM) and variance (UV) using the sup Wald test with symmetric trimming of 15%. To examine the unconditional mean of each series, we fit a constant-only linear regression model to the data. For the unconditional variance (UV), we compute $e'$ as before, but using the residuals from a constant-only linear regression model. Our findings are displayed in the bottom panel of Table E1.

These results are very similar to those obtained from the CM/CV tests. Overall, the evidence presented in Table E1 suggests that a shift in the mean of the nominal returns series exists. It also indicates the existence of a structural change in the variance of all three returns, possibly related to the effects of the macroeconomic stabilization achieved in the 1990s. Based on the analysis presented in Figure C1 (Appendix C), as well as in Appendix D, it seems that the appearance of long memory is the result of the existence of structural changes in the series.

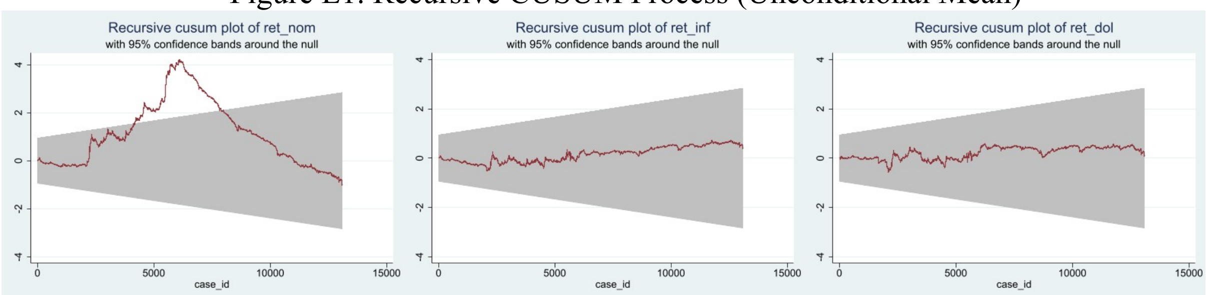
E3. Step Detection.

Step detection is the process of finding abrupt changes (steps, jumps, shifts) in the mean level of a time series or signal. We use the CUSUM (or cumulative sum) test to detect structural changes in the unconditional mean and variance of our three series. Inference is based on a sequence of sums of recursive residuals (standardized one-step-ahead forecast errors) computed iteratively from nested subsamples of the data. Under the null hypothesis of coefficient constancy, values of the sequence outside an expected range suggest structural change in the model over time.

We first examine the unconditional mean of each series by fitting a constant-only linear regression model to the data. In the case of nominal returns, the recovered test statistic value of 2.182 exceeds the 1% critical level of 1.1430. Therefore, we can reject the null hypothesis of a constant unconditional mean. The estimated test statistics for the stock returns expressed in real local consumption units and in US dollars are 0.389 and 0.423, respectively. As such, these results do not allow us to reject the null hypothesis of no structural break for these series.

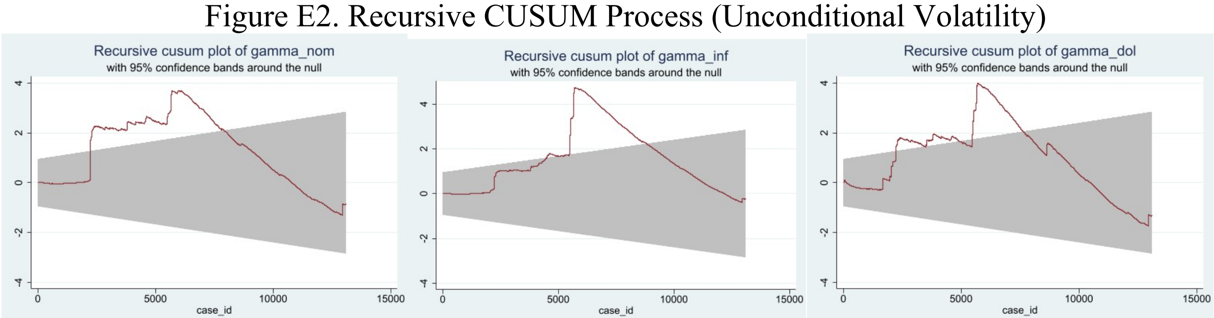
Figure E1 shows a plot of the recursive CUSUM process (red line) as well as 99% confidence bands for each of our series. We can see that the CUSUM curve for the nominal returns extends outside the confidence bands in the plot. The series appears to have two turning points. One in 1982 associated with the acceleration in the country's inflation rate and another in 1992 which is in line with the implementation of the structural stabilization plan the curved inflation.

Figure E1. Recursive CUSUM Process (Unconditional Mean)




We also examine the unconditional variance of each series by fitting a constant-only linear regression model to our estimated data of $e'$ for each series, calculated as described above. For all three series, their test statistic values exceed the 1% critical level. So, we can reject the null hypothesis of constant unconditional variance. Plots of the recursive CUSUM processes for the UV series are presented in Figure E2. The series where stock returns are measured in nominal terms and the one where they are measured in US dollars appear to have two turning points (in 1976 and 1997). They also seem to move together. In the case of stock returns expressed in real local consumption units, it looks like its two turning points correspond to 1989 and 2002.

Figure E2. Recursive CUSUM Process (Unconditional Volatility)



These findings lend further validity to the idea that the appearance of long memory in our stock returns time series is an artifact of regime switches. The persistence of shocks due to abrupt changes in a time series, on the other hand, may affect the ability of GARCH models to generate appropriate volatility forecasts. We discuss this latter issue in more detail in Appendix F.

## F. Regime Switches

The analyses reported in Appendix E suggest that at least two states, a low-volatility period, and a high-volatility one exist in the data. This finding provides further justification for the approach that we propose in our paper; specifically: (1) adopting a narrow event window; (2) focusing on changes, rather than levels, in the conditional variance; and (3) using our whole sample to estimate the long-run average daily variance of the Buenos Aires Stock Exchange's General Index. Nonetheless, checking the robustness of our main results when the assumption of constant variance across states is relaxed, seems to be a worthwhile exercise. We examine the changes in the data generating process using Markov-switching dynamic regression (MSDR). Finally, to address sudden or rapid (but sustained) "dips" and "jumps" in the data, we fit a threshold GARCH model as well as an exponential GARCH model to the nominal returns series.

### F1. Switching Process.

To allow for periods with different unconditional variances, we introduce deterministic shifts into the variance process. Rather than choosing the states in an ad hoc manner, we examine the changes in the data generating process using Markov-switching dynamic regression (MSDR). For each of our series, we fit an MSDR model with two state-dependent intercepts and variance parameters. Next, we use the predicted probabilities of being in each state, to construct an indicator variable that takes the value of one when an observation belongs to a high-volatility period, and zero when it corresponds to a low-volatility one. Finally, we run our GARCH(1,1) models including this measure in the volatility equation.

Using these estimates, we compute the pre- and post-event volatility ratios. Figure F1 shows their average when all the events listed in Table 1 of our paper, regardless of their type, are considered. The error bars indicate 95% confidence intervals, calculated using the empirical distribution of the test statistics obtained following the iterative procedure described in the paper. A comparison between Figure F1 and Figure 1 in the main body of the paper indicates that our results are virtually identical when we estimate a standard GARCH(1,1) model and when we allow for periods with different unconditional variances.

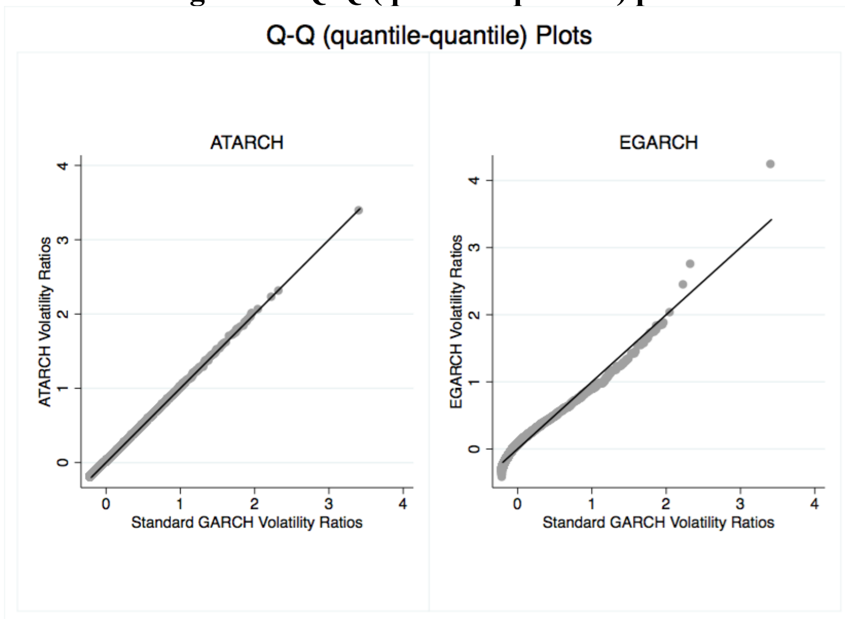
**Figure F1. Average Volatility Ratios**


F2. Asymmetric Effect of Shocks.

The existing literature suggests that at forecast horizons longer than one week, standard asymmetric GARCH models tend to be superior to Markov-switching GARCH models. We thus examine the asymmetric effect of shocks on volatility using an absolute threshold-GARCH (ATARCH) specification to estimate the return-generating process when stock returns are measured in nominal terms. We also examine the asymmetric effect of shocks on the volatility of nominal returns using an E-GARCH process. In both cases, the results indicate that the effect of unanticipated innovations is symmetric about zero.

Figure F2 presents two Q-Q (quantile-quantile) plots of the volatility ratios estimated using these two alternative models. For each specification, we compare the distribution of the volatility ratios to the one corresponding to the standard GARCH(1,1) model used in the paper. The graph's left (right) panel shows the Q-Q plot for the ATARCH (EGARCH) model. As Figure F2 shows, in both cases the distributions for the estimated volatility ratios are quite similar (i.e. the points in the Q–Q plot lie approximately on the reference line). Therefore, we conclude that the estimates presented in the main body of the paper properly account for economic shocks that repeatedly influenced Argentina's financial markets between January 2nd, 1967 and March 30th, 2020.

**Figure F2 Q-Q (quantile-quantile) plots**



## G. Full List of Events

| Date of Market Reaction | Description |
|---|---|
| | Change in Economic Steward (Change in Administration) |
| 6/18/1970 | Carlos Moyano Llerena replaces José Dagnino Pastore as Economic Minister |
| 5/28/1973 | José Ber Gelbard replaces Jorge Wehbe as Economic Minister/Alfredo Gómez Morales replaces Jorge Bermúdez Emparanza as Central Bank Governor |
| 4/5/1976 | Jose Alfredo Martinez de Hoz replaces Emilio Mondelli as Economic Minister/Adolfo C. Diz replaces Eduardo A. Zalduendo as Central Bank Governor |
| 4/1/1981 | Lorenzo Sigaut replaces Jose A. Martinez de Hoz as Economic Minister/Julio José Gómez replaces Adolfo C. Diz as Central Bank Governor |
| 12/18/1981 | Roberto Alemann replaces Lorenzo Sigaut as Economic Minister |
| 6/28/1982 | José Dagnino Pastore replaces Roberto Alemann as Economic Minister/Domingo Felipe Cavallo replaces Egidio Ianella as Central Bank Governor |
| 12/12/1983 | Bernardo Grinspun replaces Jorge Wehbe as Economic Minister/Enrique García Vázquez replaces Julio Gonzalez del Solar as Central Bank Governor |
| 7/10/1989 | Miguel Roig replaces Jesus Rodriguez as Economic Minister/Javier A. González Fraga replaces Enrique García Vázquez as Central Bank Governor |
| 12/10/1999 | José Luis Machinea replaces Roque Fernandez as Economic Minister |
| 12/20/2001 | Domingo Cavallo presents his resignation as Economic Minister |
| 1/3/2002 | Jorge Remes Lenicov replaces Rodolfo Frigeri as Economic Minister |
| 12/10/2007 | Martín Lousteau replaces Miguel Peirano as Economic Minister |
| 12/12/2011 | Hernán Lorenzino replaces Amado Boudou as Economic Minsiter |
| 12/10/2015 | Alfonso Prat-Gay replaces Axel Kiciloff as Economic Minister/Federico Adolfo Sturzenegger replaces Alejandro Vanoli as Central Bank Governor |
| 12/10/2019 | Martin Guzman replaces Hernan Lacunza as Economic Minister/Miguel Pesce replaces Guido Sandleris as Central Bank Governor |
| | Change in Economic Steward (Same Administration) |
| 6/10/1969 | José Dagnino Pastore replaces Adalbert Krieger Vasena as Economic Minister/Egidio Iannella replaces Pedro Real as Central Bank Governor |
| 10/19/1970 | Aldo Ferrer replaces Carlos Moyano Llerena as Economic Minister/Daniel Fernandez replaces Egidio Ianella as Central Bank Governor |
| 4/20/1971 | Ricardo Gruneisen replaces Daniel Fernandez as Central Bank Governor |
| 5/27/1971 | Aldo Ferrer presents his resignation as Economic Minister |
| 8/19/1971 | Ricardo Gruneisen presents his resignation as Central Bank Governor |
| 10/11/1971 | Cayetano Antonio Licciardo replaces Juan A. Quillici as Economic Minister |
| 10/11/1972 | Jorge Wehbe replaces Cayetano Licciardo as Economic Minister |
| 9/2/1974 | Alfredo Gómez Morales prsents his resignation as Central Bank Governor |
| 10/21/1974 | Alfredo Gómez Morales replaces Jose Ber Gelbard as Economic Minister |
| 6/2/1975 | Celestino Rodrigo replaces Alfredo Gómez Morales as Economic Minister |
| 7/16/1975 | Ricardo A. Cairoli resigns as Central Bank Governor |
| 7/22/1975 | Pedro José Bonanni replaces Celestino Rodrigo as Economic Minister |
| 8/11/1975 | Pedro José Bonanni presents resignation as Economic Minister |
| 2/4/1976 | Emilio Mondelli replaces Antonio Cafiero as Economic Minister/Eduardo A. Zalduendo replaces Emilio Mondelli as Central Bank Governor |
| 6/1/1981 | Egidio Iannella replaces Julio Jose Gomez as Central Bank Governor |
| 8/24/1982 | Jorge Wehbe replaces Dagnino Pastore as Economic Minister/Julio C. González del Solar replaces Domingo Cavallo as Central Bank Governor |
| 2/19/1985 | Juan Vital Sourrouille replaces Bernardo Grinspun as Economic Minister/Antonio Concepción replaces Enrique Garcia Vazquez as Central Bank Governor |
| 8/25/1986 | José Luis Machinea replaces Antonio Concepcion as Central Bank Governor |
| 3/31/1989 | Juan Carlos Pugliese replaces Juan V. Sourrouille as Economic Minsiter/Jose Luis Machinea presents his resignation as Central Bank Governor |
| 5/30/1989 | Jesús Rodríguez replaces Juan Carlos Pugliese as Economic Minister |
| 7/14/1989 | Miguel Roig passes away. He is replaced by Nestor Napanelli |
| 11/23/1989 | Egidio Iannella replaces Javier Gonzalez Fraga as Central Bank Governor |
| 12/20/1989 | Antonio Erman González replaces Nestor Rapanelli as Economic Minsiter/Rodolfo C. Rossi replaces Egidio Ianella as Central Bank Governor |
| 1/22/1990 | Enrique E. Folcini replaces Rodolfo C. Rossi as Central Bank Governor |
| 3/20/1990 | Antonio Erman González replaces Enrique Folcini as Central Bank Governor |
| 6/29/1990 | Javier A. González Fraga replaces Antonio Erman Gonzalez as Central Bank Governor |
| 1/28/1991 | Antonio Erman González presents his resignation as Economic Minister/Javier A. González Fraga presents his resignation as Central Bank Governor |
| 7/26/1996 | Domingo Cavallo presents his resignation as Economic Minister/Roque Fernandez presents his resignation as Central Bank Governor |
| 3/5/2001 | Ricardo López Murphy replaces Jose Luis Machinea as Economic Minsiter |
| 3/20/2001 | Domingo F. Cavallo replaces Ricardo López Murphy as Economic Minsiter |
| 4/26/2001 | Roque Maccarone replaces Pedro Pou as Central Bank Governor |
| 1/17/2002 | Mario Blejer replaces Roque Maccarone as Central Bank Governor |
| 4/29/2002 | Roberto Lavagna replaces Jorge Remes Lenicov as Economic Minister |
| 6/24/2002 | Aldo Rubén Pignanelli replaces Mario Blejer as Central Bank Governor |
| 12/9/2002 | Aldo Rubén Pignanelli presents his resignation as Central Bank Governor |
| 9/24/2004 | Martin Redrado replaces Alfonso Prat Gay as Central Bank Governor |
| 11/28/2005 | Felisa Miceli replaces Roberto Lavagna as Economic Minister |
| 7/16/2007 | Miguel Gustavo Peirano replaces Felisa Miceli as Economic Minsiter |
| 4/25/2008 | Carlos Rafael Fernández replaces Martín Lousteau as Economic Minister |
| 7/7/2009 | Amado Boudou replaces Carlos Fernandez as Economic Minister |
| 2/1/2010 | Martin Redrado presents his resignation as Central Bank Governor |
| 11/19/2013 | Axel Kicillof replaces Hernan Lorenzino as Economic Minister/Juan Carlos Fábrega replaces Mercedes Marcó del Pont as Central Bank Governor |
| 10/1/2014 | Alejandro Vanoli replaces Juan Carlos Fábrega as Central Bank Governor |
| 1/2/2017 | Nicolás Dujovne replaces Alfonso Prat-Gay as Economic Minister |
| 6/15/2018 | Luis Andrés Caputo replaces Federico Adolfo Sturzenegger as Central Bank Governor |
| 9/25/2018 | Guido Sandleris replaces Luis Caputo as Central Bank Governor |
| 8/20/2019 | Hernán Lacunza replaces Nicolas Dujovne as Economic Minsiter |
| | National Election |
| 3/12/1973 | Presidential Election |
| 9/24/1973 | Presidential Election |
| 10/31/1983 | Presidential and Legislative Election |
| 11/4/1985 | Legislative Election |
| 9/7/1987 | Legislative Election |
| 5/15/1989 | Presidential and Legislative Election |
| 9/9/1991 | Legislative Election |
| 10/4/1993 | Legislative Election |
| 5/15/1995 | Presidential and Legislative Election |
| 10/27/1997 | Legislative Election |
| 10/25/1999 | Presidential and Legislative Election |
| 10/15/2001 | Legislative Election |
| 4/28/2003 | Presidential Election |
| 9/15/2003 | Legislative Election |
| 10/24/2005 | Legislative Election |
| 10/29/2007 | Presidential and Legislative Election |
| 6/29/2009 | Legislative Election |
| 8/15/2011 | Primary Election |
| 10/24/2011 | Presidential and Legislative Election |
| 8/12/2013 | Primary Election |
| 10/28/2013 | Legislative Election |
| 8/10/2015 | Primary Election |
| 10/26/2015 | Presidential and Legislative Election |
| 11/23/2015 | Presidential Election |
| 8/14/2017 | Primary Election |
| 10/23/2017 | Legislative Election |
| 8/12/2019 | Primary Election |
| 10/28/2019 | Presidential Election |

| | |
|---|---|
| | Irregular Change in Adminstration |
| 6/18/1970 | Roberto Marcelo Levingston replaces Juan Carlos Ongania as President |
| 3/23/1971 | Alejandro Agustin Lanusse replaces Roberto Marcelo Levingston as President |
| 7/16/1973 | Resignation of Hector J. Campora as President |
| 7/1/1974 | Juan Domingo Peron Dies in Office |
| 4/5/1976 | Jorge Rafael Videla replaces Maria Estela Martinez de Peron as President |
| 12/11/1981 | Roberto Eduardo Viola is deposed |
| 6/18/1982 | Leopoldo Fortunato Galtieri is deposed |
| 12/20/2001 | Fernando De La Rua presents his resignation as President |
| 1/3/2002 | Eduardo Duhalde replaces Adolfo Rodriguez Saa as President |
| | Planned Succession |
| 5/28/1973 | Inauguration of Hector J. Campora |
| 10/15/1973 | Inauguration of Juan Domingo Peron |
| 4/1/1981 | Inauguration or Roberto E. Viola |
| 12/12/1983 | Inauguration of Raul R. Alfonsin |
| 7/10/1989 | Inauguration of Carlos Saul Menem |
| 12/11/1995 | Inauguration of Carlos Saul Menem |
| 12/10/1999 | Inaguration of Fernando De la Rua |
| 5/26/2003 | Inauguration of Nestor C. Kirchner |
| 12/10/2007 | Inauguration of Cristina Fernandez de Kirchner |
| 12/12/2011 | Inauguration of Cristina Fernandez de Kirchner |
| 12/10/2015 | Inauguration of Mauricio Macri |
| 12/10/2019 | Inauguration of Alberto Fernandez |
| | Terrorist Act |
| 6/1/1970 | Former President Aramburu is kidnapped by Montoneros |
| 7/30/1970 | The Fuerzas Armadas Revolucionarias (FAR) take over the Garin neighborhood (Buenos Aires) |
| 4/10/1972 | Assasination of Oberdan Sallustro |
| 8/16/1972 | Top Leaders of Armed Organizations escape from Rawson Penitentiary |
| 5/2/1973 | Assasination of Hermes Quijada |
| 5/23/1973 | Assasination of Dirk Kloosterman |
| 9/6/1973 | The Ejercito Revolucionario del Pueblo (ERP) attacks an Army unit |
| 9/27/1973 | Assasination of Jose Ignacio Rucci |
| 1/21/1974 | The Ejercito Revolucionario del Pueblo (ERP) attacks an Army unit |
| 7/15/1974 | Assasination of Arturo Mor Roig |
| 8/1/1974 | Assasination of Rodolfo Ortega Pena |
| 9/19/1974 | The Born Brothers are kidnapped by Montoneros |
| 9/30/1974 | Assasination of Gen. Carlos Prats |
| 12/2/1974 | Assasination of Humberto Viola |
| 8/25/1975 | Assasination of Julio Larrabure |
| 10/6/1975 | Montoneros attacks Regiment No.29 in Formosa |
| 12/3/1975 | Assasination of Jorge Caceres Monie |
| 12/23/1975 | The Ejercito Revolucionario del Pueblo (ERP) attacks Arsenal Battalion 601 |
| 6/18/1976 | Assasination of Cesareo Cardozo |
| 7/2/1976 | Bombing of Central Police Station |
| 12/15/1976 | Bombing of Defense Ministry |
| 8/1/1978 | Bombing targeting Admiral Lambrushini |
| 9/27/1979 | Bombing targeting Guillermo W. Klein |
| 11/13/1979 | Assasination of Francisco Soldati |
| 1/23/1989 | Attack against La Tablada Regiment |
| 3/17/1992 | Bombing of Israeli Embassy in Buenos Aires |
| 7/18/1994 | Bombing of AMIA Jewish Community Center |
| | International War |
| 4/2/1982 | Argentina invades the Malvinas/Falkland Islands |
| 6/14/1982 | End of the Malvinas/Falklands War |