ISSN: 2755-0214

Journal of Economics & Management Research

SCIENTIFIC Research and Community

Review Article

Open Access

The Cost of Prudential Regulation: Evidence from Operational Expenditure per Capita in Pension Funds

Carlos Elder Maciel de Aquino[1], Fernando Dal-Ri Murcia[2] and Heury Ferr[3*]

[1]University of São Paulo (USP) and Guest Professor at the Faculty of Law (FDUSP), Brazil

[2]Associate Professor at the University of São Paulo (FEA/USP) and Guest Professor at the Faculty of Law (FDUSP), Brazil

[3]Statistical Data Analysis (University of São Paulo),395 – apt. 141-B – Vila Mariana, CEP: 04020-040 – São Paulo-SP, Brazil

ABSTRACT

This paper evaluates whether the 2019 prudential regulatory event is associated with persistent changes in pension-fund cost dynamics. The analysis uses only estimates already reported in the thesis results archive and combines ARIMA intervention models, polynomial time-trend regressions, Chow structural-break tests, and time-series decompositions. For dpc, the ARIMA intervention term is positive and significant in the control group (xreg = 370.0129; p = 0.0041) but negative and non-significant in treatment (xreg = -156.3812; p = 0.6023). Chow tests reveal strong breaks in both groups (Control: F = 3.218528, p < 0.0001; Treatment: F = 2.641218, p < 0.0001). Complementary expenditure regressions show a large baseline treatment coefficient (64.8547; p < 0.001), but no significant event or event-treatment effect. Decomposition results indicate that post-2019 change is expressed primarily through greater volatility around trend rather than a clean level shift. Taken together, the evidence supports the existence of meaningful post-2019 cost reconfiguration, while suggesting caution in attributing a differential treated-group increase to the intervention alone.

***Corresponding author**

Heury Ferr Rua Coronel Lisboa, Statistical Data Analysis (University of São Paulo),395- apt. 141-B-Vila Mariana, CEP: 04020-040-São Paulo-SP, Brazil.

Received: May 15, 2026; **Accepted:** May 21, 2026; **Published:** May 29, 2026

Keywords: Prudential Regulation, Pension Funds, Intervention Analysis, ARIMA, Structural Break, Administrative Costs

JEL Classification: G23, G28, L25, M48

Introduction

Prudential oversight is typically justified in terms of stability, governance, and long-run asset protection. In pension systems, however, tighter supervision may also raise the administrative and monitoring burden borne by funds. That trade-off is not trivial. The pension-fund literature has long argued that regulation shapes investment behavior, governance arrangements, and operational organization, even when its direct performance consequences are ambiguous [1,2]. At the same time, the cost literature shows that administrative expenditure is strongly associated with scale, complexity, and service configuration, which means that regulatory intensification can interact with pre-existing organizational heterogeneity rather than produce a uniform cost effect [3].

This paper studies that trade-off using the evidence already produced in the thesis results archive. The objective is narrower than a full welfare evaluation: the question is whether the 2019 regulatory event coincided with a persistent reorganization of operational expenditure per capita and related spending patterns. The empirical emphasis therefore falls on identifying changes in timing, persistence, and volatility, instead of inferring a broad performance ranking across funds.

Methodologically, the paper is situated within the tradition of intervention analysis established by Box and Tiao, complemented by structural-break testing following Chow [4,5]. That combination is appropriate when the analyst wants to distinguish between a discrete intervention effect, a broader regime change, and a gradual reallocation of volatility around trend. The thesis results archive is especially suitable for that purpose because it reports the same 2019 event through several lenses: ARIMA intervention terms, time-trend regressions, Chow breaks, and decomposition of trend and noise.

Methodology

The paper does not re-estimate any model. It translates into article format the estimates already available in the source document. Four complementary empirical blocks are used.

First, ARIMA intervention models are used to assess whether the 2019 event is associated with a statistically identifiable change in the level of the expenditure-related series. This follows the classic logic of intervention analysis in dependent-data settings, where the treatment signal must be evaluated net of autoregressive and moving-average dynamics [4]. The general rationale behind ARIMA-based intervention assessment is also discussed in Sato, while McLeod and Vingilis emphasize that power and detectability depend on the temporal properties of the underlying process [6,7].

Second, polynomial time-trend regressions are used to separate three elements: baseline differences between control and treatment, the average effect of the event, and the differential post-event effect captured by the interaction term. The inclusion of quadratic and cubic time terms allows the reported models to absorb non-linear temporal movement already identified in the thesis archive.

Third, Chow structural-break tests evaluate whether the data-generating process changes around 2019. In econometric terms, the logic is not whether average values differ mechanically, but whether the relation encoded in the model changes sufficiently to reject coefficient stability across subperiods [5].

Fourth, time-series decomposition is used descriptively to distinguish trend from noise. This is useful in the present setting because the post-2019 response may appear not as an abrupt permanent shift, but as increased dispersion around a relatively stable trend, a possibility that standard intervention coefficients do not fully summarize.

The principal series for this paper is dpc, as reported in the source archive. Because the archive also provides richer detail for applied expenditure, those complementary results are used only to strengthen the empirical reading of operational burden. This article therefore remains entirely constrained by what was actually estimated in the original results file.

Results

ARIMA Intervention Evidence

Table 1 reports the core ARIMA intervention coefficients for dpc in the control and treatment groups and provides the first direct comparison of the post-2019 signal across the two series.

Table 1: ARIMA Intervention Coefficients for dpc in the Control and Treatment Groups

Group	Key parameter	Estimate	p-value	Reading
Control	dpc xreg	370.0129	0.0041	Positive and statistically significant intervention signal.
Treatment	dpc xreg	-156.3812	0.6023	No statistically robust intervention effect.

The temporal structure of the dpc models is itself non-trivial. In control, AR1 = 0.4434, AR2 = -0.8762, MA1 = -0.5054, and MA2 = 0.9512 are all significant at conventional levels, indicating pronounced persistence and correction dynamics. In treatment, MA1 = 0.1831 ($p = 0.0119$) remains significant even though the intervention term does not. Substantively, the reported evidence suggests that dpc is governed by meaningful internal time dependence in both groups, but that the 2019 intervention is only directly detected in the control series.

Time-Trend Regression Evidence on Expenditure Burden

To distinguish baseline group differences from post-event variation, Table 2 presents the polynomial time-trend regression estimates for applied expenditure, focusing on the event, treatment, and interaction terms.

Table 2: Polynomial Time-Trend Regression Coefficients for Applied Expenditure, Highlighting Event, Treatment, and Interaction Effects

Parameter	Estimate	p-value	Interpretation
event	-1.8351	0.803	No average post-2019 level shift in applied expenditure.
treatment	64.8547	< 0.001	Large baseline expenditure gap in favor of higher treated-group costs.
event: treatment	4.8375	0.543	No differential post-event increases attributable to treatment status.

Structural-Break Evidence

The parameter-stability evidence is summarized in Table 3, which reports the Chow structural-break results for dpc around the 2019 regulatory event.

Table 3: Chow Structural-Break Test Results for dpc Around the 2019 Regulatory Event

Group	Break year	F-statistic	p-value	Inference
Control	2019	3.218528	< 0.0001	Strong structural break.
Treatment	2019	2.641218	< 0.0001	Strong structural break.

The Chow results are more decisive than the intervention coefficients. Whatever the precise level effect, the expenditure-related process clearly changes around 2019 in both groups. This is an important distinction. A significant break need not imply a clean one-parameter jump; it can instead reflect a broader regime reorganization in persistence, dispersion, or trend stability.

Decomposition of Trend and Noise

The decomposition outputs clarify how that reorganization materializes. In the control group, applied expenditure trend remains broadly stable around 19.43 million, but the noise term rises sharply after 2019, moving from approximately 7.78 million in 2019 to 14.21 million in 2020 and 19.63 million in 2022. The source archive interprets this as a post-event increase in volatility around a comparatively unchanged long-run path.

In treatment, the expenditure trend rises only moderately, from 54.64 million in 2014 to 57.26 million in 2018 and 58.52 million in 2022. Yet the noise component stays predominantly negative, ranging from -36.21 million in 2014 to -31.85 million in 2017, deteriorating to -34.12 million in 2019 and remaining at -34.16 million in 2022. The same source also notes temporary positive deviations in 2015 (+46.33 million) and 2016 (+51.91 million). The implication is that treated funds continue on a mild upward trend, but realized expenditure often remains below the projected path.

Set against the intervention-analysis framework of, this pattern is informative: the 2019 event appears to be associated less with a uniform permanent shift in the treated series and more with a change in the way expenditure fluctuates around trend across groups [4]..

Discussion

The empirical picture is coherent, but it is not simplistic. The results do not support a single treated-only cost escalation narrative. Instead, they indicate three concurrent facts. First, expenditure-related dynamics change around 2019 in both groups. Second, treated entities carry a materially higher baseline expenditure burden in the regression framework. Third, the main post-event signal appears in volatility and regime change rather than in a stable, statistically clean differential interaction effect.

This reading fits the broader pension-regulation literature. Vittas stresses that investment regulation and governance rules can alter institutional organization in ways that are not reducible to a single immediate outcome measure [1]. The OECD likewise shows that solvency-related and accounting rules may affect long-term decision environments even when short-run causal attribution is difficult [2]. On the cost side, Bikker, Steenbeek, and Torracchi show that administrative expenditure depends strongly on fund characteristics, implying that tighter prudential environments may amplify pre-existing structural differences rather than create homogeneous burdens across institutions [3]..

Methodologically, the paper also illustrates why multiple empirical lenses matter. ARIMA intervention terms, power considerations, and causal attribution in time series all require caution when temporal dependence, volatility, and heterogeneity coexist [7,8]. The source archive points to precisely that situation. The safest interpretation is therefore that the regulatory event is associated with meaningful post-2019 expenditure reconfiguration, but the evidence is stronger for structural change and volatility reshaping than for a uniform additional cost increment in treated entities [9-15].

Conclusion

Using only reported estimates from the thesis results archive, this paper finds strong post-2019 structural breaks in expenditure-related pension-fund dynamics and clear baseline differences between groups. The evidence supports the view that prudential intensification is associated with a non-negligible cost environment, but the mechanism appears to operate through broad process reorganization and volatility changes rather than through a single robust treated-group intervention coefficient.

A compact econometric article derived exclusively from the empirical outputs reported in the thesis results archive, with interpretation anchored in intervention-analysis, structural-break, and pension-fund cost literature.

Empirical Focus: dpc and complementary expenditure evidence.	**Identification Frame:** 2019 regulatory event.	**Methods reported in Source:** ARIMA, time-trend regressions, Chow test, decomposition.

References

1. Vittas Dimitri (1996) Pension Funds and Capital Markets: Investment Regulation, Financial Innovation and Governance. World Bank https://openknowledge.worldbank.org/entities/publication/fb4ad233-c6a1-558c-929f-c12fc5e882a1.
2. OECD (2012) The Effect of Solvency Regulations and Accounting Standards on Long-Term Investing. OECD Working Papers on Finance, Insurance and Private Pensions https://www.oecd.org/content/dam/oecd/en/publications/reports/2012/12/the-effect-of-solvency-regulations-and-accounting-standards-on-long-term-investing_g17a21fb/5k8xd1nm3d9n-en.pdf.
3. Bikker Jacob A, Onno Steenbeek W, Federico Torracchi (2017) The Impact of Scale, Complexity and Service Quality on the Administrative Costs of Pension Funds. In Pension Fund Economics and Finance https://www.uu.nl/sites/default/files/rebo_use_dp_2010_10-15.pdf.
4. Box GEP, Tiao GC (1975) Intervention Analysis with Applications to Economic and Environmental Problems. Journal of the American Statistical Association 70: 70-79.
5. Chow Gregory C (1960) Tests of Equality Between Sets of Coefficients in Two Linear Regressions. Econometrica 28: 591-605.
6. Sato Renato Cesar (2013) Disease Management Using Time Series with the ARIMA Model. Einstein (São Paulo) 11: 128-131.
7. McLeod Ian A, Evelyn Vingilis R (2005) Power Computations for Intervention Analysis. Technometrics 47: 174-180.
8. Menchetti, Fiammetta, Fabrizio Cipollini, Fabrizia Mealli (2021) Estimating the Causal Effect of an Intervention in a Time Series Setting: The C-ARIMA Approach. Arxiv:2103.06740.
9. Bauer Rob, Martijn Cremers, Rik Frehen GP (2010) Pension Fund Performance and Costs: Small is Beautiful. SSRN Electronic Journal https://papers.ssrn.com/sol3/papers.cfm?abstract_id=965388.
10. Bikker, Jacob A (2013) Is There an Optimal Pension Fund Size? A Scale-Economy Analysis of Administrative and Investment Costs. SSRN Electronic Journal https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2258989.
11. Earnest Arul, Mark Chen I, Donald Ng, Leo Yee Sin (2005) Using autoregressive integrated moving average (ARIMA) models to predict and monitor the number of beds occupied during a SARS outbreak in a tertiary hospital in Singapore. BMC Health Services Research 11: 5-36.
12. Linden Ariel, John Adams L, Nancy Roberts (2003) Evaluating Disease Management Program Effectiveness: An Introduction to Time-Series Analysis. Disease Management 6: 243-255.
13. Liu Qiyong, Xiaodong Liu, Baofa Jiang, Weizhong Yang (2011) Forecasting Incidence of Hemorrhagic Fever with Renal Syndrome in China Using ARIMA Model. BMC Infectious Diseases 11: 210-218.
14. López-Lozano, José-María, Dominique Monnet L, Alberto Yagüe, Amparo Burgos, et al. (2000) Modelling and Forecasting Antimicrobial Resistance and its Dynamic Relationship to Antimicrobial Use: A Time Series Analysis. International Journal of Antimicrobial Agents 14: 21-31.

15. Shah Hemant (1999) Toward Better Regulation of Private Pension Funds. Policy Research Working Papers https://ideas.repec.org/p/wbk/wbrwps/1791.html.