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The Impact of Expenditures on Research and Development

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Abstract

This study seeks to investigate the relationship between research and development expenditures and the performance of the sector in Canada, Quebec, and Saskatchewan, applying the Pooled Mean Group Estimator in the context of a Panel Autoregressive Distributed Lag (PARDL) model. The series are non-stationary with data consistently drifting upwards and downwards without reverting to a stable mean. ARDL (1,1,1,1,1,1) model with linear trend specification turn out to be the best. The model shows mutual, single-direction, and unrelated connections between some indicators. In the following year, disequilibria in total research and development expenditure relative to the long-run steady state are adjusted by 35.37% for Canada, 33.55% for Quebec, and 104.5% for Saskatchewan, underscoring Saskatchewan's comparatively accelerated convergence to equilibrium. The estimated joint speed of adjustment to the long-run equilibrium is –0.577929, signifying that approximately 57.79% of the disequilibrium in total research and development expenditure is corrected within the subsequent year. Over time, a 1% adjustment in research and development spending by the business enterprise sector, federal government sector, higher education sector, provincial government sector, and provincial research organization sector is expected to raise total research and development expenditure by about 99.53%, 100.31%, 100.99%, 91.51%, and 110.24%, respectively. Moreover, the expenditure on research and development by provincial research organizations sector, higher education sector, and federal government sector has been superior. Convincingly, the pairwise Granger causality tests revealed that the provincial government sector's expenditure on research and development have a more substantial effect on total expenditure on research and development, the expenditure on research and development by business enterprise sector, and the expenditure on research and development by federal government sectors' fluctuation for the sub-region. Conversely, research and development expenditure by the higher education sector exerts a stronger influence on fluctuations in the federal government sector's expenditure within the sub-region.

***Keywords:** - ARDL (1,1,1,1,1,1), Expenditures on Research and Development, Pairwise Granger Causality, Pooled Mean Group Estimator, Stable Market Balance Rate*

1 Introduction

Canada's research and development (R\&D) ecosystem is highly diverse, with the business enterprise sector consistently acting as the main driver of expenditures. In 2022, business enterprises invested approximately CAD 19 billion in R\&D, while the federal government contributed around CAD 8.25 billion. The provinces of Quebec and Saskatchewan demonstrate distinctly different R\&D profiles: Quebec's efforts are heavily concentrated in the service and manufacturing sectors, whereas Saskatchewan's initiatives are strongly tied to natural resources and agricultural innovation. The business enterprise sector remains the largest contributor to Canadian R\&D, allocating extensive resources across information and communications technology, manufacturing, and the life sciences. Simultaneously, the federal government funds and conducts research through numerous agencies and councils that emphasize national priorities. Post-secondary institutions also play a pivotal role, focusing on basic research and training highly skilled professionals. By 2022, Canada's gross domestic expenditures on R\&D (GERD) totaled CAD 51.7 billion, signaling increased investment. However, the nation's R\&D intensity—measured as the ratio of R\&D spending to GDP—has remained relatively unchanged compared to other G7 countries. This stagnation may limit Canada's ability to enhance innovation performance and sustain competitiveness in the global knowledge economy (Science Business, 2024; Statistics Canada, 2024).

Quebec serves as a key hub for business enterprise research and development (BERD), with much of its activity stemming from the service sector. The province's manufacturing industry also plays a significant role, particularly in aerospace, pharmaceuticals, and clean technologies (Science Business, 2024; Statistics Canada, 2024).

Saskatchewan's R\&D environment, by contrast, is shaped by abundant natural resources, spurring heavy investment in agricultural research, mining, and advanced energy technologies. The province hosts a robust agricultural research sector dedicated to developing new crop varieties, optimizing farming techniques, and strengthening food security for local and international markets. As a major producer of potash, uranium, and other valuable resources, Saskatchewan directs its R\&D efforts toward improving resource extraction and devising sustainable energy solutions to address environmental challenges. Although its R\&D intensity has historically trailed behind Quebec and other provinces, Saskatchewan is actively diversifying its economy and boosting investments in research and development to secure a more innovative future (Science Business, 2024; Statistics Canada, 2024).

This study employs the PMG estimator within the PARDL framework, a method well-suited to capturing both short- and long-run dynamics in heterogeneous panel data. Drawing on the foundational work of Baltagi (2014, 2015), Baltagi and Griffin (1984, 1997), Pesaran (2007, 2012, 2015), and Pesaran, Shin, and Smith (1997, 1999), the approach provides a robust foundation for analyzing dynamic relationships while accommodating cross-sectional heterogeneity. The research evaluates how sector-specific R\&D expenditures influence total expenditures in Canada, with particular emphasis on Quebec and Saskatchewan due to their distinct economic profiles and strategic roles in the national innovation landscape.

2 Problem Formulation

Panel data analysis offers several advantages by capturing both cross-sectional and time-series variations simultaneously. This dual perspective allows for more precise estimation of dynamic relationships and better control of unobserved heterogeneity than methods relying solely on cross-sectional or time-series data. By integrating these dimensions, researchers can uncover complex interactions among variables and develop more flexible models with fewer restrictive assumptions, thereby improving the robustness and reliability of econometric results (Pesaran et al., 1995; Baltagi et al., 2000; Hsiao, 2003; Martinez-Zarzoso & Bengochea-Morancho, 2004; Baltagi, 2014, 2015).

One methodological challenge inherent in panel frameworks with individual-specific effects is the correlation between mean-differenced regressors and the error term. Such correlations can introduce bias into the estimation of Autoregressive Distributed Lag (ARDL) models. This bias diminishes only asymptotically as the time dimension increases, and cannot be eliminated simply by expanding the cross-sectional sample, underscoring the importance of sufficiently long time series for reliable estimation (Arellano, 2004).

To address these issues, Pesaran et al. (1999) introduced the Pooled Mean Group (PMG) estimator, which extends the ARDL cointegration model to panel data. This estimator permits heterogeneous short-run dynamics across cross-sectional units while constraining long-run parameters to remain common. The PMG estimator thereby accommodates variation in intercepts, short-run dynamics, and error correction terms, while maintaining homogeneity of long-run relationships. This balance between flexibility and parsimony makes the PMG approach particularly suitable for panels with large time dimensions (Baltagi & Griffin, 1984, 1997; Pesaran et al., 1997, 1999; Freeman, 2000; Baltagi et al., 2008).

In essence, the PMG estimator provides a robust framework for analyzing long-run equilibrium relationships in heterogeneous panels while capturing short-run dynamics and cross-sectional diversity. Following the methodological contributions of Anderson and Hsiao (1981, 1982), Schoenberg (1997), Baltagi et al. (2003), Gujarati (2003), and Pedroni (1999, 2004), this study employs a reformulated error correction model (1) to examine both short- and long-term dynamics within the panel data.

$$\Delta y_{i,t} = \pi_i \theta_{i,t} + \sum_{j=1}^{n-1} \lambda_{i,j} \Delta y_{i,t-j} + \sum_{j=0}^{m-1} \Delta x_{i,t-j} \beta'_{i,j} + \varepsilon_{i,t} \quad (1)$$

The adjustment coefficients, which typically range from –

1 to 0, are expected to be negative to ensure convergence toward steady-state equilibrium.

$$\pi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{ij}\right) \qquad (2)$$

The error-correction speed of adjustment can thus be expressed as:

$$\theta_{i,t} = y_{i,t-1} - \mu_i' x_{it} \qquad (3)$$

Similarly, the long-run parameters are defined as:

$$\mu_i = \frac{\sum_{j=0}^{q} \beta_{ij}}{\left(1 - \sum_k \lambda_{ik}\right)} \qquad (4)$$

The influence of informative variables on disturbances is an important consideration in the estimation of $\theta_{i,t}$, if we assume that S_{it} has finite AR representations.

The vector of constant parameters in equation (5) represents the key coefficients to be estimated for the dependent variable, with corresponding values applied to each group.

$$\lambda_{ij} = -\sum_{p-j+1}^{n} \lambda_{ip} \quad ; \quad j = 1, 2, \ldots, \mathrm{n}-1 \qquad (5)$$

The (k×1) vector of constants in equation (6) reflects parameters to be estimated on explanatory variables:

$$\beta_{ij} = -\sum_{p=j+1}^{m} \beta_{ip} \quad ; j = 1, 2, \ldots, \mathrm{m}-1 \qquad (6)$$

The (T×k) potentially time-varying covariate matrix accounts for differences across groups and time, while the j lagged values capture dynamic effects:

$X_{it} = \left(x_{i1}, \ldots, x_{iT}\right)'$; while, the j lagged values of Δx_i are given by:

$$\Delta X_i = X_i - X_{i-1} = \left(\Delta x_{\mathrm{i},1}, \Delta x_{\mathrm{i},2}, \ldots, \Delta x_{\mathrm{i},\mathrm{T_i}}\right)'$$

The (T×1) observation vectors for each group reflect the control variables, and the time-invariant component accounts for any unobservable individual-specific error terms: $Y_{it} = \left(y_{i1}, \ldots, y_{iT}\right)'$; while, the j lagged values of ΔY_i are given by:

$$\Delta Y_i = Y_i - Y_{i-1} = \left(\Delta y_{\mathrm{i},1}, \Delta y_{\mathrm{i},2}, \ldots, \Delta y_{\mathrm{i},\mathrm{T_i}}\right)'$$

The time-invariant that accounts for any unobservable individual-specific error term are given by: $\varepsilon_{it} = \left(\varepsilon_{i1}, \ldots, \varepsilon_{iT}\right)'$.

For consistent short-run estimates, disturbances must remain uncorrelated with the regressors. Additionally, the same number of lags should be applied across cross-sections for both dependent and independent variables. Under these conditions, the concentrated log-likelihood function can be expressed as the product of individual cross-sectional likelihoods, as demonstrated by Wooldridge (2000) and Gujarati (2003).

$$L_i(\varphi) = -\frac{T_i}{2} \sum_{i=1}^{N} \log\left(2\pi\sigma_i^2\right) - \frac{1}{2} \sum_{i=1}^{N} \frac{1}{\sigma_i^2} \left(\Delta Y_i - \pi_i \theta_i\right)' H_i \left(\Delta Y_i - \pi_i \theta_i\right) (7)$$

Where $\theta_i = \left(\theta_{\mathrm{i},1}, \theta_{\mathrm{i},2}, \ldots, \theta_{\mathrm{i},\mathrm{T_i}}\right)'$, $H_i = \left(I_{T_i} - R_i\left(R_i' R_i\right)^{-1} R_i'\right)^{-1}$ and $R_i = \left(\Delta Y_{i,-1}, \ldots, \Delta Y_{i,-p+1}, \Delta X_i, \Delta X_{i,-1}, \ldots, \Delta X_{i,-q+1}\right)$.

The Mean Group (MG) estimator proposed by Pesaran, Shin, and Smith allows for full heterogeneity among cross-sectional units by permitting intercepts, short-run coefficients, and error variances to vary across groups. It estimates the model separately for each unit and then computes an unweighted average of the resulting coefficients to obtain overall panel estimates.

By contrast, the Fixed Effects (FE) estimator imposes uniformity on long-run coefficients across cross-sections, assuming that these parameters remain constant while variations are captured only by unit-specific intercepts (Mundlak, 1978; Pesaran et al., 1995, 1997, 1999; Baltagi et al., 2000).

3 Problem Solution

This study draws on 129 panel data observations spanning 1979–2021 for Canada and the provinces of Quebec and Saskatchewan, obtained from the Statistics Canada database. These regions were chosen based on the availability and consistency of data. The descriptive statistics, probability values, and regression outputs generated using EViews10 software demonstrate the validity and robustness of the chosen approach.

The time series plots of total R\&D expenditure (T) across the business enterprise sector (BES), federal government sector (FGS), higher education sector (HES), provincial research organizations sector (PROS), and provincial governments sector (PGS), as illustrated in Figure 1, reveal considerable volatility and fluctuations in both mean and variance. This suggests that the panel time series data are not covariance stationary. Their time-dependent structure and irregular fluctuations necessitate formal testing for unit roots to understand their underlying behavior.

Table 1 reveals wide variation in means, indicating the presence of both high- and low-value categories. Lower means (99.12 and 24.98) are sensitive to small shifts, whereas higher means (such as 8965.92) dominate aggregate statistics. Median values also span a broad range (17.0 to 4355.0), underscoring substantial differences in central tendencies across groups and pointing to heterogeneity in data scales and magnitudes. These findings highlight the importance of data segmentation or transformation when conducting comparative or aggregate analysis.

The standard deviation values—11520.60, 6336.749, 901.1440, 4242.680, 111.0661, and 22.66070—signal significant variability across the datasets. Higher standard deviations (11520.60 and 6336.749) reflect wide dispersion, while lower values (111.0661 and 22.66070) indicate tighter clustering around the mean. These disparities should be considered during comparative analysis, potentially through standardization or scaling, to ensure valid interpretations.

Positive skewness values (1.523964, 1.487342, 1.002307, 1.734197, 1.12779, and 1.468400) show that most distributions are right-skewed, with longer right tails and occasional high-value observations pulling the mean upward. Kurtosis values (4.271030, 4.269787, 2.409028, 4.939116, 3.062695, and 4.112513) suggest that most distributions are leptokurtic (kurtosis > 3), meaning they have sharper peaks and heavier tails compared to a normal distribution, implying a greater propensity for extreme values.

The value 2.409028 (kurtosis < 3) is an exception, indicating a flatter, more uniform spread. Overall, the data shows a tendency toward peaked distributions with potential for outliers, with one exception leaning toward a more uniform spread.

Jarque–Bera test statistics—58.61645, 56.22845, 23.47653, 84.87086, 27.36723, and 53.01085—are high, indicating strong departures from normality. Extremely low p-values (commonly < 0.05) reinforce rejection of the null hypothesis of normality, implying that standard parametric assumptions may not hold without transformation or the use of non-parametric alternatives.

The probability values 0.000000, 0.000000, 0.000008, 0.000000, 0.000001, and 0.000000 are all extremely small and well below the standard significance level of 0.05. These values typically represent the p-values from normality tests (such as the Jarque-Bera test), and such low values provide strong statistical evidence to reject the null hypothesis of normality. Thus, the datasets in question are not normally distributed, and assumptions of normality used in many statistical procedures may not be valid. Consequently, non-parametric methods or data transformation may be more appropriate for accurate analysis. Thus, an empirical distribution test is required to ascertain the distribution of the series.

The kernel density plot in Figure 2, which non-parametrically estimates the probability density function, confirms that all variables deviate from normality, exhibiting skewness and multimodality. In particular, PGS and FES variables indicate the presence of multiple underlying subgroups. Table 2's p-values (< 0.05) confirm these distributional irregularities and support the conclusion that the series are non-normally distributed.

Panel unit root tests (Table 3) were conducted using LLC; Levin, Lin & Chu t* (assuming a common unit root process) alongside ADF–Fisher Chi-square and PP–Fisher Chi-square (assuming individual unit root processes). Both common and individual effects suggest unit roots in the series, as indicated by probability values exceeding the 0.05 benchmark. Thus, the series follow a random walk.

However, first-difference tests (Table 4) yield p-values below 0.05, indicating stationarity after differencing. This implies the series revert to a mean with constant variance over time, confirming the absence of trends or random walks after first differencing.

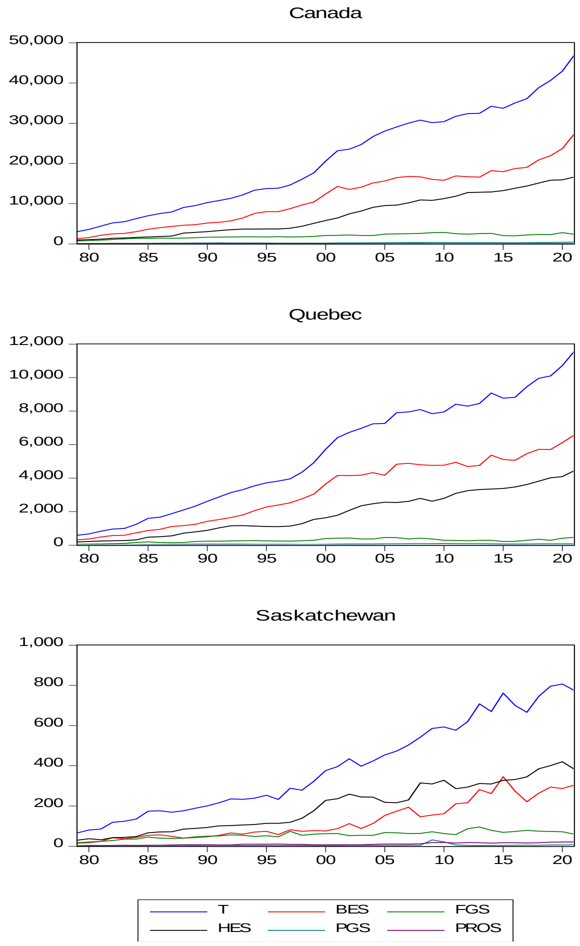

Fig. 1: Time series plot of T, BES, FGS, HES, PGS, and PROS.

Table 1. Descriptive Statistic

Statistics	T	BES	FGS	HES	PGS	PROS
Mean	8965.922	4943.047	751.2558	3111.047	99.12403	24.97674
Median	4355.000	2489.000	265.0000	1177.000	56.00000	17.00000
Maximum	46927.00	27287.00	2863.000	16624.00	414.0000	96.00000
Minimum	66.00000	15.00000	17.00000	30.00000	2.000000	2.000000
Std. Dev.	11520.60	6336.749	901.1440	4242.680	111.0661	22.66070
Skewness	1.523964	1.487342	1.002307	1.734197	1.127791	1.468400
Kurtosis	4.271030	4.269787	2.409028	4.939116	3.062695	4.112513
Jarque-Bera	58.61645	56.22845	23.47653	84.87086	27.36723	53.01085
Probability	0.000000	0.000000	0.000008	0.000000	0.000001	0.000000
Sum	1156604.	637653.0	96912.00	401325.0	12787.00	3222.000
Sum Sq. Dev.	1.70E+10	5.14E+09	1.04E+08	2.30E+09	1578968.	65728.93
Observations	129	129	129	129	129	129

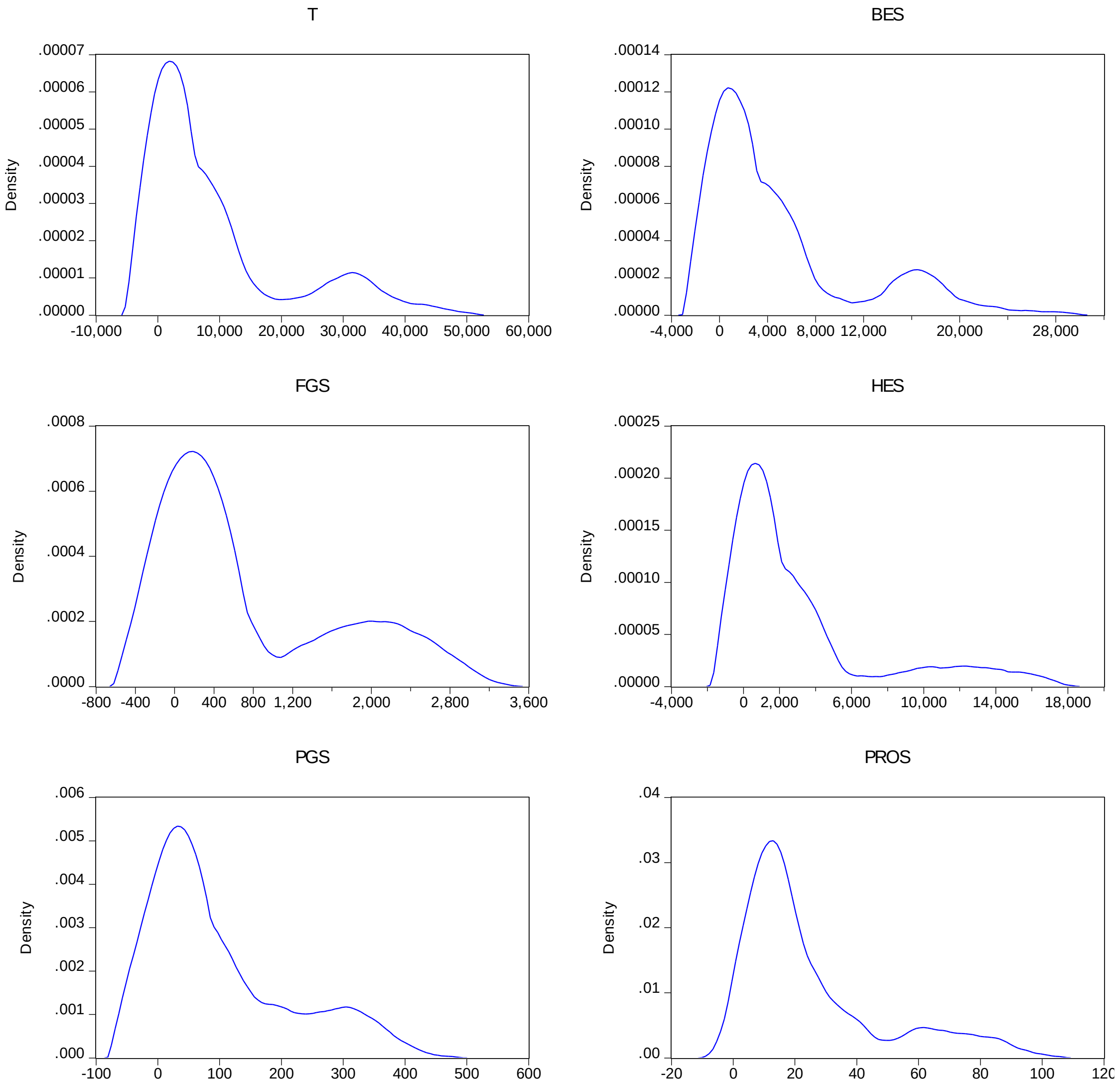

Fig. 2: Kernel Density plot of T, BES, FGS, HES, PGS, and PROS.

The ARDL (1,1,1,1,1,1) model summarized in Table 5 provides a well-structured framework for analyzing both short- and long-run relationships. Model fit statistics indicate a reasonably good specification, though comparison with alternative lag selections (AIC/BIC) is advisable for optimal performance. If cointegration is present, long-run inferences can be drawn reliably.

The Wald coefficient restriction test (Table 6) yields a p-value of 0.0000, strongly rejecting the null hypothesis that the coefficients are jointly zero. Imposing restrictions would lead to model misspecification, indicating that the unrestricted model better captures the true dynamics.

Confidence interval tests (Table 7) show that estimated coefficients fall within 90%, 95%, and 99% confidence intervals. Where intervals exclude zero, coefficients are statistically significant, underscoring the reliability of the model estimates.

Table 8 indicates that all explanatory variables have positive and statistically significant coefficients at the 1% level (p-values = 0.0000), reflecting strong long-run relationships with the dependent variable. A 1-unit increase in any independent variable corresponds to an increase in T (total R\&D expenditure), holding other factors constant. The negative and significant error correction term confirms a long-run equilibrium relationship, with about 58% of deviations from equilibrium corrected each period. Some short-run coefficients (e.g., D(HES) and D(PGS)) are significant at the 10% level, suggesting moderate short-run effects, though many variables are insignificant in the short run. Log-likelihood, AIC, and SC values indicate a well-specified model with moderate residual variance. Overall, the model demonstrates a robust long-run relationship supported by a meaningful error correction mechanism, while short-run effects are less consistently significant.

Table 9 presents the Pedroni test statistics, most of which are significant at the 5% level or below, providing strong evidence of a long-run cointegration relationship among the panel variables.

The Kao ADF statistic (Table 10) also yields a p-value below 0.05, rejecting the null hypothesis of no cointegration and confirming residual stationarity. The significant negative coefficient of RESID(-1) (–0.32) further reinforces the presence of cointegration, indicating that deviations from the long-run model are mean-reverting. These findings support the use of error correction models (ECM) or long-run causality analyses.

Tables 11–13 present the short-run dynamics and adjustment processes for Canada, Quebec, and Saskatchewan, respectively. In Canada, the negative and significant error correction coefficient shows that about 35.4% of disequilibrium is corrected each period. Short-run coefficients indicate significant positive effects of changes in sectoral expenditures on the dependent variable, while constant and time-trend terms are insignificant.

Quebec's model reveals a negative and significant error correction term, with 33.5% of deviations corrected each period. All differenced variables are significant at the 1% or 5% level, demonstrating strong short-run effects of sectoral R\&D spending on the dependent variable. A significant negative trend suggests a slight downward pattern in the dependent variable over time, while the intercept is insignificant.

Saskatchewan's model confirms a negative and highly significant error correction term, with roughly 35.4% of disequilibrium corrected per period, indicating a relatively fast speed of adjustment. All explanatory variables are positive and significant in the short run, showing that increases in sector-specific R\&D expenditures yield immediate positive effects on the dependent variable. Significant trend and constant terms suggest that dynamics are driven mainly by differenced explanatory variables rather than time or fixed effects.

Finally, the Pairwise Granger Causality Tests (Table 14) reveal a complex network of predictive relationships. Provincial government sector expenditures Granger-cause total R\&D expenditure, business enterprise spending, and federal government expenditure, and vice versa. Higher education spending Granger-causes federal government expenditure and vice versa. Federal government expenditure Granger-causes total R\&D spending, which in turn Granger-causes higher education expenditure. Provincial research organizations' spending Granger-causes total R\&D expenditure and business enterprise expenditure. Higher education spending Granger-causes provincial government expenditure, and provincial research organizations' spending Granger-causes provincial government expenditure. Overall, provincial government spending exhibits the strongest influence on total and sectoral R\&D expenditures, while higher education spending has a pronounced effect on fluctuations in federal government expenditure within the sub-region.

Table 2: Experimental Distribution Tests

		TESTS		
Variables	Statistics	Cramer-von Mises, W^2	Watson, U^2	Anderson-Darling, A^2
T	Value	2.095976	1.814984	11.84288
	Adj. Value	2.104100	1.822018	11.91334
	Prob	0.0000	0.0000	0.0000
BES	Value	2.008806	1.746197	11.34778
	Adj. Value	2.016592	1.752965	11.41529
	Prob	0.0000	0.0000	0.0000
FGS	Value	2.577409	2.385266	13.64804
	Adj. Value	2.587399	2.394511	13.72923
	Prob	0.0000	0.0000	0.0000
HES	Value	2.480370	2.150993	13.78435
	Adj. Value	2.489984	2.159330	13.86636
	Prob	0.0000	0.0000	0.0000
PGS	Value	1.517385	1.327095	8.774137
	Adj. Value	1.523267	1.332239	8.826336
	Prob	0.0000	0.0000	0.0000
PROS	Value	1.868453	1.604624	10.37509
	Adj. Value	1.875695	1.610843	10.43682
	Prob	0.0000	0.0000	0.0000

Table 3. Level Form Panel Unit Root Tests

		METHODS		
Variables	Statistics	LLC	ADF-Fisher	PP - Fisher
T	Stats	1.43208	3.01809	4.79332
	Prob	0.9239	0.8066	0.5706
BES	Stats	1.01562	2.60441	3.98716
	Prob	0.8451	0.8566	0.6784
FGS	Stats	-0.94432	8.92263	8.77425
	Prob	0.1725	0.1780	0.1867
HES	Stats	-0.82932	7.31567	4.18961
	Prob	0.2035	0.2926	0.6510
PGS	Stats	-0.88740	12.4086	8.58620
	Prob	0.1874	0.0534	0.1982
PROS	Stats	-0.22085	7.98528	10.8431
	Prob	0.4126	0.2392	0.0933

Table 4. Differenced Form Panel Unit Root Tests

	METHODS			
Variables	Statistics	LLC	ADF-Fisher	PP - Fisher
T	Stats	-2.54419	21.9662	47.5590
	Prob	0.0055	0.0012	0.0000
BES	Stats	-4.38131	34.6952	83.2203
	Prob	0.0000	0.0000	0.0000
FGS	Stats	-9.03127	79.4728	127.236
	Prob	0.0000	0.0000	0.0000
HES	Stats	-3.16111	20.3730	36.7896
	Prob	0.0008	0.0024	0.0000
PGS	Stats	-7.40835	66.0290	306.270
	Prob	0.0000	0.0000	0.0000
PROS	Stats	-9.52922	86.8812	199.003
	Prob	0.0000	0.0000	0.0000

Table 5. Review of Model Selection Standards

Model	**LogL**	**AIC***	**BIC**	**HQ**	**Specification**
1	-299.529068	5.214747	5.867542	5.479957	ARDL(1, 1, 1, 1, 1, 1)

Table 6. Wald Test on Model Parameters

Test Statistic	Value	df	Probability
F-statistic	89283.82	(5, 100)	0.0000
Chi-square	446419.1	5	0.0000

Null Hypothesis: C(1)=C(2)=C(3)=C(4)=C(5)=0

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)	0.995337	0.002268
C(2)	1.003144	0.010937
C(3)	1.009955	0.003483
C(4)	0.915119	0.024367
C(5)	1.102367	0.049418

Restrictions are linear in coefficients.

Table 7. Testing Coefficients Using Confidence Intervals

		90% CI		95% CI		99% CI	
Variable	Coefficient	Low	High	Low	High	Low	High
BES	0.995337	0.991571	0.999102	0.990837	0.999836	0.989381	1.001292
FGS	1.003144	0.984986	1.021302	0.981446	1.024843	0.974425	1.031863
HES	1.009955	1.004173	1.015737	1.003046	1.016864	1.000810	1.019100
PGS	0.915119	0.874664	0.955574	0.866775	0.963463	0.851134	0.979104
PROS	1.102367	1.020322	1.184412	1.004324	1.200410	0.972602	1.232133

Table 8. Estimation Outcomes of the Panel ARDL (1,1,1,1,1,1) Model

Target Variable: D(T)

Parameter	Coefficient	SE	t-Stat	Prob.*
Long Run Equation				
BES	0.995337	0.002268	438.8640	0.0000
FGS	1.003144	0.010937	91.72079	0.0000
HES	1.009955	0.003483	290.0031	0.0000
PGS	0.915119	0.024367	37.55546	0.0000
PROS	1.102367	0.049418	22.30716	0.0000
Short Run Equation				
COINTEQ01	-0.577929	0.233384	-2.476298	0.0150
D(BES)	0.421447	0.233590	1.804216	0.0742
D(FGS)	0.410638	0.224699	1.827499	0.0706
D(HES)	0.417798	0.235731	1.772353	0.0794
D(PGS)	0.608597	0.313661	1.940300	0.0552
D(PROS)	0.466877	0.299192	1.560459	0.1218
C	6.418736	5.013761	1.280224	0.2034
@TREND	0.255418	0.353981	0.721558	0.4723

Mean target var	441.0635	S.D. dependent var	693.0577
SError of regression	8.621777	Akaike info criterion	5.093474
SSR	7433.503	Schwarz criterion	5.736377
Log L	-299.5291	Hannan-Quinn criter	5.354699

Table 9. Pedroni Residual-Based Cointegration Test

Alternative hypothesis: common AR coefs. (within-dimension)

	Stat	Prob	Weighted Stat	Prob
Panel v-Statistic	1.999170	0.0228	0.973573	0.1651
Panel rho-Statistic	-0.993394	0.1603	-2.935288	0.0017
Panel PP-Statistic	-1.678609	0.0466	-4.743753	0.0000
Panel ADF-Statistic	-0.664232	0.2533	-2.041103	0.0206

Alternative hypothesis: individual AR coefs. (between-dimension)

	Stat	Prob
Group rho-Statistic	-2.324908	0.0100
Group PP-Statistic	-4.817397	0.0000
Group ADF-Statistic	-1.903230	0.0285

Table 10. Kao Panel Residual Test for Cointegration

	t-Stat	Prob
ADF	-5.034116	0.0000
Residual variance	75.52713	
HAC variance	58.73720	

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESID)

Parameter	Coefficient	Std. Error	t-Stat	Prob
RESID(-1)	-0.320642	0.072151	-4.444063	0.0000
D(RESID(-1))	-0.017656	0.092411	-0.191064	0.8488

R-squared	0.164683	Mean dependent var	-0.155227
Adjusted R-squared	0.157780	S.D. dependent var	9.308322
S.E. of regression	8.542484	Akaike info criterion	7.144107
Sum squared resid	8829.859	Schwarz criterion	7.189834
Log likelihood	-437.3626	Hannan-Quinn criter.	7.162681
Durbin-Watson stat	1.975797		

Table 11. Short-Run Coefficient Estimates (Canada, Cross-Sectional)

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.353728	0.013772	-25.68468	0.0001
D(BES)	0.643055	0.013922	46.18985	0.0000
D(FGS)	0.628280	0.014230	44.15157	0.0000
D(HES)	0.645248	0.014944	43.17785	0.0000
D(PGS)	1.008434	0.019975	50.48570	0.0000
D(PROS)	1.023496	0.046119	22.19260	0.0002
C	16.21444	56.47547	0.287106	0.7927
@TREND	0.963316	0.505668	1.905037	0.1529

Table 12. Short-Run Coefficient Estimates (Quebec, Cross-Sectional)

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-0.335481	0.012334	-27.19917	0.0001
D(BES)	0.666816	0.012215	54.59210	0.0000
D(FGS)	0.642321	0.012382	51.87706	0.0000
D(HES)	0.661712	0.012378	53.45781	0.0000
D(PGS)	0.827307	0.026558	31.15127	0.0001
D(PROS)	0.378772	0.034325	11.03490	0.0016
C	3.377361	2.550722	1.324081	0.2773
@TREND	-0.106785	0.022488	-4.748614	0.0177

Table 13. Short-Run Coefficient Estimates (Saskatchewan, Cross-Sectional)

Variable	Coefficient	Std. Error	t-Statistic	Prob. *
COINTEQ01	-1.044579	0.023324	-44.78544	0.0000
D(BES)	-0.045532	0.023089	-1.972048	0.1432
D(FGS)	-0.038688	0.023700	-1.632365	0.2011
D(HES)	-0.053568	0.023354	-2.293718	0.1056
D(PGS)	-0.009948	0.021688	-0.458676	0.6777
D(PROS)	-0.001638	0.028408	-0.057675	0.9576
C	-0.335595	0.152396	-2.202118	0.1149
@TREND	-0.090277	0.002335	-38.65577	0.0000

Table 14: Bivariate Granger Causality Tests

Null Hypothesis:	Obs	F Stat	Prob	Result	Causality
BES does not Granger Cause T	123	0.53623	0.5864	accept	unrelated connections
T does not Granger Cause BES		1.54231	0.2182	accept	unrelated connections
FGS does not Granger Cause T	123	3.54724	0.0319	reject	single direction
T does not Granger Cause FGS		1.03307	0.3591	accept	unrelated connections
HES does not Granger Cause T	123	0.37420	0.6887	accept	unrelated connections
T does not Granger Cause HES		17.9971	2.E-07	reject	single direction
PGS does not Granger Cause T	123	4.03516	0.0202	reject	mutual direction
T does not Granger Cause PGS		20.3197	3.E-08	reject	
PROS does not Granger Cause T	123	3.55520	0.0317	reject	single direction
T does not Granger Cause PROS		1.24256	0.2924	accept	unrelated connections
FGS does not Granger Cause BES	123	10.9131	4.E-05	reject	single direction
BES does not Granger Cause FGS		0.27490	0.7601	accept	unrelated connections
HES does not Granger Cause BES	123	0.46651	0.6283	accept	unrelated connections
BES does not Granger Cause HES		22.1257	7.E-09	reject	single direction
PGS does not Granger Cause BES	123	4.14609	0.0182	reject	mutual direction
BES does not Granger Cause PGS		12.8727	9.E-06	reject	
PROS does not Granger Cause BES	123	3.31484	0.0398	reject	single direction
BES does not Granger Cause PROS		0.43836	0.6461	accept	unrelated connections
HES does not Granger Cause FGS	123	11.8034	2.E-05	reject	mutual direction
FGS does not Granger Cause HES		5.52231	0.0051	reject	
PGS does not Granger Cause FGS	123	3.15931	0.0461	reject	mutual direction
FGS does not Granger Cause PGS		4.91550	0.0089	reject	
PROS does not Granger Cause FGS	123	2.25785	0.1091	accept	unrelated connections
FGS does not Granger Cause PROS		0.05325	0.9482	accept	unrelated connections
PGS does not Granger Cause HES	123	2.59265	0.0791	accept	unrelated connections
HES does not Granger Cause PGS		4.68114	0.0111	reject	single direction
PROS does not Granger Cause HES	123	1.60476	0.2053	accept	unrelated connections
HES does not Granger Cause PROS		2.43210	0.0922	accept	unrelated connections
PROS does not Granger Cause PGS	123	6.87779	0.0015	reject	single direction
PGS does not Granger Cause PROS		2.67764	0.0729	accept	unrelated connections

4. Conclusion

This study assessed how research and development (R\&D) expenditures affect sectoral performance in Canada, focusing on the provinces of Quebec and Saskatchewan, by employing the Pooled Mean Group (PMG) Estimator within a Panel Autoregressive Distributed Lag (PARDL) framework. The data revealed non-stationarity, with series fluctuating over time without reverting to a fixed mean. Among several specifications, an ARDL (1,1,1,1,1,1) model with a linear trend produced the most reliable results.

The analysis uncovered bidirectional, unidirectional, and independent relationships among various indicators. Deviations from long-run equilibrium in total R\&D expenditures are corrected annually at rates of 35.37% for Canada, 33.55% for Quebec, and 104.5% for Saskatchewan, with Saskatchewan demonstrating the fastest adjustment. On average, about 57.79% of disequilibrium is corrected each year across all regions.

In the long run, a 1% increase in sectoral R\&D expenditures—across business enterprises, the federal government, higher education institutions, provincial governments, and provincial research organizations—is projected to increase total R\&D expenditures by approximately 99.53%, 100.31%, 100.99%, 91.51%, and 110.24%, respectively. Expenditures from provincial research organizations, higher education institutions, and the federal government proved particularly influential.

The Pairwise Granger causality tests further demonstrated that provincial government R\&D spending exerts the strongest influence on total and sectoral expenditures, while higher education spending has a more pronounced effect on fluctuations in federal government spending within the sub-region.

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Authors Contributions

Olorunpomi Temitope Olubunmi managed data collection, interpretation, and simulation while ensuring the validity, originality, and reliability of the study's findings. Olorunpomi Christiana Kehinde organized the manuscript for publication, ensuring its logical flow and improving the structure and presentation of the content.

Ethics

This manuscript represents original research, and no ethical concerns are anticipated following its publication. Both authors have read and approved the final version of the manuscript.

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