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ECONOMIC ACTIVITY AND CONSUMPTION TAX REVENUE IN BRAZILIAN STATES

ATIVIDADE ECONÔMICA E ARRECADAÇÃO DE IMPOSTOS SOBRE O CONSUMO NOS ESTADOS BRASILEIROS

ACTIVIDAD ECONÓMICA Y RECAUDACIÓN POR IMPUESTOS AL CONSUMO EN LOS ESTADOS BRASILEÑOS

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ABSTRACT

This study examines the dynamic relationships between economic activity and revenue from ICMS, Brazil's state tax on goods and selected services. Annual data for the 26 states and the Federal District cover 2000–2019. A panel vector autoregression relates ICMS revenue to GDP per capita, gross value added in services and industry, industrial establishments, local units of high-growth firms, and population. The model selection criteria favor a first-order specification. The ICMS equation shows positive and statistically significant coefficients for population and industrial establishments and a negative and statistically significant coefficient for high-growth firms. Granger tests indicate bidirectional predictive relationships between ICMS revenue and services value added, industrial establishments, GDP per capita, high-growth firms, and industrial value added. These relationships describe conditional predictability within the estimated system. The findings indicate that the composition of economic activity and business dynamics are relevant to understanding state revenue patterns. They support considering sectoral and firm indicators alongside aggregate output when selecting information for revenue forecasting and fiscal monitoring.

Keywords: ICMS. State Tax Revenue. Economic Activity. Fiscal Federalism. Panel Vector Autoregression. Brazil.

RESUMO

Este estudo examina as relações dinâmicas entre a atividade econômica e a arrecadação do ICMS, imposto estadual brasileiro sobre a circulação de mercadorias e a prestação de certos serviços. Utilizam-se dados anuais dos 26 estados e do Distrito Federal, referentes ao período de 2000 a 2019. Um modelo de autorregressão vetorial em painel (panel VAR) relaciona a arrecadação do ICMS ao PIB per capita, ao valor adicionado bruto nos setores de serviços e indústria, ao número de estabelecimentos industriais, ao número de unidades locais de empresas de alto crescimento e à população. Os critérios de seleção de modelo apontam para uma especificação de primeira ordem. A equação do ICMS apresenta coeficientes positivos e estatisticamente significativos para a população e para os estabelecimentos industriais, e um coeficiente negativo e estatisticamente significativo para as empresas de alto crescimento. Testes de causalidade de Granger indicam relações preditivas bidirecionais entre a arrecadação do ICMS e o valor adicionado no setor de serviços, os estabelecimentos industriais, o PIB per capita, as empresas de alto crescimento e o valor adicionado no setor industrial. Tais relações descrevem uma previsibilidade condicional dentro do sistema estimado. Os resultados indicam que a composição da

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atividade econômica e a dinâmica empresarial são relevantes para a compreensão dos padrões de arrecadação estadual. Eles reforçam a importância de considerar indicadores setoriais e empresariais, juntamente com o produto agregado, ao selecionar informações para a previsão de receitas e o monitoramento fiscal.

Palavras-chave: ICMS. Arrecadação Tributária Estadual. Atividade Econômica. Federalismo Fiscal. Autorregressão Vetorial em Painel. Brasil.

RESUMEN
Este estudio examina las relaciones dinámicas entre la actividad económica y la recaudación del ICMS, el impuesto estatal brasileño sobre bienes y determinados servicios. Se utilizan datos anuales de los 26 estados y el Distrito Federal correspondientes al periodo 2000–2019. Mediante un modelo de vectores autorregresivos con datos de panel, se relaciona la recaudación del ICMS con el PIB per cápita, el valor añadido bruto de los sectores de servicios e industria, el número de establecimientos industriales, las unidades locales de empresas de alto crecimiento y la población. Los criterios de selección del modelo favorecen una especificación de primer orden. La ecuación del ICMS arroja coeficientes positivos y estadísticamente significativos para la población y los establecimientos industriales, mientras que, para las empresas de alto crecimiento, el coeficiente obtenido es negativo y estadísticamente significativo. Las pruebas de causalidad de Granger indican relaciones predictivas bidireccionales entre la recaudación del ICMS y el valor añadido de los servicios, los establecimientos industriales, el PIB per cápita, las empresas de alto crecimiento y el valor añadido industrial. Estas relaciones describen una predictibilidad condicional dentro del sistema estimado. Los resultados sugieren que la composición de la actividad económica y la dinámica empresarial son factores relevantes para comprender los patrones de recaudación a nivel estatal. Asimismo, respaldan la conveniencia de considerar indicadores sectoriales y empresariales —además de la producción agregada— al seleccionar información para la previsión de ingresos y el seguimiento fiscal.

Palabras clave: ICMS. Recaudación Fiscal Estatal. Actividad Económica. Federalismo Fiscal. Modelos de Vectores Autorregresivos con Datos de Panel. Brasil.

1 INTRODUCTION

Fiscal management in Brazil became increasingly centralized during the military regime, with the federal government assuming responsibility for national public finances. Democratization subsequently established a new allocation of taxing powers, broadening state and municipal tax bases and advancing fiscal decentralization. This arrangement increased the financial autonomy of state governments, while expenditure coordination and oversight remained important institutional challenges.

The economic stabilization achieved through the Real Plan in 1994 exposed fiscal difficulties at the state level. In 1997, state debt was renegotiated and repayment maturities were extended. Federal oversight of subnational finances was subsequently strengthened, including through Complementary Law No. 101/2000, the Fiscal Responsibility Law (FRL). After a period of greater fiscal stability, the slowdown associated with the global economic crisis affected state finances. The policy response emphasized tax relief, public investment, and credit expansion (Marino et al., 2016).

The recovery of economic activity and state gross domestic product (GDP) did not always translate into higher revenue from the Tax on the Circulation of Goods and the Provision of Interstate and Intermunicipal Transportation and Communication Services, known by its Portuguese acronym ICMS (CONFAZ, 2015; IBGE, 2017). As a major source of states' own tax revenue, ICMS plays a central role in budget financing. Divergence between economic growth and tax collection therefore raises questions about the composition of the tax base and the fiscal capacity of state governments.

Changes in the productive structure provide one possible explanation for this divergence. Bulla (2012) links deindustrialization to declining ICMS revenue in São Paulo. In the Brazilian economy, manufacturing and total industry have lost shares of aggregate value added, while services have gained importance (IPEA, 2017). These changes can affect state revenue when the coverage and effective taxation of different activities vary.

Fiscal adjustment was consequently a pressing issue for states facing liquidity constraints and difficulties complying with the FRL. Falling own revenue and federal transfers impaired some governments' capacity to pay suppliers and public employees and maintain essential services. At the same time, mandatory spending, particularly personnel expenditure, absorbed a substantial share of state budgets. This expenditure rigidity restricted the scope for adapting spending to revenue capacity (FIRJAN, 2016).

The literature has examined the evolution of state public finances and fiscal accounts (Meneghetti Neto, 2010), tax incentives and their relationships with GDP, ICMS revenue, and manufacturing employment (Nascimento, 2008), fiscal effort and federal transfers (Ribeiro, 1998), changes to interstate ICMS taxation (Khair, 2011), the effects of higher ICMS rates on state economies (Meneghetti Netto, 2007), and tax revenue forecasting (Castelar, Ferreira, and Linhares, 1996). These contributions provide the context for studying how economic activity and state tax collection evolve together.

This study contributes to that discussion by examining the relationships between economic activity and ICMS revenue across Brazilian states from 2000 to 2019. We use a panel vector autoregression (PVAR) framework to examine dynamic interactions among revenue, GDP per capita, sectoral value added, industrial establishments, high-growth firms, and population. The framework combines the temporal structure of a conventional vector autoregression with the cross-sectional information in panel data (Holtz-Eakin, Newey, and Rosen, 1988; Abrigo and Love, 2015).

The sample begins in the year in which the FRL entered into force, May 2000. Although the institutional framework was associated with lower state indebtedness, substantial debt burdens persisted in several states, including Rio de Janeiro, Rio Grande do Sul, and Minas Gerais (Borges et al., 2013). In Rio Grande do Sul, growth in economic activity coexisted with fiscal difficulties, illustrating why changes in output alone may provide an incomplete account of revenue performance (Estado do Rio Grande do Sul, 2019).

The growing contribution of services to GDP also motivates the analysis. FIRJAN (2018) reports that the tax burden on services approached 23% in 2016, compared with approximately 45% for manufacturing, and that ICMS accounted for roughly 28% of the taxes paid by firms. These estimates suggest that changes in the composition of economic activity may have fiscal consequences. They also motivate an examination of sectoral indicators alongside aggregate GDP, rather than assuming that similar output growth produces similar revenue growth across states.

2 METHODOLOGY

2.1 THEORETICAL FRAMEWORK

Time-series vector autoregressions (VARs) originated in macroeconometrics as an alternative to multivariate simultaneous-equation models (Sims, 1980). Variables in a VAR system are generally treated as endogenous. Restrictions grounded in economic theory or

statistical assumptions can subsequently be imposed to identify the effects of exogenous shocks.

Holtz-Eakin, Newey, and Rosen (1988) extended the VAR framework to panel data. Panel VAR models have since been applied in several fields. A PVAR with k variables, lag order p, and panel-specific fixed effects can be represented by the following system of linear equations:

$$Y_{it} = \sum_{j=1}^{p} Y_{i(t-j)} A_j + X_{it} B + u_{it} + e_{it} \quad i \in \{1,2,\dots,N\}, t \in \{1,2,\dots,T_i\} \qquad (1)$$

Here, Y_{it} is a 1 × k vector of dependent variables; X_{it} is a 1 × l vector of exogenous covariates; and u_{it} and e_{it} are 1 × k vectors of variable-specific panel effects and idiosyncratic errors, respectively. The k × k matrices A_1, A_2, …, A_p and the l × k matrix B contain the parameters to be estimated. The innovations satisfy $E[e_{it}] = 0$, $E[e_{it}{}' e_{it}] = \Sigma$, and $E[e_{it}{}' e_{is}] = 0$ for t > s.

As Abrigo and Love (2015) explain, the parameters may be estimated jointly with the fixed effects or, after an appropriate transformation, separately from them using equation-by-equation ordinary least squares (OLS). However, the presence of lagged dependent variables on the right-hand side creates bias even when the number of panels N is large (Nickell, 1981). Although the bias approaches zero as the time dimension T increases, Judson and Owen (1999) find substantial bias in their simulations even when T = 30.

Generalized method of moments (GMM) estimators have therefore been developed to obtain consistent estimates of Equation (1), particularly in settings with fixed T and large N. Assuming serially uncorrelated errors, equations transformed by first differencing can be estimated using suitable lagged observations as instruments for the endogenous regressors (Anderson and Hsiao, 1982).

First differencing nevertheless has drawbacks in unbalanced panels. When an observation Y_{it-1} is unavailable, differences that require that observation are also missing. The minimum time coverage required for estimation increases with the lag order of the panel VAR. For example, a second-order specification using instruments in levels requires at least five observations for each panel.

Arellano and Bover (1995) propose forward orthogonal deviations as an alternative transformation. Each observation is expressed relative to the mean of its available future

observations, which reduces the loss of information in unbalanced panels. Potentially, only the final observation is unavailable for the transformed equation. Under the relevant moment conditions, past observations remain valid instruments because they do not enter the transformation.

Holtz-Eakin, Newey, and Rosen (1988) also propose forming instruments from observed realizations and replacing missing entries in the instrument matrix with zeros, subject to the assumption that the instruments are uncorrelated with the errors. Equation-by-equation GMM can yield consistent panel VAR estimates, while joint estimation of the system may improve efficiency.

Let the common set of L ≥ kp + l instruments be represented by the row vector Z_{it}, with X_{it} included in Z_{it}. Superscripts index the individual equations. The transformed panel VAR corresponding to Equation (1) can then be written more compactly as follows:

$$\begin{aligned} Y_{it}^{*} &= \overline{Y^{*}}_{it} A + e_{it}^{*} \\ Y_{it}^{*} &= [y_{it}^{1*} \quad y_{it}^{2*} \quad \cdots \quad y_{it}^{k-1*} \quad y_{it}^{k*}] \\ \overline{Y^{*}}_{it} &= [Y_{it-1}^{*} \quad Y_{it-2}^{*} \quad \cdots \quad Y_{it-p+1}^{*} \quad Y_{it-p}^{*} \quad X_{it}^{*}] \\ e_{it}^{*} &= [e_{it}^{1*} \quad e_{it}^{2*} \quad \cdots \quad e_{it}^{k-1*} \quad e_{it}^{k*}] \\ A' &= [A_1' \quad A_2' \quad \cdots \quad A_{p-1}' \quad A_p' \quad B'] \end{aligned} \tag{2}$$

An asterisk denotes a transformation of the original variable. For an original variable m_{it}, first differencing gives $m_{it}^{*} = m_{it} - m_{it-1}$. Forward orthogonal deviations give:

$$m_{it}^{*} = (m_{it} - \overline{m_{it}}) \sqrt{\frac{T_{it}}{T_{it}+1}}$$

where T_{it} is the number of available future observations for panel i at time t and $\overline{m_{it}}$ is their mean.

Stacking observations across panels and time yields the following GMM estimator:

$$A = \left(\overline{Y^{*}}' Z \hat{W} Z' \overline{Y^{*}} \right)^{-1} \left(\overline{Y^{*}}' Z \hat{W} Z' Y^{*} \right) \tag{3}$$

The L × L weighting matrix $\hat{W}$ is assumed to be nonsingular, symmetric, and positive semidefinite. Under the moment condition $E[Z' e] = 0$ and the rank condition rank $E\left[\overline{Y}^{*\prime} Z\right]$ = kp + l, the GMM estimator is consistent. The weighting matrix can be chosen to maximize efficiency (Hansen, 1982).

Joint estimation also facilitates tests of restrictions across equations. Wald tests can be implemented using the GMM estimate of A and its covariance matrix. Granger predictability tests assess the joint null hypothesis that the coefficients on all lags of variable m are zero in the equation for variable n.

PVAR specification requires selecting the lag order and the moment conditions. Andrews and Lu (2001) develop consistent moment and model selection criteria (MMSC) for GMM models using Hansen's (1982) J statistic for overidentifying restrictions. These criteria are analogous to the Akaike information criterion (AIC; Akaike, 1969), the Bayesian information criterion (BIC; Schwarz, 1978; Rissanen, 1978; Akaike, 1977), and the Hannan–Quinn information criterion (HQIC; Hannan and Quinn, 1979).

Applied to the GMM estimator in Equation (3), the Andrews and Lu (2001) criteria select the combination of model lag order p and instrument lag order q that minimizes:

$$MMSC_{BIC,n}(k,p,q) = J_n(k^2p, k^2q) - (|q| - |p|)k^2 \ln n \quad (4)$$

$$MMSC_{AIC,n}(k,p,q) = J_n(k^2p, k^2q) - 2k^2(|q| - |p|) \quad (5)$$

$$MMSC_{HQIC,n}(p,q) = J_n(k^2p, k^2q) - Rk^2(|q| - |p|)\ln \ln n, R > 2 \quad (6)$$

Here, J_n(k, p, q) denotes the statistic for overidentifying restrictions in a k-variable panel VAR of order p, with moment conditions based on q lags and sample size n. The MMSC require an overidentified specification, with q > p in this formulation. An alternative measure, the overall coefficient of determination (CD), can also be calculated for just-identified GMM models. Let Ψ denote the k × k unrestricted covariance matrix of the dependent variables. The CD measures the proportion of variation explained by the panel VAR and is calculated as:

$$CD = 1 - \frac{det(\Sigma)}{det(\Psi)} \quad (7)$$

For notational simplicity, Abrigo and Love (2015) omit the exogenous variables and focus on the autoregressive component of Equation (1). Lütkepohl (2005) and Hamilton (1994) show that a VAR is stable when every eigenvalue of its companion matrix has modulus strictly below one. The companion matrix is:

$$\overline{A} = \begin{bmatrix} A_1 & A_2 & \cdots & A_p & A_{p-1} \\ I_k & 0_k & \cdots & 0_k & 0_k \\ 0_k & I_k & \cdots & 0_k & 0_k \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0_k & 0_k & \cdots & I_k & 0_k \end{bmatrix} \quad (8)$$

Stability allows the PVAR to be represented as an infinite-order vector moving average (VMA), providing the basis for impulse response functions and forecast error variance decompositions. The coefficients ϕ_i of the VMA representation are obtained recursively. The resulting reduced-form impulse responses do not, on their own, identify causal effects.

$$\phi_i = \begin{cases} I_k, & i = 0, \\ \sum_{j=1}^{i} \phi_{t-j} A_j, & i = 1,2, \ldots \end{cases} \quad (9)$$

Because the innovations e_{it} may be contemporaneously correlated, an innovation in one variable can coincide with innovations in others. Let P satisfy $P\ ' P = \Sigma$. The matrix P can be used to orthogonalize the innovations as $e_{it}P^{-1}$ and transform the VMA coefficients into orthogonalized impulse responses, $P\phi_i$. This transformation imposes identifying restrictions on the dynamic system.

Sims (1980) proposes using a Cholesky decomposition of Σ to impose a recursive structure on a VAR. The resulting orthogonalized responses depend on the ordering of the variables. Confidence intervals can be derived analytically from the asymptotic distribution of the estimated PVAR parameters and the cross-equation error covariance matrix. The methodological literature also considers Monte Carlo and bootstrap procedures for interval estimation.

The h-step-ahead forecast error can be expressed as:

$$Y_{it+h} - E[Y_{it+h}] = \sum_{i=0}^{h-1} e_{i(t+h-i)}\, \phi_i \quad (10)$$

Here, Y_{it+h} is the observed vector at time t + h, and $E[Y_{it+h}]$ is the h-step-ahead forecast formed at time t. As with the impulse responses, the innovations are orthogonalized using P to separate each variable's contribution to forecast error variation. The orthogonalized innovations $e_{it}P^{-1}$ have covariance matrix I_k, allowing forecast error variance to be decomposed. The contribution of innovations in variable m to the h-step-ahead forecast error variance of variable n is:

$$\sum_{i=0}^{h-1} \theta_{mn}^2 = \sum_{i=1}^{h-1} \left(i_n' P \phi_i i_m\right)^2 \tag{11}$$

Here, i_s denotes the s-th column of I_k. In applications, these contributions are usually normalized by the total h-step-ahead forecast error variance of variable n:

$$\sum_{i=0}^{h-1} \theta_{.n}^2 = \sum_{i=1}^{h-1} i_n' \phi_i' \Sigma \phi_i i_n \tag{12}$$

PVAR models thus provide a framework for examining dynamic interrelationships through estimated coefficients, impulse response functions, and forecast error variance decompositions. Impulse responses describe how variables respond over time to an innovation, subject to the chosen identification scheme. Variance decompositions quantify the contribution of individual innovations to forecast uncertainty (Hamilton, 1994).

2.2 EMPIRICAL SPECIFICATION, DATA, AND VARIABLES

We apply a PVAR framework to examine the relationship between economic activity and Brazilian state ICMS revenue. Panel data combine observations across states and over time, increasing the information available for estimation (Oliveira, 2016). The approach follows Holtz-Eakin, Newey, and Rosen (1988). The variables entering the empirical analysis are summarized in Equation (13):

$$\begin{aligned} ICMS_{it} =& \alpha_i + \beta_1 PIB_{it} + \beta_2 VABS_{it} + \beta_3 UI_{it} \\ &+ \beta_4 EMP_{it} + \beta_5 VABI_{it} + \beta_6 POP_{it} + \eta_{it} + \varepsilon_{it} \end{aligned} \tag{13}$$

$ICMS_{it}$ denotes ICMS revenue in state i and year t, with i = 1, …, 27 covering the 26 states and the Federal District. The intercept is denoted by α_i. PIB_{it} is state GDP per capita; $VABS_{it}$ is gross value added by services; UI_{it} is the number of industrial establishments; EMP_{it} is the number of local units of high-growth firms; $VABI_{it}$ is industrial gross value added; and POP_{it} is the state population. The state-specific fixed effect captures unobserved heterogeneity that is constant over time, and ε_{it} is the idiosyncratic error.

The sample consists of annual observations for the 27 federative units from 2000 to 2019. In addition to ICMS revenue and GDP per capita, the analysis includes gross value added in services and industry, industrial establishments, population, and local units of high-growth firms. Table 1 summarizes the variables and their sources.

Table 1

Variables and data sources

Variable	Description	Source
ICMS	ICMS revenue	CONFAZ (2020)
GDP per capita (PIB)	GDP per capita = GDP / estimated population	IBGE (2019) IBGE (2020b)
Services GVA	Gross value added in services	IBGE (2019)
Industrial establishments	Industrial establishments	IBGE (2018)
High-growth firms	Local units of high-growth firms	IBGE (2020a)
Industry GVA	Gross value added in industry	IBGE (2019)
Population	State population	IBGE (2020b)

Source: IBGE and CONFAZ.

The data were obtained from the Brazilian Institute of Geography and Statistics (IBGE) and the National Council for Financial Policy (CONFAZ). Monetary series were deflated using the Broad National Consumer Price Index (IPCA). Estimation was carried out in R, with the PVAR estimation and inference framework described by Abrigo and Love (2015) serving as a methodological reference.

3 RESULTS AND DISCUSSION

We first select the model lag order using the Andrews and Lu (2001) criteria. All three reported criteria, MMSC-BIC, MMSC-AIC, and MMSC-HQIC, attain their minimum values at one lag. Table 2 therefore supports a first-order specification among the four lag orders considered.

Table 2

Andrews and Lu lag selection criteria

Lag	MMSC_BIC	MMSC_AIC	MMSC_HQIC
1	-671.15*	-234.52*	-431.68*
2	-666.03	-232.89	-428.47
3	-661.39	-231.75	-425.76
4	-657.06	-230.90	-423.34

Source: Authors' estimates. Notes: An asterisk marks the minimum value of each criterion.

The ICMS equation shows positive and statistically significant coefficients for population and industrial establishments, and a negative and statistically significant coefficient for local units of high-growth firms. Table 3 presents the coefficients and the accompanying estimation statistics.

Table 3

PVAR estimates for the ICMS equation

Variable	ICMS
ICMS lag 1	0.0582 (0.1711)
Services GVA	0.0216 (0.0894)
Population	0.4394 ** (0.1410)
Industrial establishments	0.0007 ** (0.0002)
High-growth firms	-0.0002 ** (0.0001)
GDP per capita (PIB)	0.0255 (0.0461)
Industry GVA	-0.0073 (0.0724)

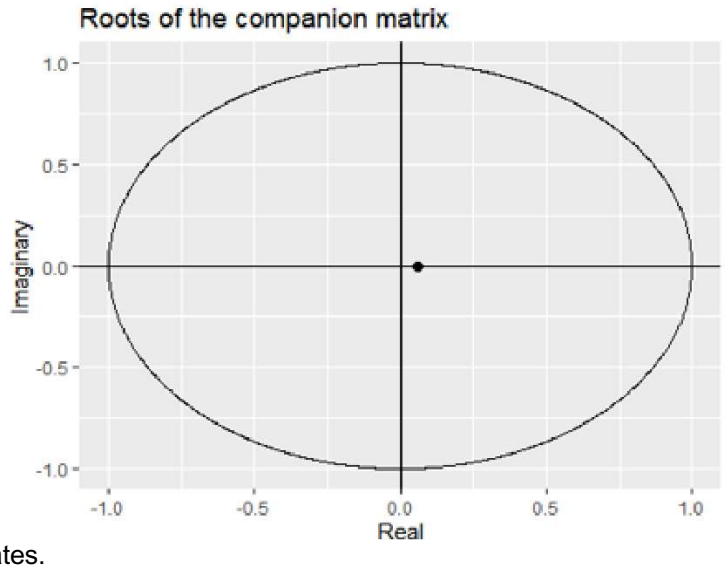
Source: Authors' estimates. Notes: ** denotes p < .05.

Figure 1 presents the eigenvalue stability diagnostic associated with the estimated specification.

Figure 1

Eigenvalue stability diagnostic

	Eigenvalue
1	0.05816578



Source: Authors' estimates.

The stability diagnostic indicates that the estimated model satisfies the eigenvalue condition for dynamic stability. This supports the analysis of persistence and forecast behavior within the specified system. Table 4 presents the Granger predictability test results.

Table 4

Granger predictability test results

Equation	Excluded variable	z
ICMS	Population	-0.84058
	Services GVA	5.58***
	Industrial establishments	3.328***
	GDP per capita (PIB)	7.2726***
	High-growth firms	13.646***
	Industry GVA	10.864***
Population	ICMS	0.10568
	Services GVA	-1.7009*
	Industrial establishments	-2.1367**
	GDP per capita (PIB)	-1.8531*
	High-growth firms	14.319***

Equation	Excluded variable	z
	Industry GVA	-2.3252**
Services GVA	Population	2.5474**
	ICMS	4.8416***
	Industrial establishments	1.6692*
	GDP per capita (PIB)	5.6693***
	High-growth firms	13.13***
	Industry GVA	11.083***
Industrial establishments	Population	-2.4027**
	Services GVA	-2.7878***
	ICMS	-2.28**
	GDP per capita (PIB)	-2.7873***
	High-growth firms	10.453***
	Industry GVA	-2.0487**
GDP per capita (PIB)	Population	2.4266**
	Services GVA	5.8559***
	Industrial establishments	1.5028
	ICMS	7.7296***
	High-growth firms	14.552***
	Industry GVA	13.451***
High-growth firms	Population	8.8588***
	Services GVA	-1.7913*
	Industrial establishments	11.931***
	GDP per capita (PIB)	-2.2923**
	ICMS	-1.9769**
	Industry GVA	-1.7328*
Industry GVA	Population	-0.080774
	Services GVA	9.4495***
	Industrial establishments	-0.50525
	GDP per capita (PIB)	11.27***
	High-growth firms	15.793***
	ICMS	10.942***

Source: Authors' estimates. Notes: ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

The Granger results indicate bidirectional predictive relationships between ICMS revenue and services value added, industrial establishments, GDP per capita, high-growth firms, and industrial value added. For these variables, the reported tests reject the exclusion of the activity indicator from the ICMS equation and the exclusion of ICMS from the corresponding activity equation. Neither direction of the population–ICMS relationship is statistically significant at the reported levels.

3.1 ECONOMIC INTERPRETATION OF THE ICMS EQUATION

The positive population coefficient is consistent with the relationship between the scale of a state economy and its consumption tax base. A larger population can support a wider market for taxable goods and services. The coefficient is conditional on the other included variables and should be interpreted in the units of the estimated specification. Population also captures differences in market size and economic organization that are not fully represented by GDP per capita. This conditional association coexists with the absence of a significant population–ICMS relationship in the Granger results.

The positive coefficient on industrial establishments is compatible with the importance of production and commercial transactions for ICMS collection. Establishment counts may capture the breadth of the productive base, supply relationships, and the presence of registered firms. Industrial gross value added, by contrast, has a negative coefficient that is not statistically significant at the reported levels. The number of establishments and the monetary scale of industrial activity thus convey different information about revenue within the estimated specification.

The negative coefficient on high-growth firms concerns an employment-based measure of business dynamics. In the IBGE definition applicable to the sample period, high-growth status depends on sustained expansion of salaried employment (IBGE, 2020a). Employment growth need not coincide with growth in taxable sales or tax payments. Differences in sectoral composition, effective taxation, and the timing of employment and sales provide possible explanations for the negative conditional association. The estimate captures the relationship between this indicator and ICMS revenue within the sample.

The coefficients on services value added, GDP per capita, and industrial value added are not statistically significant at the reported levels. Their point estimates provide limited evidence of separate conditional relationships in the ICMS equation. Nevertheless, the distinction between aggregate growth and the composition of the tax base is economically relevant. During the sample period, ICMS covered goods and selected services, including communication and interstate and intermunicipal transport, while other services fell under different tax arrangements (Brazil, 1996). Growth in total services value added could consequently affect ICMS through taxable inputs, household consumption, and supply relationships even when much of that value added was outside its direct scope.

3.2 PREDICTIVE INTERDEPENDENCE AND FISCAL IMPLICATIONS

The bidirectional Granger results indicate that the histories of revenue and several activity indicators contain information useful for predicting one another within the estimated system. Such feedback is economically plausible: economic activity generates taxable transactions, while revenue availability can be associated with government purchases, public investment, and the payment of suppliers. Common macroeconomic conditions, changes in tax policy, and other omitted influences can also generate these patterns. The reported tests establish conditional predictability; a structural interpretation of fiscal transmission would require additional identifying assumptions.

The distinction between productive expansion and tax collection also connects the results to the literature on state taxation. Nascimento (2008) examines GDP, ICMS revenue, and employment as separate outcomes of interstate tax competition. The different coefficient patterns for establishment counts, industrial value added, and high-growth firms similarly indicate that these dimensions of economic activity should be examined separately. Meneghetti Neto (2010) emphasizes the role of tax exemptions in the divergence between economic activity and ICMS performance in Rio Grande do Sul. Together, these perspectives help explain why a broader productive base may coexist with uneven revenue growth across states.

For fiscal management, the results motivate forecasting systems that combine aggregate activity with indicators of the productive base. Population, industrial establishments, and firm dynamics can help organize monitoring of revenue developments, provided their forecasting value is assessed in the relevant state and period. Reliance on GDP growth alone may overlook shifts between activities with different tax coverage. At the

same time, these estimates do not quantify the revenue effects of a particular tax incentive, an industrial policy, or a change in tax rates. Decisions on those instruments require evidence on their fiscal costs and the economic behavior they induce.

Expenditure rigidity makes this distinction consequential. When revenue responds unevenly to the composition of activity, commitments based solely on anticipated aggregate growth may expose state budgets to shortfalls. The fiscal concerns documented by FIRJAN (2016) therefore support careful revenue monitoring and realistic spending commitments. The PVAR results inform the selection of indicators for that monitoring, while leaving the size of appropriate fiscal buffers and the effects of specific budget rules to separate analysis.

3.3 SCOPE AND LIMITATIONS

The panel framework summarizes relationships across states with different productive structures, tax administrations, and exposure to national shocks. A common coefficient specification may conceal differences between industrial, service-oriented, and resource-dependent economies. Annual data can also combine adjustment processes that occur within the year. Consequently, pooled estimates should not be interpreted as state-specific elasticities or used to infer the timing of short-run responses without further evidence. The scale of the variables and their transformations must be considered before giving the coefficients a quantitative policy interpretation.

The findings pertain to the economic structure and tax arrangements prevailing from 2000 to 2019. Their application to subsequent periods requires attention to changes in the composition of activity, business organization, and the distribution of taxing powers. Evaluating those changes would clarify the continuing relevance of the relationships estimated for the sample.

4 CONCLUSIONS

This study examined the relationships between economic activity and state ICMS revenue in Brazil from 2000 to 2019 using a PVAR framework for the 26 states and the Federal District. The lag selection criteria favor a first-order specification. In the ICMS equation, population and industrial establishments have positive and statistically significant coefficients, while local units of high-growth firms have a negative and statistically significant coefficient. Services value added, GDP per capita, industrial value added, and lagged ICMS revenue are not statistically significant at the reported levels.

The Granger results identify bidirectional predictive relationships between ICMS revenue and five indicators of economic activity: services value added, industrial establishments, GDP per capita, high-growth firms, and industrial value added. These findings support considering the evolving composition of state economies when selecting indicators for revenue forecasting. They also show that the interactions captured by the model extend beyond a simple contemporaneous relationship between aggregate output and tax collection.

The relationship between economic expansion and state revenue depends on the activities through which growth occurs. Industrial establishment counts and industrial value added have different coefficient patterns, while employment growth among firms need not track growth in taxable transactions. The negative high-growth-firm coefficient therefore describes a conditional relationship between an employment-based indicator and ICMS revenue over the sample period.

The main fiscal implication is to broaden the information used to monitor the ICMS base. State revenue projections can consider sectoral composition and business dynamics alongside aggregate output, with attention to uncertainty in the relationship between activity and collection. These indicators provide a basis for further forecasting assessment and for monitoring the revenue consequences of changes in state economies.

The scope of the conclusions reflects the use of annual observations and a common coefficient specification across states. Differences in productive structure and fiscal institutions may generate responses that are only partly captured by the pooled estimates. The findings provide an aggregate account of the relationships observed from 2000 to 2019 and a basis for examining variation across state economies.

Further research could assess differences across groups of states and evaluate out-of-sample revenue forecasts. Examining how the relationships vary with productive specialization, tax incentives, and institutional changes would help determine their relevance to different fiscal settings. Extending the observation period would also allow an assessment of whether the patterns documented for 2000–2019 persist under subsequent economic and tax arrangements.

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