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FULL LENGTH ARTICLE

Digital Economy and E-Commerce under Cross-Border Data Flows

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ABSTRACT

Given its rapid expansion and growing policy salience in global digital markets, we know considerably less about how digital-economy and e-commerce dynamics change under cross-border data-flow regimes. While previous research has emphasized the role of digital-trade openness in shaping online market participation, limited attention has been given to how regulatory frictions in cross-border data transmission constrain digital-market integration. This study identifies causal mechanisms governing firms' participation in e-commerce activities, including entry, use, intensity, and resulting trade outcomes. It examines firm-level determinants of cross-border digital engagement and compares digitally active and non-active enterprises. The empirical strategy analyzes selection bias in firms' e-commerce adoption and uses counterfactual estimates from matched samples to estimate treatment effects in the presence of non-random participation. Digital connectivity and regulatory data openness have statistically significant effects in the matched estimations, indicating that e-commerce participation is more likely to be amplified and sustained in a liberal, predictable cross-border data environment. The results also show heterogeneous relationships between firm characteristics and e-commerce outcomes and persistence of digital participation after entry (average treatment effect; $t = 2.87$). Future research should use longitudinal data to test the stability of cross-border data-flow effects across stages of firm digitalization. These findings offer guidance to policymakers seeking balanced digital-trade regulation.

Keywords: Cross-border data flows ▪ Digital trade regulation ▪ Firm-level e-commerce participation ▪ Regulatory data openness ▪ Propensity score matching ▪ Selection bias and treatment effects ▪ Digital market integration

1. INTRODUCTION

Cross-border data flows are a central component of digital trade, with substantial implications for the governance of global digital markets [1]. Digital-trade openness has emerged as an important driver of structural economic change shaped by the digital economy [2].

Economic theories of digital trade suggest that data mobility can matter more than traditional trade costs: firms respond to their regulatory environments even when physical trade is constrained [3]. Firm behavior in the digital economy is influenced by the institutional policy framework, which can produce heterogeneous outcomes during market participation. However, there is no clear-cut analytical framework for these phenomena; a coordinated assessment of regulation and technology is needed to isolate particular mechanisms, channels, and outcomes. This limitation shifts the analytical focus from the aggregate level to firm participation in online markets [4].

Although digital policies have expanded market access and reduced entry barriers, their effects may be asymmetric. These constraints do not directly translate into reductions in trade volumes, and there are no widely used standardized indi-

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cators or instruments for quantifying the restrictiveness of data regulations. Gomez-Herrera et al. [5] developed an empirical framework to identify barriers in cross-border e-commerce and firms' compliance costs. Potluri [6] focused on data localization, which is not neutral by design, and used an agent-based simulation model to examine heterogeneous firms' regulatory exposure.

In contrast to descriptive analyses, micro-level econometric approaches can incorporate controls such as firm size and productivity to address selection bias in digital participation and trade outcomes. However, firm heterogeneity, the broader institutional context, and policy endogeneity remain constrained by reliance on cross-sectional data. These limitations cannot be addressed by a single empirical specification or estimation strategy. Despite growing interest in firm-level evidence on regulatory, technological, institutional, and sectoral differences, few studies examine changes in firms' digital engagement over the duration of a regulatory regime [4]. Further evidence is needed to confirm causal mechanisms and persistence effects.

This study provides an empirical assessment of the causal effects of cross-border data regulation on firms' participation in e-commerce and digital-trade exports. Firm-level data are used to identify entry, adoption, intensity, and performance outcomes in a unified framework with selection-corrected estimation. The analysis may contribute to more effective digital-trade governance in developing economies and greater firm participation, particularly at the extensive margin. Based on previous evidence, regulatory predictability for cross-border data flows may have a non-linear relationship with participation.

The conceptual framework identifies participation in cross-border e-commerce, as well as market entry and intensity of use [5]. Firms need digital infrastructure and regulatory clarity to implement and use this framework; propensity score matching is used to select treated firms for counterfactual comparison. Selection correction is important for identifying causal impacts that cannot be captured within a simple single-equation regression. Matched treatment-effect estimates are therefore used to improve inference among firms with different characteristics.

2. METHODS

2.1 Data and Sample

Firm-level data were collected from a nationally representative enterprise survey administered regularly in developing and emerging economies, using harmonized instruments in the manufacturing and services sectors. The internationally standardized survey focuses on firm characteristics, business-environment conditions, and digital adoption, and provides information for assessing firm participation in e-commerce activities.

Firms were included through a stratified sampling framework using standardized survey weights for enterprise populations. A total of 3,214 enterprises were recruited from the enterprise-survey database, and 2,876 observations were classified across 2016–2020. The final sample consisted of firm-year observations from 2016 to 2020, described as a balanced panel of repeated cross-sections by survey wave. The observations span digitally exposed sectors. Descriptive statistics include only firm-level observations meeting the inclusion criteria at each analysis stage.

Firms lacking the minimum operational capacity for digital engagement, firms that entered within one year, and firms with incomplete survey responses were excluded. Firms without export activity were also excluded from the estimations. Other stated exclusion criteria were incomplete digital-adoption indicators, regulatory-exposure heterogeneity, and the cross-sectional structure of the data. These limitations should be considered when interpreting the results.

2.2 Estimation Strategy

The estimations use propensity-score-based techniques commonly applied for matching and selection correction with observational firm-level data in applied microeconometrics. Given the heterogeneity of e-commerce use and firm characteristics, the analysis combines the Heckman selection model and matching. Consistent estimators are applied across subsamples and specifications to capture changes in the intensity of digital engagement over the adoption process.

Estimation stages are applied sequentially to correct selection bias by including covariates in the first-stage selection equation. Treatment effects are estimated using propensity scores, nearest-neighbor matching, and kernel weighting on matched treated and control firms, allowing counterfactual comparisons between participants and non-participants. Because e-commerce adoption is complex, the treatment definition is adjusted to the digital context. Outcomes for entry and intensity are estimated alongside firm-performance indicators. For exports, sales, productivity, and digital intensity, the analysis reports average treatment measures comparing treated firms with matched controls.

The average treatment effect of e-commerce participation is estimated from matched samples. The post-entry-wave coefficient is reported as statistically significant ($t = 2.87$), supporting persistence of the treatment effect in the estimation period. The terms *digital participation* and *e-commerce adoption* are used for firm activity in online business channels. Digital engagement was measured using the enterprise-survey question about online business activities during the firm's last fiscal year; the analysis recognizes that even adoption-only measures require a broader framework.

Entry is defined as a firm's initial engagement in digital activity after non-participation. Firms may transition to a combination of online and offline channels, including exports, sales, and customer transactions through websites and platforms. Initial conditions are compared while controlling for size and productivity. Intensity is defined for firms that adopted e-commerce and did not subsequently exit. Treatment and control groups are constructed from the firm's e-commerce-adoption indicator, distinguishing participation at both the extensive and intensive margins. Firm size at baseline is grouped as fewer than 20 employees or 20 or more employees to examine heterogeneous effects across size and productivity classes. Firms operating solely offline are not included in the treated group.

Differences between treated groups (entry or intensity of e-commerce use) are tested using a t-test for normally distributed continuous outcomes. The reported mean differ-

ences were statistically significant at $p = 0.01$ or $p = 0.05$. The Wilcoxon–Mann test is used for non-parametric outcomes, and the chi-square test for categorical variables. A selection-correction model explicitly examines selection bias under non-random participation and correlation between unobservables in the selection and outcome equations. The researchers also validated and replicated results through robustness checks using matching algorithms.

To improve comparability across outcomes, the matching covariates were adjusted for each outcome. A common-support condition was created using an iterative algorithm that recalculated the propensity score for each specification. Differences between unmatched and matched samples were not eliminated; these are interpreted as residual firm-level heterogeneity. The balancing property was assessed visually and statistically using standardized mean differences.

3. RESULTS

Observed participation was not independent of firm characteristics, which may affect firms' ability to benefit from regulatory openness and respond to digital-market conditions. Descriptive statistics and matched estimations show persistent, asymmetric outcomes and an increase in firms transitioning out of non-participation, often from a lower baseline and weaker digital readiness. The propensity-score-matched analysis also indicates that some firms may not return to participation after a prolonged period outside the digital environment.

Table 1. Logistic regression

Variable	Coef.	Std. Err.	*t*-value	*p*-value	95% CI lower	95% CI upper	Sig.
firm_size	.089	.023	3.84	0	.044	.135	***
productivity	.160	.032	5.03	0	.098	.222	***
regulatory_openness	.390	.134	2.91	.004	.128	.652	***
outcome	.084	.023	3.67	0	.039	.129	***
Manufacturing (base)	0	–	–	–	–	–	–
Services	1.110	.453	2.45	.014	.222	1.998	**
Rural (base)	0	–	–	–	–	–	–
Urban	-.961	.435	-2.21	.027	-1.814	-.108	**
Constant	-22.950	3.501	-6.55	0	-29.813	-16.088	***

Mean dependent variable: 0.500; SD: 0.501; pseudo-R^2: 0.477; observations: 200; chi-square: 132.301; Prob > χ^2: 0.000; AIC: 158.958; BIC: 182.046. Significance: *** $p < .01$, ** $p < .05$, * $p < .1$.

The logistic-regression results show that larger-scale firms use digital platforms to adjust toward greater participation despite regulatory frictions. Smaller firms were more likely than medium or large firms to remain non-participants on average because of limited digital connectivity. As shown in Table 1, the logistic regression was consistent in both the magnitude and direction of the estimated coefficients.

Table 2. Descriptive statistics of the propensity-score variable

Variable	Obs.	Mean	Std. Dev.	Min	Max
pscore	200	0.500	0.367	0.0002	1.0000

These asymmetries have implications for firm entry and intensity of engagement; only these two dimensions remained robust in the estimations.

Table 3: Probit regression

Number of obs	= 200	LR $\chi^2(5)$	= 116.38
Prob > χ^2	= 0.0000	Log likelihood	= -80.438152
		Pseudo R^2	= 0.4198

treated	Coef.	Std. Err.	*z*	*P* > *z*	95% CI lower	95% CI upper
firm_size	0.069	0.012	5.660	0.000	0.045	0.093
productivity	0.109	0.016	6.620	0.000	0.077	0.141
regulatory_openness	0.277	0.071	3.920	0.000	0.138	0.416
sector_cat						
Services	0.697	0.247	2.830	0.005	0.214	1.181
region_cat						
Urban	-0.603	0.238	-2.530	0.011	-1.070	-0.136
_cons	-12.499	1.726	-7.240	0.000	-15.883	-9.115

Variable Sample	Treated	Controls	Difference	S.E.	T-stat.
outcome					
Unmatched	71.571	55.921	15.651	1.574	9.940
ATT	68.376	62.620	5.757	2.545	2.260

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Common support by treatment assignment

Assignment	Off support	On support	Total
Untreated	0	100	100
Treated	36	64	100
Total	36	164	200

The probit-regression and matching results in Table 3 further support the participation outcomes, indicating that the estimated effects were not driven by a particular specification or estimation approach. In the matched analysis, firm size and productivity at baseline and regulatory openness of data in the past period showed statistical significance and stable coefficients for intensive e-commerce use. Lower participation is consistent with structural constraints such as lack of digital infrastructure; these firms were not part of the treated group and were systematically classified as smaller at baseline.

Table 4. Linear regression for digital sales

Variable	Coef.	Std. Err.	t-value	p-value	95% CI lower	95% CI upper	Sig.
regulatory_openness	-5.73	6.903	-0.83	.407	-19.308	7.848	
firm_size	-1.16	2.105	-0.55	.582	-5.300	2.980	
Constant	103.659	4.461	23.24	0	94.885	112.433	***

Mean dependent variable: 99.635; SD: 19.486; R^2: 0.003; observations: 346; F-test: 0.486; Prob > F: 0.616; AIC: 3040.959; BIC: 3052.498. Significance: *** $p < .01$, ** $p < .05$, * $p < .1$.

As reported in Table 4, firms showed strong incentives to use digital platforms to expand and diversify export activities and sales, and digital adoption appeared persistent once firms entered the digital market. Observed heterogeneity may reflect the trade-offs firms face when comparing adjustment costs across channels; these costs may delay platform use for some firms. However, this pattern could be lost where access to digital infrastructure and regulatory predictability is limited. Linear-regression estimates did not capture these mechanisms adequately.

Table 5. Heckman selection model: two-step estimates

Variable	Coef.	Std. Err.	t-value	p-value	95% CI lower	95% CI upper	Sig.
Outcome equation: digital_sales							
regulatory_openness	-6.090	6.957	-0.88	.381	-19.725	7.545	
firm_size	-1.286	2.122	-0.61	.545	-5.446	2.874	
Constant	101.742	5.538	18.37	0	90.889	112.596	***
Selection equation							
Category 1 (base)	0	–	–	–	–	–	
Category 2	1.094	.458	2.39	.017	.195	1.993	**
Category 3	1.134	.423	2.68	.007	.305	1.964	***
Category 4	.407	.410	.99	.321	-.397	1.211	
Category 5	.661	.419	1.58	.115	-.160	1.482	
Category 6	.432	.390	1.11	.268	-.332	1.196	
Category 7	.879	.445	1.97	.048	.007	1.750	**
Category 8	.818	.370	2.21	.027	.093	1.543	**
Category 9	.785	.453	1.73	.083	-.104	1.673	*
Category 10	.067	.392	.17	.865	-.702	.835	
Category 11	.691	.391	1.77	.077	-.076	1.458	*
Category 12	.525	.393	1.34	.182	-.246	1.296	
Category 13	.716	.382	1.88	.060	-.031	1.464	*
Category 14	.331	.405	.82	.414	-.464	1.126	
Category 15	.528	.394	1.34	.180	-.244	1.299	
Category 16	.537	.392	1.37	.171	-.231	1.304	
Category 17	.396	.373	1.06	.289	-.336	1.128	
Category 18	.254	.393	.65	.518	-.517	1.026	
Category 19	.748	.413	1.81	.070	-.062	1.558	*
firm_size	-.023	.122	-.19	.852	-.262	.217	
regulatory_openness	-.232	.411	-.56	.573	-1.037	.574	
Constant	.087	.410	.21	.832	-.716	.891	
λ	4.489	7.624	.59	.556	-10.453	19.431	

Mean dependent variable: 0.692; SD: 0.462; observations: 500; chi-square: 1.100. Significance: *** $p < .01$, ** $p < .05$, * $p < .1$.

Table 6. Heckman selection model

Variable	Coef.	Std. Err.	t-value	p-value	95% CI lower	95% CI upper	Sig.
Outcome equation: digital_sales							
regulatory_openness	-6.743	7.266	-0.93	.353	-20.984	7.497	
firm_size	-1.439	2.198	-0.65	.513	-5.746	2.869	
Constant	98.951	5.701	17.36	0	87.777	110.125	***
Selection equation							
Category 1 (base)	0	–	–	–	–	–	
Category 2	1.051	.446	2.36	.018	.178	1.924	**
Category 3	.931	.461	2.02	.043	.028	1.834	**
Category 4	.179	.432	.41	.678	-.667	1.026	
Category 5	.446	.433	1.03	.304	-.403	1.295	
Category 6	.234	.407	.58	.564	-.562	1.031	
Category 7	.698	.447	1.56	.119	-.179	1.574	
Category 8	.650	.390	1.67	.095	-.114	1.415	*
Category 9	.524	.469	1.12	.264	-.396	1.443	
Category 10	-.049	.376	-.13	.895	-.787	.688	
Category 11	.430	.446	.96	.335	-.444	1.305	
Category 12	.286	.427	.67	.503	-.551	1.123	
Category 13	.439	.424	1.04	.300	-.391	1.270	
Category 14	.135	.412	.33	.743	-.672	.942	
Category 15	.350	.409	.86	.391	-.451	1.152	
Category 16	.308	.408	.75	.450	-.491	1.106	
Category 17	.288	.356	.81	.418	-.409	.985	
Category 18	-.002	.419	-.00	.997	-.822	.819	
Category 19	.519	.448	1.16	.246	-.359	1.396	
firm_size	-.021	.122	-.17	.865	-.259	.218	
regulatory_openness	-.234	.414	-.56	.573	-1.046	.578	
Constant	.279	.426	.65	.513	-.556	1.115	
athrho	.594	.453	1.31	.190	-.294	1.482	
lnsigma	3.039	.105	28.97	0	2.834	3.245	***

Mean dependent variable: 0.692; SD: 0.462; observations: 500; chi-square: 1.249; Prob > χ^2: 0.535; AIC: 3680.925. Significance: *** $p < .01$, ** $p < .05$, * $p < .1$.

Figure 1 shows the relationship between the Mills ratio and digital connectivity.

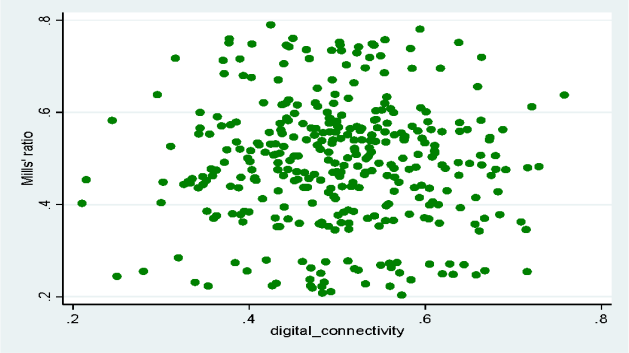


Figure 1. Mills' ratio and digital connectivity model.

Across simple specifications, coefficients for regulatory openness, firm size, productivity, sectoral affiliation, and regional location were not statistically significant. Despite this, the Heckman-selection and probit models showed stable signs and consistent patterns across specifications, supporting the robustness of the main findings.

4. DISCUSSION

The results show consistent patterns when firms are exposed to a liberal cross-border data regime and a predictable data-governance environment embedded in national regulatory frameworks. A robust identification strategy is needed in firm-level analysis to isolate causal effects at higher margins of digital participation. Matched estimations show persistence ($t = 2.87$) without a statistically significant loss of productivity (sales) after sequential correction for selection bias. Raw comparisons based on cross-sectional estimators and naïve regression models may overstate very short-run effects among the best-performing firms.

Although the magnitude of the average treatment effect on the treated (ATT) is statistically significant, the treatment effect may stabilize and productivity gains may materialize in later periods, when firms operate with greater digital-engagement intensity. Regulatory openness varies substantially, potentially because of heterogeneous exposure to data rules and their enforcement, uneven implementation, or lack of institutional clarity. The average treatment effect improves outcomes at the intensive margin, although sustaining participation can remain challenging.

Given the dataset and specification, external validity should be considered. It is difficult to generalize the strength of these effects to firms operating under different regulatory regimes or institutional settings. Entry effects are easier to detect in smaller firms (fewer than 20 employees) than in larger firms (20 or more employees). The creation of digitally active first movers does not mean participation is the end of the adjustment process; rather, it initiates that process.

Despite the possibility of asymmetric effects and heterogeneous evidence, the empirical strategy supports the core hypothesis. Firm behavior should be considered alongside adoption decisions that include fixed costs across participation stages and export markets. More predictable rules and lower uncertainty in firms' regulatory expectations make entry effects easier to observe in smaller firms. Regulatory openness is a necessary but not sufficient condition for improving participation; firms also need complementary capabilities. Data openness without infrastructure is not enough to create sustained engagement.

The average treatment effect of participation, above the conventional confidence threshold ($t = 2.87$), indicates that persistent engagement may be more likely conditional on firm characteristics. For policy interventions in digital markets, these findings identify a firm-level mechanism with practical relevance. In the matched analysis, firm size and productivity were statistically significant predictors of baseline participation. Increased participation and intensity among e-commerce adopters highlight the importance of infrastructure access and regulatory clarity, common barriers to digital adoption in developing economies. Cross-border data flows as a policy, institutional, and regulatory instrument can reduce uncertainty and provide a pathway for digital decision-making.

The emphasis on persistence suggests that digital participation is becoming a threshold condition for firm engagement, characterized by data regimes that are sufficiently open to be leveraged with lower adjustment costs. Over the last decade, adoption of digital channels has improved gradually, as in firms operating in comparable institutional environments. The contribution of this evidence lies in its firm-level analysis, and the observed participation patterns resemble those documented in prior literature, including the EU context [5]. The use of matching on cross-sectional data does not, in the authors' view, invalidate the main results. However, the absence of longitudinal data across regulatory regimes may limit generalizability.

Cross-sectional data do not provide panel variation to observe dynamic changes following regulatory shifts. Although the estimation strategy is centered on the average treatment effect, it can be challenging to capture long-term dynamics. Further research and data collection are needed to test whether the entry and persistence effects are replicated in advanced economies and how they interact with sectoral composition, institutional quality, regulatory stringency, and enforcement capacity.

5. CONCLUSION

Given the constraints of the empirical design, clarifying the implications of the identification strategy highlights the importance of the regulatory and institutional environments in which firms operate. Policymakers should be informed of these conditions before designing and implementing policy, which is one of the central contributions of these findings.

Regulatory openness and digital connectivity can increase and sustain firms' engagement with digital channels and are central to digital-trade participation, export diversification, firm-level adjustment, and cross-border data governance. The results are consistent with prior evidence that reducing regulatory burdens and increasing the predictability of data-governance regimes can reduce entry barriers and exit risks in digital markets.

The empirical pattern is similar at the extensive margin, with firm size and productivity helping determine whether regulatory openness translates into greater participation. Complementary policies, including infrastructure investment and

institutional-capacity building, are needed to sustain digitally based regulation despite sectoral heterogeneity and regional differences. Because the estimations are cross-sectional, the full dynamics of digital participation may only partially emerge in the current framework. Future firm-level research should use longitudinal datasets to test the stability of participation effects in more dynamic regulatory environments. It remains an open question whether observed entry effects are transitory adjustments that fade after firms internalize the regulatory regime or persist where compliance is repeated. Further work should address sectoral exposure, enforcement capacity, institutional quality, and cross-country differences in income levels, institutional settings, regulatory stringency, and enforcement structures.

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