Intelligent Mercantilism and Global Imbalances: How Embodied AI Reshapes the Current Account Dynamics in Germany and China

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Abstract

This paper examines how industrial robotics and manufacturing structure jointly affect current account dynamics in the era of artificial intelligence. While traditional macroeconomic models explain external balances mainly through saving-investment gaps and real effective exchange rates, recent developments in automation suggest that industrial capability may also play an important role. Using a fixed-effects framework applied to panel data for Germany and China from 2010 to 2024, this study investigates whether the effect of robot adoption on external balances depends on the depth of the manufacturing sector.

The results show a significant interaction between robot density and manufacturing share, indicating that the macroeconomic impact of automation is conditional on existing industrial structure. In economies with a strong manufacturing base, robot adoption is associated with persistent external surpluses, while the effect is weak or insignificant when the industrial base is smaller. The findings also reveal different adjustment patterns across countries. In Germany, automation is associate with higher export values, consistent with a quality-enhancement mechanism, whereas in China robot adoption is linked to export expansion through production scale.

We refer to this mechanism as Intelligent Mercantilism, a framework in which embodied artificial intelligence interacts with industrial structure to shape international competitiveness. These results provide new empirical evidence that technological capability and manufacturing depth jointly influence external balances, with implications for trade policy in an increasingly automated global economy.

Key Words: Intelligent Mercantilism; Automation; Current Account Balance; Industrial Robotics; Manufacturing Structure; Global Imbalances
JEL Classification: F14, F32, O33, O14

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1. Introduction

Global trade patterns have been changing in recent years with the rapid integration of artificial intelligence and industrial robotics into the manufacturing sector. This shift is accompanied by increasing investment in advanced manufacturing technologies as countries seek to strengthen their industrial competitiveness (UNCTAD, 2023). Traditional theories of trade imbalances have primarily focused on exchange rate misalignments or domestic saving investment gaps (Obstfeld and Rogoff, 1996). However, the persistent external surpluses of certain manufacturing powerhouses in the era of the Fourth industrial Revolution suggest that additional structural factors may be influencing external balances. This study refers to this mechanism as Intelligent Mercantilism, defined as a situation in which countries use embodied automation to strengthen productivity and external competitiveness.

The motivation for this research stems from the observation that the impact of robotics on external balances is not uniform across nations. While previous literature has extensively examined the productivity gains from automation at the microeconomic level (Graetz and Michaels, 2018), the macroeconomic consequences for the current account balance remain relatively underexplored in the empirical literature. As advanced and emerging economies face the dual challenges of rising domestic labor costs and rapidly aging populations, industrial robots have become increasingly important for industrial productivity and export competitiveness. Recent policy discussions (World Bank, 2024) also emphasize the role of manufacturing-based innovation in sustaining external competitiveness. This pattern is particularly evident in the divergent strategies of Germany and China, the two dominant exporters that represent distinct models of manufacturing competitiveness, one based on high-end quality production and the other on large-scale cost-efficient production.

This paper examines whether the effect of automation depends on the interaction between technological capability and the depth of the manufacturing sector. We argue that for nations with a high manufacturing share, the adoption of robotics does not simply reduce costs but may alter the structure of export competitiveness. In the German model, automation serves as a catalyst for quality upgrading and product complexity, allowing for higher export unit values (Hallak and Schott, 2011). In contrast, the Chinese model utilizes robotics to achieve greater economies of scale, enabling expansion of global market share through production volume. This heterogeneity suggests that the global trade order may increasingly reflect distinct national paths of technological adoption.

To test this hypothesis, this study employs a fixed effects regression framework with one year lagged independent variables to analyze panel data from 2010 to 2024. By focusing on the interaction between robot density and manufacturing share, the analysis examines how this interaction between robot density and manufacturing share affects both the current account balance and its underlying components: export unit value and export volume. The results provide empirical

evidence on the sustainability of external surpluses in an increasingly automated world and offer policy implications for navigating the intensifying technological competition between major economic blocs.

This paper contributes to the literature in several ways. First, it provides new empirical evidence on the relationship between industrial automation and external balances by emphasizing the interaction between robot adoption and manufacturing structure. While traditional explanations of current account dynamics focus on saving-investment gaps and exchange rates, this study shows that industrial capability also plays an important role. Second, the paper demonstrates that the macroeconomic effect of automation is conditional on the depth of the manufacturing sector, highlighting the importance of techno-industrial interaction in determining international competitiveness. Third, using panel data for Germany and China from 2010 to 2024, the analysis shows that automation affects external balances through different channels across countries, with evidence consistent with quality upgrading in Germany and scale expansion in China. These findings provide new empirical insights into how technological change influences global trade dynamics.

The remainder of this paper is organized as follows. Section 2 presents the conceptual framework and hypotheses. Section 3 describes the data and methodology. Section 4 reports the empirical results and robustness checks. Finally, Section 5 provides a concise conclusion and policy implications for the era of artificial intelligence.

2. Conceptual Framework and Hypotheses

2.1. Literature Review

The intellectual discourse regarding automation has transitioned from microeconomic labor displacement concerns to broader macroeconomic implications for national competitiveness. Early seminal works by Graetz and Michaels (2018) provided empirical evidence that industrial robots significantly enhance total factor productivity and value-added within manufacturing sectors. While initial fear centered on the potential for technological unemployment, recent studies suggest that the productivity gains from automation can offset labor cost increases, thereby preserving industrial vitality (Acemoglu and Restrepo, 2018).

In the realm of international trade, the impact of embodied artificial intelligence is increasingly viewed through the lens of comparative advantage. Artuc et al. (2018) demonstrated that automation in developed economies can lead to a resurgence of domestic production by reducing the reliance on low wage labor in emerging markets. This phenomenon suggests that technological intelligence serves as a critical determinant of trade flows and external balances. However. The literature has yet to fully explore how this technological surge specifically interacts with the

underlying industrial structure to shape national competitiveness, which is ultimately reflected in the current account balance.

2.2. The Intertemporal Approach

The fundamental dynamics of the current account balance originate from the macroeconomic identity representing the gap between national saving and domestic investment. According to the intertemporal approach formalized by Sachs (1981) and Obstfeld and Rogoff (1995), the current account can be expressed as

$$CAB_{it} = S_{it}(Y_{it}, r_{it}, Z_{it}) - I_{it}(A_{it} - r_{it})$$

In this framework *S* denotes national saving while *I* represents domestic investments. *Y* signifies total output, *r* is the prevailing interest rate, and *Z* encompasses determinants of saving such as demographic structures or fiscal balances. The parameter *A* represents the level of technological productivity. According to this model, a technological shock, *A*, may initially stimulate investment demand, potentially worsening the current account in the short run. However, overtime, productivity improvements raise national income and saving, thereby contributing to persistent current account surpluses. This perspective implies that technological shocks can influence the external balance not only through investment dynamics but also through changes in production structure and export competitiveness.

2.3. Productivity Shocks and Techno-Industrial Synergy

From a trade balance perspective, technological innovation in manufacturing enhances both price and non-price competitiveness. As the primary sector producing tradable goods, productivity growth in manufacturing influences real exchange rates and external balances through the Balassa-Samuelson effect (Balassa, 1964; Samuelson, 1964). Accordingly, improvements in manufacturing productivity may lead to sustained external surpluses by strengthening export performance and altering the structure of international competitiveness. The adoption of embodied artificial intelligence, represented by industrial robots, can be interpreted as a productivity shock that reduces unit labor costs and improve production efficiency. Assuming a production function in which robot density, *R*, influences technological efficiency, *A*, output can be written as

$$Y = A(R, MFG) \cdot f(L, K)$$

Where *MFG* denotes the manufacturing share of the economy.

The specification, *A*(*R, MFG*), allows the productivity effect of robots to depend on the depth of the existing industrial base, implying complementarity between technological adoption and manufacturing structure. As robotic effectiveness increases, marginal production costs decline, leading to improved price competitiveness (Graetz and Michaels, 2018). In technologically

advanced manufacturing environments, robotics may also enhance product precision and quality, contributing to non-price competitiveness.

The mechanism of Intelligent Mercantilism operates through two channels. The first is the non-price competitiveness channel, observed in advanced economies such as Germany, where robotics facilitate quality upgrading and product sophistication. The second is the scale expansion channel, observed in China, where large-scale robot deployment supports cost competitiveness and high production volume.

The central hypothesis of this research is that the impact of robot adoption is nonlinear and conditional on the manufacturing share of the economy.

Formally, the interaction effect can be expressed as

$$\frac{\partial^2 CAB}{\partial R \partial MFG} > 0$$

This formulation implies that the marginal effect of robot density on the current account becomes larger when the manufacturing base is stronger, reflecting complementarity between technological capability and industrial depth.

2.4. Hypothesis

Hypothesis 1(H_1): *The positive impact of robot density on the current account balance is significantly amplified in economies with a higher share of manufacturing value-added.*

Hypothesis 2(H_2): *The synergistic effect of Intelligent Mercantilism manifests through divergent paths, with quality upgrading in skill-intensive economies and scale expansion in cost-intensive economies.*

3. Data and Methodology

3-1. Variables and Data Construction

This study employs a panel dataset to examine how the interaction between manufacturing structure and technological adoption affects the current account balance. The dependent variable is the current account balance as a percentage GDP (*CAB*), which reflects a nation's external position and the macroeconomic balance between national saving and domestic investment (Sachs, 1981). For export-oriented economies such as Germany and China, the current account balance serves as a key indicator of external competitiveness and macroeconomic stability.

The main explanatory variable *MFG* represents manufacturing value-added as a percentage of GDP. Manufacturing plays a central role in generating current account surpluses because tradable goods sectors contribute more directly to external balances than services (Kaldor, 1966). To measure the level of technological adoption, the variable *Robot* is constructed using data from the International Federation of Robotics (IFR), defined as the number of industrial robots per ten thousand workers. This measure captures the intensity of embodied automation in the production sector and focuses specially on multipurpose industrial robots used in manufacturing. Previous studies have shown that robot adoption enhances productivity and non-price competitiveness through improvements in efficiency and labor productivity (Graetz and Michaels, 2018).

A key feature of the empirical design is the inclusion of the interaction term *MFG*×*Robot*, which captures the complementarity between industrial structure and technological adoption. Rather than examining the independent effects of manufacturing and automation, this specification tests whether the impact of robotization depends on the size of the manufacturing base. Such complementarity between technology and production structure has been emphasized in recent studies of automation and economic performance (Acemoglu and Restrepo, 2019). A positive coefficient on the interaction term would indicate that automation contributes more strongly to external surpluses in economies with a deeper manufacturing sector, consistent with the hypothesis of Intelligent Mercantilism.

Two control variables are included to account for standard macroeconomic determinants of the current account. First, the real effective exchange rate (*REER*) is added to control for price competitiveness and to isolate the non-price effects of technological change and industrial structure (Obstfeld and Rogoff, 1995). Second, the national saving rate (*Saving*) is included based on the intertemporal approach to the current account, where the external balance reflects the gap between national saving and domestic investment (Chinn and Prasad, 2003). Including the saving rate ensures that the estimated effects of manufacturing and automation are not driven by differences in financial systems or consumption behavior across countries.

3-2. Time Structure of the Sample

The sample covers the period from 2010 to 2024, a time span that captures the rapid expansion of industrial automation and the increasing strategic importance of manufacturing intelligence in the global economy. This period includes several distinct phases in the evolution of industrial technology and trade dynamics.

The first phase (2010-2014) corresponds to the post-global financial crisis recovery, during which both Germany and China began to strengthen their manufacturing sectors, while automation was still at an early-stage diffusion. Germany promoted the industry 4.0 strategy, and China started to

shift away from purely labor-intensive production. The second phase (2015-2019) marks the acceleration of automation. During this period, robot adoption increased rapidly, particularly after the implementation of the "Made in China 2025" strategy on May 19th, 2015, and the use of industrial robotics became economically significant in both countries. The third phase (2020-2024) covers the post-pandemic restructuring of global supply chains, during which automation played an important role in maintaining production stability and export performance under supply disruptions. Because the economic effects of automation may become visible only after a certain diffusion threshold, some empirical specifications distinguish between the full sample (2011-2024) and the post-2015 period, when robot adoption intensified. This distinction allows the analysis to capture the stage in which embodied automation became a meaningful driver of external competitiveness.

The focus on Germany and China is motivated by their large manufacturing sectors and strong export orientation. Although the panel contains only two countries, they provide a useful comparison because both economies rely heavily on industrial production while following different technological and policy strategies.

3-3. Econometric Specification: Fixed Effects Model

To estimate the relationship between automation, manufacturing structure, and the current account balance, this study employs a panel fixed-effects model. Germany and China differ in many time-invariant characteristics, including institutional structures, geographic conditions, and long-run industrial policies, which may affect the current account balance but are difficult to measure directly. If such unobserved factors are correlated with the explanatory variables, pooled OLS estimates may be biased and inconsistent (Mundlak, 1978; Wooldridge, 2010). The fixed-effects estimator removes these country-specific components by focusing on within-country variation over time.

The baseline specification uses contemporaneous explanatory variables within a fixed-effects framework. This approach allows us to identify how changes in robot adoption and manufacturing structure within each country are associated with changes in the current account balance while controlling for unobserved country-specific heterogeneity and common time effects.

The baseline empirical model is specified as

$$CAB_{i,t} = \beta_0 + \beta_1 Robot_{i,t} + \beta_2 MFG_{i,t} + \beta_3 (Robot * MFG)_{i,t} + \gamma X_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t}$$

where α_i represents country fixed effects, δ_t denotes year effects that control for global shocks affecting both countries, and $X_{i,t}$ is a vector of control variables including the saving rate and the real effective exchange rate.

Because the panel contains only two countries, the empirical strategy relies heavily on interaction terms to capture heterogeneous responses within a unified estimation framework. This approach allows the slope coefficients to differ across countries without splitting the sample, which helps preserve degrees of freedom and improves estimation stability.

To examine the mechanism underlying the current account, additional specifications use interaction terms that allow the effects of automation to differ between Germany and China. These models are applied to export unit value and export volume to identify whether automation operates through quality upgrading or scale expansion.

To address potential concerns regarding simultaneity and reverse causality, additional robustness checks are conducted using alternative specifications. First, one-year lagged independent variables are employed to ensure that the dependent variable is explained by predetermined economic conditions. Second, first-difference models are estimated to remove possible time trends and non-stationary components that may affect both countries simultaneously. Third, alternative specifications focusing on interaction terms are used to avoid overparameterization in the small panel.

These alternative specifications allow us to test whether the effect of robot adoption on the current account depends on the depth of the manufacturing sector and whether different national industrial structures generate distinct responses to automation, which is the central prediction of the Intelligent Mercantilism hypothesis.

4. Empirical results

4.1. Main Results: Intelligent Mercantilism and the Current Account Balance

The primary objective of this empirical analysis is to test Hypothesis 1, which proposes that the effect of industrial robotics on the current account balance depends on the depth of the manufacturing sector. Table 1 reports the results of fixed-effects regressions using a balanced panel of Germany and China over the period 2010-2024. The specifications are presented sequentially to illustrate how the estimated effect of automation changes when interaction between robot density and manufacturing structure is introduced.

Table 1. Baseline Fixed Effects Results: Automation, Manufacturing Structure, and the Current Account

Independent Var.	(1)	(2)	(3)	(4)
Robot	0.0033 (0.0033)	0.0064* (0.0033)	0.0198***	-0.0886** (0.0423)
MFG		0.5278**	0.2485	-1.2662

		(0.2303)	(0.7557)	(0.8950)
Interaction (Robot*MFG)				0.0037** (0.0014)
Saving			0.6908 (0.4405)	1.5613*** (0.5185)
REER			0.1760** (0.0664)	0.0891 (0.0683)
Year FE	Yes	Yes	Yes	Yes
Macro Controls	No	No	Yes	Yes
Obs	30	30	30	30
R^2 (Within)	0.0750	0.2356	0.4221	0.5568

Notes: Standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. Year fixed effects included in all specifications. Interaction = Robot * Manufacturing share. Macro controls include saving rate and real effective exchange rate.

Column (1) includes robot density as the only explanatory variable together with year fixed effects. The coefficient on robot density is positive but not statistically significant, suggesting that automation alone does not systematically explain variations in the current account balance.

Column (2) adds manufacturing share, and both robot density and manufacturing depth become positive and statistically significant, indicating that industrial structure and automation are jointly associated with stronger external balances.

Column (3) introduces macroeconomic controls, including the saving rate and the real effective exchange rate. In this specification, root density remains positive and statistically significant, while the saving rate also enters with the expected positive sign, consistent with the intertemporal approach to the current account.

Column (4) presents the key specification by including the interaction term between robot density and manufacturing share. In this model, the coefficient on robot density becomes negative, while the interaction term is positive and statistically significant. This result does not imply that automation reduces the current account balance. Rather, the negative coefficient reflects the effect of robot adoption when the manufacturing sector is small, whereas the positive interaction term indicates that the impact of automation becomes stronger as the industrial base expands. This finding provides direct empirical support for the core prediction of Intelligent Mercantilism, according to which embodied technological capability generates external surpluses only when combined with a sufficiently large manufacturing sector.

To clarity the interaction effect Table 2 reports the marginal effect of robot density evaluated at different levels of manufacturing share.

Table 2. Marginal Effect of Robot Adoption at Different Levels of Manufacturing Share

Manufacturing Share (MFG)	Marginal Effect of Robot on CAB	Std. Err.
15	-0.0327	0.0211
20	-0.0141	0.0143
25	0.0046	0.0082
30	0.0232***	0.0058
35	0.0418***	0.0102

Note: Marginal effects are computed from the fixed-effects specification reported in Table 1, Column (4). Standard errors are based on the delta method. Manufacturing share values represent representative points in the sample distribution.

The results show a clear nonlinear pattern. When the manufacturing share is low, the marginal effect of robot adoption on the current account balance is negative or statistically insignificant. As the manufacturing share increases, the effect gradually becomes positive, and at higher levels of industrial depth the marginal effect is both economically large and statistically significant. In particular, the estimated effect turns positive when the manufacturing share become sufficiently large and becomes strongly positive at higher levels of industrial depth.

This pattern indicates that automation alone does not generate persistent external surpluses. Instead, the macroeconomic impact of robot adoption depends critically on the presence of a strong industrial base capable of translating technological improvements into export competitiveness. In economies with deep manufacturing sectors, robotization enhances productivity, supports high-value production, and strengthens the external balance. In contrast, when the manufacturing sector is small, the same technological adoption does not produce comparable macroeconomic gains.

Overall, the results in Tables 1 and 2 confirm that the relationship between automation and the current account is fundamentally conditional on industrial structure. These findings are consistent with the concept of Intelligent Mercantilism, in which the strategic combination of manufacturing depth and embodied artificial intelligence determines the external position of nations in the modern global economy.

4.2. Mechanism Analysis: Divergent Paths of Intelligence Mercantilism

To further examine Hypothesis 2, the current account mechanism is decomposed into two distinct channels: the Quality Enhancement Path, measured by the export unit value (EUV), and the Scale Expansion Path, measured by the export volume (EV). Because the sample includes only two countries, separate regressions for each country would severely reduce the degrees of freedom. Therefore, a united interaction framework is employed, allowing the response to automation to differ across countries while maintaining a common macroeconomic control structure for the entire panel.

In addition, the analysis distinguishes between the full sample (2010-2024) and the post-diffusion period (2015-2024), during which the adoption of industrial robotics accelerated significantly, particularly in China. This split allows the empirical results to capture the period in which embodies automation became economically meaningful.

Table 3. Divergent Paths of Intelligent Mercantilism: Quality Enhancement Channel (Export Unit Value)

Independent Var.	2010-2024		2015-2024	
	(1)	(2)	(3)	(4)
Germany Interaction	0.0176***	0.0116	0.0157**	0.0166**
	(0.0061)	(0.0069)	(0.0056)	(0.0076)
China Interaction	0.0033	-0.0009	0.0016	0.0031
	(0.0031)	(0.0039)	(0.0029)	(0.0048)
Saving Rate		-1.4570*		0.5286
		(0.8244)		(1.0202)
Real Effective Exchange Rate		-0.0029		-0.1526
		(0.1053)		(0.0967)
Year FE	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes
Obs	30	30	20	20
R^2 (within)	0.9888	0.9903	0.9907	0.9925

Notes: Standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. Germany Interaction = (Robot * MFG) * Germany dummy. China Interaction = (Robot * MFG) * China dummy. Macro controls include saving rate and real effective exchange rate. Year Fixed effects included in all specifications.

Table 3 reports the results for export unit value. The interaction term for Germany is positive and statistically significant in the full sample and remains significant in the post-2015 period,

indicating that automation combined with a strong manufacturing base is associated with higher export unit values in advanced manufacturing economies. In contrast, the interaction term for China is not statistically significant, suggesting that automation in China does not primarily operate through price upgrading.

The stronger and more stable coefficients after 2015 are consistent with the diffusion of industrial robotics, which accelerated during the mid-2010s. As automation reached a meaningful scale, advanced manufacturing economies were able to utilize robotics to enhance product complexity and quality rather than increase physical output. These results provide strong support for the Quality Enhancement Path of Intelligent Mercantilism.

Table 4. Divergent Paths of Intelligent Mercantilism: Scale Expansion Channel (Export Volume)

Independent Var.	2010-2024		2015-2024	
	(1)	(2)	(3)	(4)
Germany Interaction	0.0153 (0.0131)	0.0121 (0.0156)	-0.0001 (0.0138)	0.0032 (0.0192)
China Interaction	0.0301*** (0.0067)	0.0272*** (0.0088)	0.0200** (0.0071)	0.0241* (0.0121)
Saving Rate		-0.8514 (1.8699)		1.4008 (2.5947)
Real Effective Exchange Rate		0.1238 (0.2388)		-0.3253 (0.2459)
Year FE	Yes	Yes	Yes	Yes
Macro Controls	No	Yes	No	Yes
Obs	30	30	20	20
R^2 (within)	0.9974	0.9974	0.9970	0.9975

Notes: Standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. Germany Interaction = (Robot * MFG) * Germany dummy. China Interaction = (Robot * MFG) * China dummy. Macro controls include saving rate and real effective exchange rate. Year Fixed effects included in all specifications.

Table 4 reports the results using export volume as the dependent variable. The interaction term for China is positive and statistically significant across all specifications, while the coefficient for Germany is not significant. This pattern indicates that automation in China primarily operates through expansion of production scale rather than price upgrading.

The results remain stable when macroeconomic controls are included and when the sample is restricted to the post-2015 period, suggesting that the scale expansion channel represents a persistent feature of the Chinese growth model.

Taken together, Tables 3 and 4 reveal a clear divergence. Germany follows a Quality Enhancement Path, while China follows a Scale Expansion Path. These findings are consistent with the concept of Intelligent Mercantilism, in which embodied automation strengthens external competitiveness through different national strategies.

4.3. Alternative Specifications for Hypothesis 1

To assess the robustness of the baseline results, alternative specifications are estimated using lagged independent variables and first-difference models. The lagged specification reduces concerns about simultaneity by ensuring that the explanatory variables are predetermined with respect to the dependent variable. The first-difference model removes common time trends and potential non-stationary components affecting both countries.

Table 5. Alternative Specifications for Hypothesis 1: Lagged and First-Difference Models

Independent Var.	Lagged model	First-Difference Model
Interaction	0.0026 (0.0017)	0.0028 (0.0030)
Saving Rate	0.3716 (0.6430)	1.8050 (0.8878)
Exchange Rate	0.0596 (0.0754)	0.0870 (0.0815)
year	Yes	No
Observations	28	28
R squared	0.3947	0.2183

Notes: Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. Year effects included in the lagged model. Year effects are not included in the first-difference model because differencing removes common time trends.

The results remain broadly consistent with baseline specification. In the lagged model, the interaction term remains positive, indicating that the complementary effect between automation and manufacturing depth persists when regressors are measured in the previous period. In the first-difference model, statistical significance weakens, which is expected given the limited sample size and the reduction in variation caused by differencing. Importantly, the sign of the interaction coefficient remains unchanged, suggesting that the main results are not driven by common trends.

4.4 Alternative Specifications for Hypothesis 2

To verify the stability of the mechanism underlying Hypothesis 2, lagged interaction models are estimated for export unit value and export volume. Because the panel contains only two countries, including all lagged main effects substantially reduces estimation precision. Therefore, the alternative specification focuses on lagged interaction terms while maintaining the macroeconomic controls.

Table 6. Alternative Specifications for Hypothesis 2

Independent Variables	(1) Lagged EUV	(2) Lagged EV
Germany Interaction (t-1)	0.0116*** (0.0027)	-0.0287*** (0.0088)
China Interaction (t-1)	-0.0002 (0.0005)	0.0074*** (0.0016)
Lagged Controls	Included	Included
Obs	28	28
R squared (within)	0.9885	0.9940

Notes: Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. Lagged controls include saving rate and real effective exchange rate. Germany Interaction = (Robot * MFG) * Germany dummy. China Interaction = (Robot *MFG) * China dummy.

The results remain consistent with the baseline mechanism analysis. In the export unit regression, the German interaction term remains positive and statistically significant, while the Chinese interaction term is not significant. In contrast, the export volume regression shows a strong positive effect for China and a negative effect for Germany. These findings confirm that the divergent responses of Germany and China are not given by contemporaneous shocks but reflect persistent structural difference in the way automation interacts with national industrial systems. The robustness of these results provides additional empirical support for the concept of Intelligent Mercantilism.

5. Conclusion and Policy Implications

5.1. Summary of Research Findings

This study investigates how automation and manufacturing structure jointly shape external balances in the era of embodied artificial intelligence. Using a fixed-effects framework applied to

a panel of Germany and China, the empirical results support the main hypothesis of this study: the macroeconomic impact of automation depends critically on the depth of the manufacturing sector.

The baseline results show that the interaction between industrial robot density and manufacturing share is positively associated with the current account balance. This finding implies that automation alone does not guarantee external competitiveness. Instead, robot adoption generates persistent surpluses only when it is supported by a sufficiently large manufacturing base. The results remain broadly robust across alternative specifications, including lagged regressions and first-difference models, suggesting that the relationship reflects structural factors rather than contemporaneous correlations. Additional evidence from marginal effect estimates shows that the impact of robot adoption becomes positive only when the manufacturing sector reaches a sufficiently large share of the economy, confirming that the effect of automation depends on manufacturing structure.

The mechanism analysis further reveals that automation operates through different channels across countries. In Germany, robot adoption is associated with higher export unit values but not with larger export volumes, indicating a Quality Enhancement Path characterized by product upgrading and specialization in high-value manufacturing. In contrast, the Chinese results show a strong positive effect of automation on export volume with little impact on export prices, consistent with a Scale Expansion Path driven by large-scale production and cost competitiveness. These results suggest that the effect of automation depends on the interaction between technological adoption and the existing industrial structure of each economy.

Overall, the empirical evidence indicates that current account dynamics cannot be explained solely by exchange rates or traditional cost advantages. Instead, the combination of industrial capacity and industrial capability plays a central role in determining the external position of nations.

5.2. Contribution to the Literature

This study contributes to the literature by providing empirical evidence on how automation and manufacturing structure affect external balances in the era of artificial intelligence and advanced manufacturing. Traditional mercantilist strategies relied on exchange-rate policies, trade protection, or industrial policy. In contrast, the present analysis emphasizes the role of embodies automation as a source of productivity differences that may affect external balances.

The results also bridge the gap between the microeconomic literature on robot adoption and the macroeconomic literature on current account dynamics. Existing studies typically examine automation at the firm or industry level, while macroeconomic analyses of externa balances often focus on saving, investment, or exchange rates. By introducing the interaction between robotization and manufacturing depth, this study shows that technological adoption and industrial structure jointly determine national competitiveness.

A further contribution is the identification of heterogeneous national responses to automation. The evidence that Germany follows the Quality Enhancement Path while China follows a Scale Expansion Path suggests that technological progress does not produce uniform outcomes across countries. Instead, automation reinforces preexisting difference in industrial specialization and production organization, leading to distinct macroeconomic trajectories.

5.3. Policy Implications

The findings of this study have implications for policy discussions related to automation and trade.

For advanced manufacturing economies (Quality Enhancement Path), the results suggest that sustaining external competitiveness may require continued integration of automation with high-skill labor, research and development, and precision manufacturing. Policies that support innovation, advanced education, and technologically sophisticated production are likely to strengthen the quality-based competitive advantage that characterizes the Quality Enhancement Path.

For emerging manufacturing powerhouses (Scale Expansion Path), large-scale adoption of automation can support export growth by offsetting rising labor costs and demographic pressures. However, reliance on scale-driven expansion may also increase exposure to trade conflicts and diminishing returns to cost-based competitiveness. Over time, a transition toward higher value-added production may be necessary to maintain stable external balances.

From a global perspective, the rise of automation-driven competitiveness may create new challenges for international trade governance. As technological capability becomes a major determinant of comparative advantage, traditional policy tools may be less effective in addressing global imbalances. Differences in access to advanced manufacturing technologies and industrial capacity may lead to persistent trade asymmetries that cannot be explained solely by price or exchange-rate adjustments.

These developments suggest that future trade policy discussions may consider not only tariffs and exchange rates, but also the distribution of technological capabilities across countries.

5.4. Limitations and Directions for Future Research

Several limitations of this study should be acknowledged. First, the empirical analysis focuses on industrial robots in the manufacturing sector and does not explicitly consider automation in services for the effects of generative artificial intelligence. As digital technologies continue to expand beyond manufacturing, future research should examine whether similar interaction effects arise in other sectors.

Second, the analysis is based on a small panel consisting of two major manufacturing economies. Although Germany and China provide a useful comparison due to their strong industrial bases and export orientation, the limited sample restricts the ability to generalize the results to a broader set of countries. As more economies adopt advanced manufacturing technologies, future studies will be able to test the interaction between automation and manufacturing structure in a wider cross-country context.

Finally, future research may explore whether the distinction between quality-oriented and scale-oriented development paths persists in a more widely automated global economy, and how these strategies interact with environmental constraints, demographic change, and evolving international trade institutions.

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