Trade Barriers and Technological Advancement: Analyzing the Effects of Mercosur's Tariff Reductions on Brazilian Innovation

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Abstract: This paper investigates the effects of trade liberalization on innovation within the Mercosur bloc, focusing on Brazil's experience from 1992 to 1995, a period of significant tariff reductions. Utilizing a difference-in-differences approach, the study explores the correlation between the removal of trade barriers and patent filings, employing patent data as a direct measure of innovation. While previous literature has primarily concentrated on R&D expenditures, this research capitalizes on patent filings to assess innovation more directly, thereby offering a fresh perspective on the link between trade policies and technological advancement. The analysis demonstrates a consistent, though not statistically significant, negative correlation between tariff increases and patent filings, suggesting that lower tariffs may encourage innovation. Despite this, variations in data categorization and missing observations introduce some uncertainty, underscoring the need for cautious interpretation of the results. The paper contributes to the understanding of economic dynamics within trade blocs and underscores the importance of trade liberalization in fostering an innovative economy. It also highlights the necessity for further research to solidify these findings and guide policy decisions effectively.

1 Introduction

Globalization stands as a pivotal force that has profoundly reshaped the contemporary world as we recognize it today. Several social and economic improvements have emerged in parallel to the advancement of globalization, including technological advancements and industry-wide innovations. Trade integration and innovation are thus deeply intertwined. Given that international trade significantly influences firm profitability, impacting both market size and the level of product market competition, it is reasonable to anticipate its pivotal contribution to shaping innovation and growth (Melitz and Redding, 2021). A product of this and other economic ideas is the creation of economic blocks that aim to enhance regional trade, stimulate economic growth, and gain market access advantages. This is particularly the case when understanding the reasoning behind economic blocks composed of developing economies, such as Mercosur. Established in 1991 through the signing of the Treaty of Asunción, Mercosur emerged as a pact among Argentina, Brazil, Paraguay, and Uruguay. The treaty advocated for the unrestricted flow of goods, services, and production factors among member nations. Such agreement's impact goes beyond increase in total exports and imports and extrapolates to other areas, such as innovation.

Other pieces of literature have studied the effects of trade liberalization in innovation in respect to specific countries within the block. In this paper, I expand upon previous studies to understand the effect of trade liberalization on innovation in Brazil within the Mercosur framework. This research capitalizes on exogenous variations, specifically focusing on the substantial reduction of tariffs to zero between Brazil and Argentina from 1992 to 1995. Therefore, my question is:

How has trade liberalization in Mercosur impacted Innovation in Brazil?

The varying degrees of this tariff reduction across different industries will serve as a crucial dimension for analysis in this investigation. The predetermined and substantial reduction of tariffs, reaching zero, are used to perform a differences in differences approach, utilizing both the different degrees of changes of tariffs in different industries and the years as the variation source. As a metric for innovation, I choose to deviate from previous research that focused on increases in R&D expenditures, and utilize total patent filings in Brazil. The results of this research are consistent with the economic idea behind my logic: that a decrease in tariffs suggests an increase in patent filings, or innovation, and vice versa. It is crucial to note that several limitations prohibit the result of my research to be significantly conclusive at this point. Firstly, industry is categorized differently in the tariff data and in the patent data. I explain how I deal with this later on further parts of my paper. Secondly, missing data is a concern. Therefore, even though one specification achieved a 10% significance, I argue that that is not enough to conclude that there was a significant change in patent filings between the years of 1992 and 1995 in Brazil, in the context of Mercosur. Still, my results seem to point in the main direction and suggest that further research is needed to derive more certain results.

Even without significant results, multiple other pieces of literature, together with a constant direction sign in my regression specifications, highlight the link between trade liberalization and innovation. Thus, Analyzing the effects of trade liberalization on innovation within the Mercosur context, particularly focusing on Brazil, gains further significance in light of BRICS' ascension. As Brazil is a pivotal member of both Mercosur and BRICS, studying the interplay between trade liberalization, innovation, and economic dynamics provides insights not only into regional dynamics but also the broader impact on emerging economies.

2 Literature Review

To better guide how I approached my question, I leveraged both conceptual and statistical papers. Conceptual studies are crucial to understand the economic and historical context of Mercosur. Statistical studies are necessary to understand what strategies have been developed to study the relationship in question.

Starting with conceptual review, multiple scholars have studied the effect of trade liberalization in innovation and growth. A study done by Shu and Steinwender (2019) analyzed the mechanism behind trade liberalization on firm innovation. They study both direct measures of innovation, such as R&D spending, patents, and product mix, and indirect measures like labor productivity and total factor productivity, revealing that import competition yields mixed results on firm productivity and innovation. In comparison, export opportunities and access to imported intermediates generally demonstrated positive effects. The review notes regional variations, particularly in emerging economies like Latin American countries, where trade is predominantly associated with positive effects on firm productivity and innovation, particularly for larger and more productive firms.

One possible mechanism through which increased trade activity influences technology and innovation adoption is through an increase in productivity. Marc J. (2003) examines this relationship and builds a dynamic industry model to analyze the intra-industry effects of international trade. The study demonstrates that as the industry becomes more exposed to trade, there is a continual shift of resources toward the more productive firms. Moreover, the paper illustrates that the overall growth in industry productivity resulting from these reallocations contributes to an improvement in overall welfare.

Melitz and Redding (2021) developed a study that examines the mechanisms through which trade affects aggregate innovation and growth, including knowledge spillovers and the role of international trade as a conduit for these spillovers. The paper also discusses models of innovation and technology diffusion, the role of protectionism in promoting innovation, and the impact of international knowledge spillovers on economic growth and welfare.

To understand more about the environment at which Mercosur emerged, I analyzed Gabriela Campos' (2016) study on ‘From Success to Failure: Under What Conditions did Mercosur Integrate?’. Campos (2016) concluded that leadership has been crucial in directing Mercosur’s integration. By employing Malamud’s theory of inter-presidentialism and Mattli’s theory of regional integration, the study analyzes the historical development of the block and focuses on the impact of political leadership and economic conditions on its integration. It is crucial to understand such context to better control for potential confounding factors.

Continuing with statistical papers, Cassiolato, J., & Lastres, H. (2000) performed a study where they examined, among other topics, how the macroeconomic environment and innovation policies (both explicit and implicit) of the 1990s have affected selected local productive arrangements.Cassiolato, J., & Lastres, H. (2000) found that the majority of cases indicated a decrease in innovation efforts towards new products, affecting both their core capabilities and learning processes. Although the findings are not supportive of the general economic logic behind the question here established, the paper does not utilize a statistical and economical analysis on the issue, but instead uses empirical research on 12 selected "case studies". Thus, there is a necessity for a more in-depth analysis to determine the actual effect of interest.

Another study by Petia Topalova (2004) examined the effects of recent trade liberalization in India using a panel of firm- level data by employing intertemporal and across-industry variations in trade protection to identify the effect of trade policies. Patalova (2004) found that trade liberalization in India causes increased efficiency among firms.

Specifically, a decrease in tariffs by 10 percent leads to about 0.5 percent increase in Total Firm Productivity.

Building upon this idea, Paula Bustos (2009) studied the impact of Mercosur's tariff reduction between 1992 - 1995 on innovation in Argentinian Firms. To perform this study, she utilized firm-level data on one side, and an in-depth analysis of the tariff schedule between Brazil and Argentina during the first 4 years of the economic block. Brazil's tariffs are characterized by a good source of exogenous variation due to them falling from an average of 29% in 1991 to zero in 1995, and varying largely across industries. She utilizes a differences in differences approach where the sources of variation are the changes in Brazil's tariffs for imports from Argentina across time (1996 - 1992) and across 4-digit-SIC industries. On the firm-level side, she measures technology as spending in technology, spending in technology per worker and spending in productivity.

Differently from other papers in the literature, my research focuses on the direct relationship between trade liberalization and innovation, whereas other studies have tried to link the two forces through different mechanisms. Understanding the direct impact between trade and innovation contributes to a broader understanding of economic impacts of trade blocs, which could help policymakers perform more informed decision-making.

Furthermore, while other studies in this section utilize diverse metrics to gauge innovation, my approach is to employ total patent filings as the primary indicator. Patents are issued for inventions that are novel, non-obvious, and useful. This legal acknowledgment not only confirms that an innovation has met specific criteria of novelty and utility, but also serves as a valuable proxy for the innovation's economic worth. It is plausible that trade liberalization prompts firms to increase their investments in R&D; however, the direct effects of this augmented R&D spending are not captured by any conventional measure. By measuring innovation through patent filings, I directly assess the impact of trade liberalization on innovative activities.

To conclude, to my knowledge, no study has yet specifically explored the impact of tariff reductions on innovation in Brazil. While Bustos' research adopts an approach similar to mine, employing tariffs between Brazil and Argentina as one of her variables, it primarily assesses the impact on innovation in Argentina. Therefore, I aim to contribute to filling this gap by focusing on the Brazilian context.

3 Data Summary

3.1 Data sources and scope

There are 3 sources of data for this research. The first one is the data regarding the tariff reduction between 1992 and 1995 across all 2-digit industries and between Argentina and Brazil. The second is the patent data filtered from years prior to the start of Mercosur, during it and after (arbitrary choice of 1988 until 1995). The third one is exports from Argentina for the year of 1993.

3.1.1 Tariff Data

The source of the tariff data is UNCTAD-TRAINS Database through the World Bank website (https://databank.worldbank.org/source/unctad-%5E-trade-analysis-information-system-(trains). The variables for this data are: reporter country, product, partner country, time and tariff indicator. Reporter country relates to countries that impose a tariff on another country (partner country). Product variable refers to all products categorized by 6-digit HS codes. HS code is a numerical code that represents a specific product or group of products. As an example, the first two digits represent the chapter, which broadly categorizes products into different groups (e.g., live animals, vegetables, textiles), and the last two digits offer even more detailed subcategories. Time variable is available for all years starting 1988 until 2014. Tariff indicator has multiple options available, such as simple average %, weighted average, min rate % and max rate %.

Regarding data reliability, the UNCTAD-TRAINS Database is generally robust; however, it does contain numerous instances of N/A observations. Strategies for addressing these gaps will be discussed in the subsequent section.

3.1.2 Patent Data

The source of the patent data is WIPO IP Statistics Data Center (https://www3.wipo.int/ipstats/ips-search/search-result?type=IPS&selectedTab=patent&indicator=23&reportType=15&fromYear=1980&toYear=2022&ipsOffSelValues=BR&ipsOriSelValues=BR&ipsTechSelValues=). The following variables are available: indicator, report type, years, office, field of technology and origin. Indicator relates to different tariff indicators such as ‘Patent publications by technology’ and ‘Patent grant by technology’. Report type has options ‘Total count by filling office’, ‘Total count by applicant’s origin’ and ‘Count by filling office and applicant's origin'. Field of Technology is segmented into 35 categories. Information is available for the years of 1980-2022.

Concerning data reliability, the WIPO IP Statistics Data Center is recognized for its reliability and is frequently used as a reputable source for patent data. Notably, in my examination of the variables, no instances of missing data were identified.

3.1.3 Exports Data

The source of the exports data is WITS - World Integrated Trade Solution (https://wits.worldbank.org/) utilizing UN Comtrade by country period information. The available variables include Reporter Country, Nomenclature, which relates to how industries are categorized, year, flow and partner country.

Regarding how reliable the data is, the World Integrated Trade Solution (WITS) is considered a reliable source for trade data. WITS is widely used by researchers, policymakers, and economists to analyze global trade flows, tariff data, and trade barriers. Its reliability stems from its use of official data and the rigorous methods employed in gathering and presenting this data.

3.2 Data selection

3.2.1 Tariff Data

For the reporter country, I selected the 3 remaining Mercosur's countries (Uruguay, paraguay, Argentina) as the reporter of the tariff, and Brazil as the partner country. It will only be necessary to utilize one of the 3 countries as the baseline. One concern with this dataset is the amount of missing observations. After careful consideration and analysis of the data between Brazil and the 3 Mercosur countries, I choose to perform my analysis using Argentina as a baseline. This is due to two factors. Firstly, out of all the 3 countries, Argentina has the least amount of missing rows. For Argentina, 3478 out of 6000 observations are missing. Uruguay has 3960 missing, and Paraguay lacks all 1992 data. Secondly, Bustos (2014) has utilized a similar design for her research by using Brazil as a baseline for Argentina. This suggests that this choice is not only justified by the data quality but also aligns with established research methodologies. Using Argentina as a baseline provides a more reliable dataset compared to the alternatives and allows for a more consistent comparison with past studies, enhancing the credibility and comparability of the results.

For the product variable , I selected all 2 coded HS products available. For the time variable, I selected the years 1992 (right at the reduction of tariffs), 1993 and 1995 (when all tariffs lowered to 0 for all industries). All tariff data between Brazil and Argentina is missing for the year 19924. An ideal study would also consider possible lag effects and include further years for analysis. However, due to the nature of the historical events, tariffs started to go up again in the year of 1996, which indicates conflicting mechanisms happening for this and upcoming years. For this reason, I restricted my analysis for years between 1992 and 1995. For the tariff indicator variable, I select the weighted average of products. As a result, the final dataset utilized includes the weighted average of 2 HS digit products between Argentina and Brazil for the years of 1992, 1993 and 1994. There are a total of 91 industries tariffed that latter will have to be matched with the industries in the patent data.

3.2.2 Patent Data

The "Indicator" variable offers a choice between 'Patent publications by technology' and 'Patent grants by technology.' Because the time-frame of my research is somewhat short term, I opt to download data from ‘Patent publications'. For the ‘report type’ variable I downloaded data for 'Total count by filing office' and filtered the filing office to Brazil. For the 'years' variable, I incorporated data spanning years both preceding the establishment of Mercosur and the subsequent tariff reductions. This inclusive approach, covering the period from 1987 to 1995, aims to establish parallel trends before the tariff adjustments and to investigate the effects of interest. For the variable ‘Field of technology’ I include all fields. There are a total of 35 industry categories for the patent data.

3.2.3 Exports Data

I utilize gross exports in USD dollars from Argentina to Brazil for the year of 1993. Ideally, I would download exports data for all years in my dataset (1992, 1993 and 1995). Due to the scope of my research, I chose to simplify my analysis and use only exports in 1993, which is the first year of exports data for Argentina.

3.3 Data limitations

Regarding Tariff Data, there are notable data gaps. The entire year of 1991 has no available data, as well as the year of 1994. This restricts the analysis to only the years 1992, 1993 and 1995. Therefore, this could impact the significance of my results. Another potential limitation is related to how industries were categorized. The two main datasets categorize industries very differently. The tariff dataset, which is categorized into 91 two-digit HS (Harmonized System) industries, needs to be mapped onto the 35 broader categories used in the patent dataset. It's important to note that this mapping might not fully utilize all 35 patent industry categories if none of the two-digit HS categories correspond to certain patent industries. As an example, two (or likely more) of the tariff categories will fall in the same patent category. Thus, the final dataset averages the tariff reductions for the tariff industries' categories that fall in the same broader category from the patent data. However, this method introduces a potential variability in outcomes based on the chosen categorization scheme. The arbitrary nature of industry categorization could significantly influence the research findings. I address this by running the regression with different industry categorizations to test the validity of my results.

3.4 Data transformations

3.4.1 Merging categories

Due to the tariff data and the patent data having different industry categorizations, there was a need to match them so the final dataset could be achieved. To do this, I downloaded the 'category' columns from both the tariff and patent datasets and manually aligned them with each other. In my setup, each unique two-digit HS industry was matched with potentially multiple corresponding patent industries. Thus, I average the tariff reductions for the tariff industries' categories that fall in the same broader category from the patent data to form one unique row per category and per year. This is when I utilize the exports data from Argentina to perform a weighted average of the 2 HS products. I group by industry category and calculate the individual weight of each product, further applying a weighted average approach. To arrive in the final dataset, I match the datasets together to arrive at a table with 4 columns: tariff, year, industry and patent. I also choose to calculate the differences in patent filings between 1995 - 1993 and 1993 - 1992, and the differences in tariffs between the same years, thus adding two new columns in the dataset.

4 Empirical Strategies

The strategy centers on a difference-in-differences (DiD) framework, aiming to isolate the causal impact of tariff changes on patent filings in specific industries. It compares changes over time between industries with different levels of tariff reduction, accounting for industry fixed effects and time fixed effects to minimize time-invariant influences. The tariff reductions were programmed in 1991, and reached a level of zero for all industries in 1995. An important assumption is that this change was exogenous. I adopt a rationale akin to Bustos (2002) to support the exogeneity of tariff changes: since tariff adjustments are preset, they cannot be influenced by political influences stemming from the liberalization effects in Brazil or Argentina, nor by simultaneous shocks to industrial performance. Furthermore, since these changes align with Argentina's global trade policies, it's also improbable that the findings are influenced by Argentine tariffs being initially high in sectors where Brazil holds a comparative advantage. While the aforementioned points help mitigate concerns about reverse causality, it is important to note that Brazil's initial tariff framework is not arbitrary but shaped by specific industry characteristics. Ignoring these could introduce significant bias. Therefore, I also perform my analysis in first differences to eliminate the effects of constant industry traits.

Ideally, the implementation should be performed starting with the year of 1991 and continuing until 1995, with the possibility of extending the years to cover possible long-term effects of the tariff reduction. In my first analysis, I select only the years of 1992, 1993 and 1995 due to the fact that tariff data for the year of 1991 is unavailable, and tariffs went up again in 1996, which might disturb the rationale for long-term effects. The validity of the implementation also hinges on the crucial assumption of parallel trends. This assumption assumes that industry’s patent fillings were following a similar path prior to the implementation of the new tariff schedule, and that in the absence of the tariff reduction, they would continue on their original and alike paths, and thus any differences arising from the change in tariffs are assumed to be caused by the change in tariffs.

Table 1 shows how tariffs were reduced from their original levels in 1992 until 1995. This result is consistent with the approach utilized: tariffs were reduced differently between different industries, meaning that in industries where tariffs were not reduced by much, we expect patents to either remain the same level or reduce less than in other industries.

Table 1: Differences in tariff levels between 1995 and 1992 for different industries	
Industry	Tariff Reduction
1 - Electrical machinery, apparatus, energy	-14.58
2 - Audio-visual technology	-7.52
9 - Optics	-11.23
14 - Organic fine chemistry	-8.98
16 - Pharmaceuticals	-9.50
18 - Food chemistry	-5.24
20 - Materials, metallurgy	-14.29
23 - Chemical engineering	-11.11
24 - Environmental technology	-5.00
25 - Handling	-11.90
26 - Machine tools	-14.44
27 - Engines, pumps, turbines	-21.83
28 - Textile and paper machines	-14.94
30 - Thermal processes and apparatus	0.00
32 - Transport	-17.63
33 - Furniture, games	-19.47
34 - Other consumer goods	-12.20
35 - Civil engineering	-8.07
Note: This table shows the first industry categorization utilized in my research. This is to demonstrate the differences between tariff reductions across industries within this time-period.	

Table 2 offers a more comprehensive view of the shifts in tariff levels prior to their reductions, specifically between 1987 and 1992. Although the changes in patent filings do not uniformly follow the same direction (either increasing or decreasing) across all industries, there is a notable consistency in trend direction in most industries before the policy intervention.

Table 2 : Differences in patent fillings by industry between 1987 and 1992		
Field of Technology	**Level Difference**	**Percentage Differerence**
1 - Electrical machinery, apparatus, energy	-168	-37.25055432
2 - Audio-visual technology	12	9.160305344
9 - Optics	-31	-28.44036697
14 - Organic fine chemistry	-112	-26.79425837
16 - Pharmaceuticals	46	104.5454545
18 - Food chemistry	28	54.90196078
20 - Materials, metallurgy	-178	-39.55555556
23 - Chemical engineering	-102	-25.18518519
24 - Environmental technology	5	4.854368932
25 - Handling	-40	-10.28277635
26 - Machine tools	-90	-30
27 - Engines, pumps, turbines	-30	-12.24489796
28 - Textile and paper machines	-90	-26.62721893
30 - Thermal processes and apparatus	-4	-3.25203252
32 - Transport	-66	-15.98062954
33 - Furniture, games	4	1.403508772
34 - Other consumer goods	-112	-38.48797251
35 - Civil engineering	-40	-11.46131805

This baseline similarity suggests that any post-intervention differences in outcomes can more reliably be attributed to the policy change itself, rather than to pre-existing trends. Therefore, while further analysis might strengthen the case, the current evidence reasonably supports the parallel trends assumption necessary for a valid DiD analysis.

I firstly run my regression on absolute levels and include controls for both industry and time variables:

$$\text{Patents}_{it} = \beta_0 + \beta_1 \text{Tariff}_{it} + \beta_2 \text{Industry}_i + \beta_3 \text{Time}_t + \epsilon_{it}$$

Where "Patents_it" represents the total number of patents filed within a specific industry i at a given time t in Brazil, serving as a direct measure of innovative activity and technological output in that industry during the specified period. "Tariff_it" denotes the tariff level imposed on goods related to industry i at time t, which can influence the economic landscape by affecting prices, competition, and the incentive structure for innovation within the industry. "Industry_i" is a one-hot encoded variable that uniquely identifies each industry. In a one-hot encoding scheme, each industry is represented by a binary vector containing one '1' and the rest '0's, corresponding to the presence of a particular industry in the dataset, allowing models to handle categorical data effectively. Similarly, "Time_t" is a one-hot encoded variable representing the year t, capturing temporal variations and trends, allowing the analysis to adjust for time-specific effects that could influence the overall dynamics of the studied variables.

I then run my second regression with the following specifications, where I calculate everything in first differences to eliminate the effects of constant industry traits:

$$\text{PatentDifference}_{it} = \beta_0 + \beta_1 \text{TariffDifference}_{it} + \beta_2 \text{Industry}_i + \beta_3 \text{Time}_t$$

The variables follow a similar interpretation as the previous specification, where 'PatentDifference' and 'TariffDifference' are now the differences between the years in the dataset. More specifically, the difference between 1995 and 1993, and 1993 and 1992.

5 Empirical Results

5.1 Levels Regression

Table 3 presents the findings from my initial model specification, where I examine the relationship between patent filings and tariffs, while accounting for industry and time fixed effects. The model is based on a dataset comprising 54 observations, encompassing 18 industries across three years (1992, 1993, and 1995). To enhance the reliability of the estimates, the regression employs robust standard errors, which are clustered by industry. This approach is intended to address potential correlations and interactions within industries, thereby providing a more accurate reflection of the effects under study.

Table 3 Regressing tariff levels on patent levels			
	(1)		
VARIABLES	patent	Coefficient s	P>|t|
tariff	-1.047	1.859955	0.581
	(1.860)		
	-		
industry (omi	-		
1993	9.737		
	(6.376)		
1995	-2.480		
	(16.60)		
Constant	230.3***		
	(18.38)		
Observations	54	6.375947	0.145
R-squared	0.961	16.59893	0.883
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			
Notes: Clustering for industry, robust std			
Robust standard errors in parentheses			
Controls are added for both year and industry fixed effects			

The elevated R-squared of the model is expected due to the various controls added for robustness. The coefficient for tariff levels is -1.04662, suggesting that an increase in tariffs might lead to a decrease in patent filings, although this relationship is not statistically significant (p-value of 0.581). This lack of significance, along with the wide confidence interval ranging from about -4.97 to 2.88, indicates substantial uncertainty about the effect of tariffs on patent filings.

Regarding time effects, the year 1993 shows a positive but non-significant association with patent filings, suggesting a potential increase in patents during this year compared to the baseline year (p-value of 0.145). On the other hand, the year 1995 shows a negative association, also non-significant, which suggests a potential decrease in patent filings (p-value of 0.883). These results imply that while there might be some fluctuations in patent filings over time, these changes are not consistently significant across the years studied. To elaborate on this, I run a second regression using a first differences approach.

5.2 First Differences Regression

In expanding my analysis, I conducted a second regression using a first differences approach. This method focuses on the changes in the variables from one time period to the next, rather than the absolute levels of the variables themselves. By differencing the data, this approach effectively removes any influences from time-invariant characteristics—those aspects that do not change over time—within each industry. This is particularly useful in empirical research where the goal is to isolate the impact of specific policy changes or interventions, such as changes in tariff levels. Thus, the coefficients derived from this regression more accurately reflect the causal impact of changes in tariffs on patent filings, giving a clearer picture of the dynamic response of industries to policy changes. Table 4 refers to the results of this specification.

Table 4 Regressing tariff differences on patent differences

VARIABLES	patent difference
tariff difference	-3.099*
	(1.738)
	-
industry (omitted)	
	-
1995	-38.75**
	(15.88)
Constant	6.280
	(8.469)
Observations	36
R-squared	0.593

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Clustering for industries, robust std
Each regression corresponds to a different specification/categorization of industries
Controls are added for both industry and year fixed effects

The coefficient for tariff changes is -3.099228, suggesting a negative relationship between tariff increases and patent filings. While the p-value of 0.092 is close to the conventional threshold for statistical significance, it suggests that there is a potential economic mechanism where higher tariffs might discourage innovation. Economically, this could be explained by increased tariffs raising the cost of imported goods and materials, which are essential for research and development activities. Consequently, firms may have less incentive or ability to invest in innovative processes when facing higher import costs.The significant negative coefficient for the year 1995 (-38.7537 with a p-value of 0.026) indicates a distinct drop in patent filings compared to other years in the dataset. The findings indicate a nuanced relationship between tariffs and innovation. The 10% significance of the main coefficient of interest shows the negative impact of tariff increases on patent filings and underscores the potential economic implications of trade policies on a country's innovative output. This aligns with economic theories that posit that restrictive trade policies can hinder a firm's access to cutting-edge technologies and inputs, thus stifling innovation.

As previously noted, a significant limitation of this approach stems from the method of industry categorization. To address this, I conducted the same regression using three different versions of the dataset, each featuring a unique industry categorization. These variations are intended to serve as robustness checks to validate the consistency of my results. It is crucial to recognize that because each version categorizes industries differently, the total number of industries varies, consequently altering the number of observations in each dataset.

In table 5, I show the results of my original first differences regression, together with 3 new regressions that utilize different industry categorizations.

5.2.1 First Differences - multiple categorizations

Table 5 Regressing tariff differences on patent differences

	(1)	(2)	(3)	(4)
VARIABLES	patent difference	patent difference	patent difference	patent difference
tariff difference	-3.099*	-2.443	-2.126	-1.744
	(1.738)	(2.931)	(3.289)	(2.369)
	-	-	-	-
industry (omitted)				
	-	-	-	-
1995	-38.75**	-33.83	-41.30	-34.56
	(15.88)	(32.40)	(33.85)	(29.89)
Constant	6.280	5.529	8.898	8.212
	(8.469)	(14.05)	(14.99)	(10.46)
Observations	36	22	26	28
R-squared	0.593	0.612	0.575	0.584

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Clustering for industries, robust std
Each regression corresponds to a different specification/categorization of industries
Controls are added for both industry and year fixed effects

Across all four models, the relationship between tariff changes (tariff_diff) and patent filings (patent_diff) consistently exhibits a negative sign, suggesting that increases in tariffs are associated with decreases in patent filings. The coefficient in the first model is statistically significant at the 10% level, indicating a potentially genuine adverse effect of higher tariffs on innovation activities. However, this significance is not consistently observed in the alternative models, where the coefficients, though still negative, do not reach conventional levels of statistical significance. This variability suggests that while there may be a negative impact of tariffs on patent filings, the effect is sensitive to how industries are categorized and analyzed.

The coefficient for the specific year variable (year_n) in the first model is significant, indicating a substantial drop in patent filings during this period. This effect varies across the other models but remains negative, highlighting potential temporal influences or external economic factors impacting patent activities during that year. The presence of significant year effects underscores the importance of considering temporal dynamics when analyzing patent filings. The inclusion of different industry categorizations across the models results in variations in both the number of observations and the statistical robustness of the results. Despite these differences, the negative direction of the tariff impact remains consistent, lending some support to the initial findings. However, the fluctuating significance levels highlight the influence of industry classification on the analysis, suggesting that conclusions drawn from such models should be viewed with caution.

6 Robustness

Initially, my analysis utilized a dataset with a fixed industry categorization to assess how changes in tariffs affect patent filings. Recognizing the potential limitations inherent in any given method of industry classification, I expanded my analysis to include three additional models. Each of these models employs a unique industry categorization, thus varying the total number of industries and, consequently, the number of observations within each dataset. This approach allows us to test the sensitivity of our findings to changes in how industries are grouped and analyzed.

Across all models, the coefficient for tariff changes (tariff_diff) consistently exhibits a negative sign, suggesting a potential deterrent effect of increased tariffs on patent filings. This negative relationship is statistically significant at the 10% level in the original model, indicating a robust adverse effect of tariffs on innovation. However, this significance is not consistently observed across the alternative models, which, although still showing negative coefficients, do not reach conventional levels of statistical significance. A possible reason for the non-significance of the results is the low number of observations in the other 3 datasets. This would be addressed with an industry categorization that contains more industries, or by utilizing other years in the study, such as 1994.

7 Conclusion

Several economic theories link innovation and trade liberalization through multiple mechanisms. Melitz, Marc J’s "The Impact of Trade on Intra-Industry Reallocations and

Aggregate Industry Productivity" explores how trade liberalization forces firms to innovate to survive in more competitive markets. The model reveals that trade liberalization benefits more productive firms, leading to industry-wide productivity gains as resources shift towards these firms. This reallocation enhances overall economic welfare, offering a deeper understanding of globalization's impact on firm dynamics and economic outcomes.

Paul Krugman's paper "Scale Economies, Product Differentiation, and the Pattern of Trade" is a foundational work in New Trade Theory. It challenges traditional trade models by emphasizing the role of scale economies and product differentiation. Krugman argues that countries trade similar goods not just for resource differences but to exploit economies of scale and meet diverse consumer preferences, leading to increased welfare. This framework indirectly links to innovation by suggesting that economies of scale and market size can drive companies to innovate, thereby enhancing their competitiveness in domestic and international markets.

The results of my study underscore the complex relationship between tariff increases and innovation, as reflected in patent filings. Across all models, the regression analyses consistently revealed negative coefficients for tariff changes, reinforcing the proposed adverse link between higher tariffs and innovation. Specifically, the first model showed a statistically significant negative relationship at the 10% level, suggesting that tariff hikes may indeed dampen innovation activities. This finding points to the potential discouraging effect of increased tariffs on the innovative output.

However, in subsequent models, while the coefficients for tariff changes remained negative, they failed to reach statistical significance. This inconsistency underscores a nuanced interpretation of the data, suggesting that the impact of tariff changes on patent filings is influenced by varying industry classifications and may fluctuate over time. The initial strong negative relationship appears to be contingent on the specific categorization of industries, emphasizing the critical role of industry-specific dynamics in assessing the economic implications of trade policies.

Concluding that the decrease in tariffs directly led to a reduction in patent filings between 1992 and 1995 would be premature without significant results across all model specifications. Although the findings do not uniformly confirm a significant impact, they strongly suggest an underlying negative effect of tariffs on innovation. This highlights the need for further research and more detailed analysis to clarify these effects.

To extend this research, including additional data from the year 1994 might provide a more comprehensive view and potentially reveal more consistent results. Such an expansion of the dataset could enhance the robustness of the findings and offer deeper insights into the relationship between trade policies and innovation.

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Appendix:

Appendix 1: Industry Categorization - First specification

Category tariff	Corresponding category patent
01 -- LIVE ANIMALS	18 - Food chemistry
02 -- MEAT AND EDIBLE MEAT OF	18 - Food chemistry
03 -- FISH AND CRUSTACEANS, MC	18 - Food chemistry
04 -- DAIRY PRODUCE; BIRDS' EG(	18 - Food chemistry
05 -- PRODUCTS OF ANIMAL ORIG	18 - Food chemistry
06 -- LIVE TREES AND OTHER PLAI	24 - Environmental technology
07 -- EDIBLE VEGETABLES AND CE	18 - Food chemistry
08 -- EDIBLE FRUIT AND NUTS; PE	18 - Food chemistry
09 -- COFFEE, TEA, MATE AND SPI(	18 - Food chemistry
10 -- CEREALS	18 - Food chemistry
11 -- PRODUCTS OF THE MILLING	18 - Food chemistry
12 -- OIL SEEDS AND OLEAGINOU!	18 - Food chemistry
13 -- LAC; GUMS, RESINS AND OTI	14 - Organic fine chemistry
14 -- VEGETABLE PLAITING MATE	18 - Food chemistry
15 -- ANIMAL OR VEGETABLE FAT:	18 - Food chemistry
16 -- PREPARATIONS OF MEAT, OF	25 - Handling
17 -- SUGARS AND SUGAR CONFE(	18 - Food chemistry
18 -- COCOA AND COCOA PREPAR,	18 - Food chemistry
19 -- PREPARATIONS OF CEREALS,	18 - Food chemistry
20 -- PREPARATIONS OF VEGETAB	18 - Food chemistry
21 -- MISCELLANEOUS EDIBLE PRE	18 - Food chemistry
22 -- BEVERAGES, SPIRITS AND VII	18 - Food chemistry
23 -- RESIDUES AND WASTE FRON	34 - Other consumer goods
24 -- TOBACCO AND MANUFACTU	34 - Other consumer goods
25 -- SALT; SULPHUR; EARTHS ANI	35 - Civil engineering
26 -- ORES, SLAG AND ASH	20 - Materials, metallurgy
27 -- MINERAL FUELS, MINERAL O	30 - Thermal processes and apparatus
28 -- INORGANIC CHEMICALS; OR(	14 - Organic fine chemistry
29 -- ORGANIC CHEMICALS	14 - Organic fine chemistry
30 -- PHARMACEUTICAL PRODUC	16 - Pharmaceuticals
31 -- FERTILISERS	24 - Environmental technology
32 -- TANNING OR DYEING EXTRA	14 - Organic fine chemistry

33 -- ESSENTIAL OILS AND RESINO	14 - Organic fine chemistry
34 -- SOAP, ORGANIC SURFACE-/	14 - Organic fine chemistry
35 -- ALBUMINOIDAL SUBSTANCE	23 - Chemical engineering
36 -- EXPLOSIVES; PYROTECHNIC I	25 - Handling
37 -- PHOTOGRAPHIC OR CINEMA	2 - Audio-visual technology
38 -- MISCELLANEOUS CHEMICAL	14 - Organic fine chemistry
39 -- PLASTICS AND ARTICLES THE	25 - Handling
40 -- RUBBER AND ARTICLES THEI	25 - Handling
41 -- RAW HIDES AND SKINS (OTH	25 - Handling
42 -- ARTICLES OF LEATHER; SADD	34 - Other consumer goods
44 -- WOOD AND ARTICLES OF WC	35 - Civil engineering
45 -- CORK AND ARTICLES OF COR	35 - Civil engineering
46 -- MANUFACTURES OF STRAW,	20 - Materials, metallurgy
47 -- PULP OF WOOD OR OF OTHE	20 - Materials, metallurgy
48 -- PAPER AND PAPERBOARD; A	28 - Textile and paper machines
49 -- PRINTED BOOKS, NEWSPAPE	34 - Other consumer goods
50 -- SILK	34 - Other consumer goods
51 -- WOOL, FINE OR COARSE ANI	28 - Textile and paper machines
52 -- COTTON	28 - Textile and paper machines
53 -- OTHER VEGETABLE TEXTILE	28 - Textile and paper machines
54 -- MAN-MADE FILAMENTS; STF	28 - Textile and paper machines
55 -- MAN-MADE STAPLE FIBRES	28 - Textile and paper machines
56 -- WADDING, FELT AND NONW	28 - Textile and paper machines
57 -- CARPETS AND OTHER TEXTIL	28 - Textile and paper machines
58 -- SPECIAL WOVEN FABRICS; TL	28 - Textile and paper machines
59 -- IMPREGNATED, COATED, CO	28 - Textile and paper machines
60 -- KNITTED OR CROCHETED FAI	28 - Textile and paper machines
61 -- ARTICLES OF APPAREL AND (	28 - Textile and paper machines
62 -- ARTICLES OF APPAREL AND (	28 - Textile and paper machines
63 -- OTHER MADE-UP TEXTILE AI	28 - Textile and paper machines
64 -- FOOTWEAR, GAITERS AND TI	34 - Other consumer goods
65 -- HEADGEAR AND PARTS THEI	34 - Other consumer goods
66 -- UMBRELLAS, SUN UMBRELL/	34 - Other consumer goods

67 -- PREPARED FEATHERS AND D	34 - Other consumer goods
68 -- ARTICLES OF STONE, PLASTEI	35 - Civil engineering
69 -- CERAMIC PRODUCTS	20 - Materials, metallurgy
70 -- GLASS AND GLASSWARE	20 - Materials, metallurgy
71 -- NATURAL OR CULTURED PE/	20 - Materials, metallurgy
72 -- IRON AND STEEL	26 - Machine tools
73 -- ARTICLES OF IRON OR STEEL	26 - Machine tools
74 -- COPPER AND ARTICLES THER	20 - Materials, metallurgy
75 -- NICKEL AND ARTICLES THERI	20 - Materials, metallurgy
76 -- ALUMINIUM AND ARTICLES	20 - Materials, metallurgy
78 -- LEAD AND ARTICLES THEREC	20 - Materials, metallurgy
79 -- ZINC AND ARTICLES THEREO	20 - Materials, metallurgy
80 -- TIN AND ARTICLES THEREOF	20 - Materials, metallurgy
81 -- OTHER BASE METALS; CERM	20 - Materials, metallurgy
82 -- TOOLS, IMPLEMENTS, CUTLE	26 - Machine tools
83 -- MISCELLANEOUS ARTICLES C	20 - Materials, metallurgy
84 -- NUCLEAR REACTORS, BOILEF	26 - Machine tools
85 -- ELECTRICAL MACHINERY AN	1 - Electrical machinery, apparatus, energy
86 -- RAILWAY OR TRAMWAY LOC	32 - Transport
87 -- VEHICLES OTHER THAN RAIL	32 - Transport
88 -- AIRCRAFT, SPACECRAFT, ANE	32 - Transport
89 -- SHIPS, BOATS AND FLOATIN(	32 - Transport
90 -- OPTICAL, PHOTOGRAPHIC, CI	9 - Optics
91 -- CLOCKS AND WATCHES AND	33 - Furniture, games
92 -- MUSICAL INSTRUMENTS; PA	2 - Audio-visual technology
93 -- ARMS AND AMMUNITION; P	27 - Engines, pumps, turbines
94 -- FURNITURE; BEDDING, MAT	33 - Furniture, games
95 -- TOYS, GAMES AND SPORTS R	33 - Furniture, games
96 -- MISCELLANEOUS MANUFACT	34 - Other consumer goods

Appendix 2: Other specifications

This effort aimed to bridge the categorical disparities between two fundamentally different datasets, crucial for merging diverse data sources into a coherent framework for further research or application. The methods and considerations discussed reflect the complexities involved in synthesizing information across disciplines and data structures. Throughout this process, ChatGPT served as a tool to facilitate the identification of potential category matches and to assist in programming tasks related to data management and analysis. This work is part of my research for the final thesis, utilizing the insights and technical support provided in this consultation.

The following key steps were undertaken:

1. Matching Process: Initial examination involved aligning subsets of categories from the first dataset with the appropriate categories from the second dataset. For categories that were more general or lacked a clear direct counterpart, logical or potential connections were established based on broader industrial or technological implications.
2. Creation of Detailed Tables: Detailed tables were constructed to display the possible matches between the categories of the two datasets. These tables included notes on the nature of the relationships, whether direct or inferred, highlighting the need for sometimes broad interpretations due to the fundamental differences between the dataset focuses.
3. Handling of Multiple Potential Matches: For categories in the first dataset with more than one potential match in the second dataset, multiple options were provided. Additionally, random combinations of these matchings were generated to illustrate how different alignments could be configured.