Local economic and environmental externalities of Chinese-Australian bilateral trade flows

Impact on South Pacific Island Countries

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April 24th 2022

Mémoire majeur - Directeur : Guillaume DAUDIN

Abstract

This paper examines the local negative externalities of the China/Australia trade relationship on South Pacific Island countries (SPIC). Through a panel data fixed effects approach, the paper first finds that over the 2000-2019 period, a 1% increase in China-Australia trade volume leads to a decrease of 0.03% in GDP, with the effect mostly being due to Australian exports to China. With a counterfactual approach, we also find that the Chinese Australian Trade Agreement (CHAFTA) signed in 2015 has reduced regional GDP by about 1% over the period, caused a loss of SPIC shares in Chinese imports of 7-10% and a reduction in fishing yields of about 0.3%. These results are obtained via the analysis two channels through which the effects on GDP could have taken place : trade diversion and environmental externalities of transport. First, an analysis of the trade diversion channel finds that only about 10% of that effect can be explained through Australian competition, which means that most of the negative externalities from trade in the region must come from other sources. One of these channels could be the reduction in fishing yields due to transport, analyzed through a spatial autocorrelation model (SDM). The results show a strong direct effect between ship traffic and fishing yields reduction.

Introduction

This paper seeks to quantify the local negative externalities of the Australia/China trade relationship, as well as Australian trade more generally, on the South Pacific Island Countries (SPIC). Region or country-specific externalities have not been studied as much as global effects of international trade in the literature. These externalities are especially important in a region like the South Pacific that is massively dependant on international trade for its welfare (over 50% of regional GDP [33]).

SPIC, when taken together, constitute one of the poorest region in the world with a regional GDP of 21 Bn EUR in 2020 (1750 EUR/capita). The region includes 12 major countries : Papua New Guinea, Fiji, Solomon Islands, Vanuatu, Palau, Samoa, Tonga, Tuvalu, Kiribati, Marshall Islands, Micronesia and Cook Islands, as well as some overseas territories like American Samoa or New Caledonia.[1]

[1]This paper will only focus on sovereign nations as including overseas territories would likely bias the estimates considering the complex economic relationships they share with their home countries

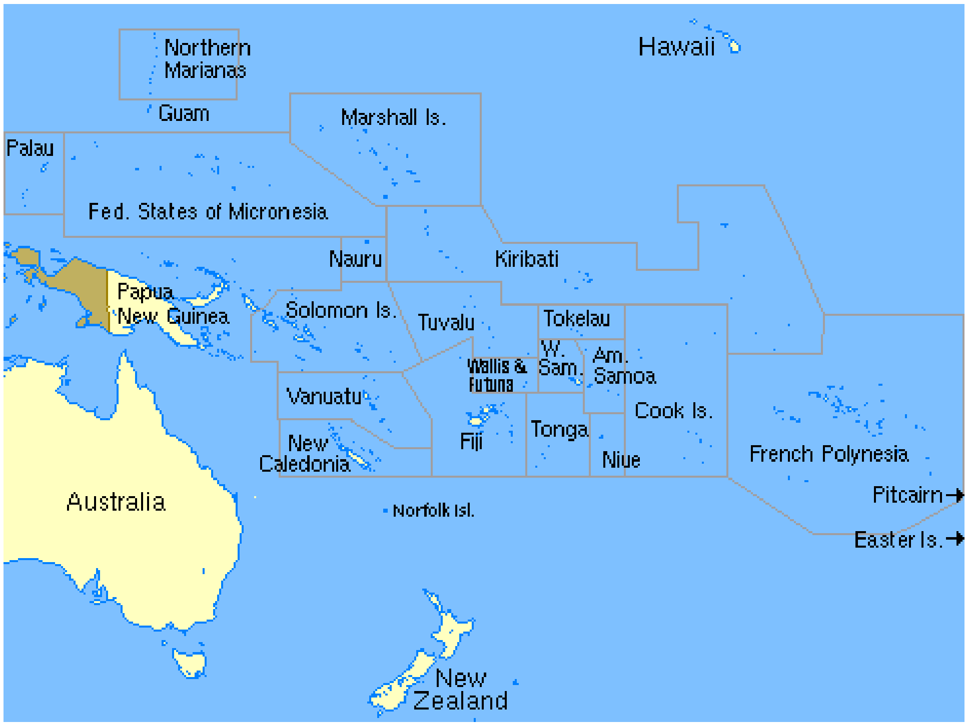


Figure 1: Map of the South Pacific region - Source : Pacific Islands Legal Information Institute [19]

International trade between Australia and its partners (mostly China) has also been growing rapidly in the past twenty years : Between 2000 (when China entered the WTO) and 2020, Australian exports to China have been multiplied by 38 in real terms, whereas Australian exports in general have only grown by a factor of 5. Imports have grown in similar proportions. China and Australia have both experienced massive economic growth since the turn of the millennium, which in turn bolstered their bilateral economic relationships. More specifically, the growing industry in China has led to a vast increase in demand for both iron and coal, that coincided with Australia's mining boom, a huge production shock specifically on these two resources. This bilateral relationship is by far the largest in the South Pacific : to give an order of magnitude, Australian exports to China in 2020 were 5 times higher than the GDP of every SPIC combined. This trend has been accelerated in 2015 when Australia and China signed the Chinese Australian Free Trade Agreement, which eliminated tariffs on most strategic goods exchanged between the two countries.

The depth of this relationship and its impacts on Australia and China have been discussed at length both in the literature (see for instance Collins, Sun and Li [24] for a supply-chain analysis of AUS/CN bilateral trade) and in the media [23], and the impact of the massive

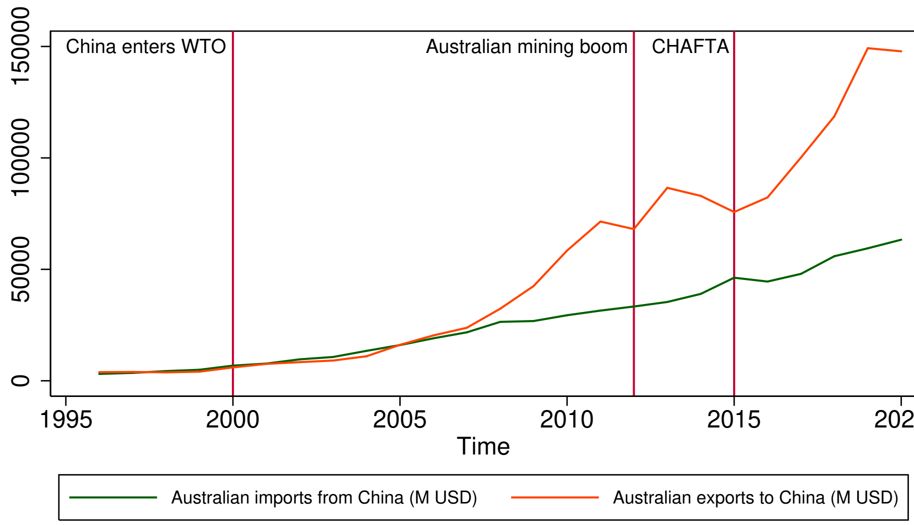


Figure 2: Evolution of China-Australia bilateral trade in goods (constant 2015 USD)

iron and coal exports from Australia on CO2 emissions has also been brought to light by several studies (like Wang, Zhao and Wiedmann [37]). These effects, both in terms of trade and environment, are computed on a global level and can therefore hardly be applied to any one country, which limits their policy use. Greenhouse gas emissions are by nature a long-term, global phenomenon, and while reports like the Stern Review [29] discuss their economic impact, these are not applied to any one country on region in the short-run. Furthermore, to this day, there is no quantification of how much Australian/China trade costs with its externalities to a specific region like the South Pacific.

While providing an exact answer to the quantification question is beyond the scope of this paper, it will try to contribute to it by providing partial elements on the local externalities of both the China/Australia trade relationship and more specifically the CHAFTA. The goal is to establish partial effects on SPIC GDP through the channels of international trade diversion and reduced fishing yields due to biodiversity loss. This endeavour contributes to the literature in three ways : i/ It starts to create a frame through which local externality effects of bilateral trade can be studied in general, not just in the South Pacific, ii/ It analyses general equilibrium effects of CHAFTA using a PPML approach, which, to our knowledge, has not yet been done in the literature on actual trade data (only previsions can be found in Qi and Zhang [35] on 2011 data). These effects on Australia/China bilateral trade are then used to assess the local externalities in the South Pacific through the trade diversion channel. iii/ It contributes to a political discussion on compensation mechanisms for international trade by providing evidence of the negative effects it can have on surrounding countries.

This paper is constructed with a dual economic and environmental approach. Section 1 provides a global literature review on the study of international trade and its externalities, section 2 focuses on the overall effect of bilateral trade on SPIC GDP, while sections 3 and 4 identify two specific channels through which this effect can be understood : trade diversion and reduction in fishing yields. Finally, a discussion on the political implications of these findings is provided in the conclusion.

1 Literature review

1.1 International trade and externalities

The externalities of bilateral trade (both economic and environmental) have been extensively studied in the literature, albeit with a systematic global approach rather than a country-specific one. On the economic side, two approaches have been mainly employed in the past few decades : a micro-economic, tariff-based approach (i) and a macro-economic, equilibrium-based approach (ii).

(i) Micro-economic models of trade externalities tend to look at the welfare impact of bilateral trade within the countries engaged in the relationship. More specifically, authors like Choi [8], Limao and Saggi [22], and Fujiwara [10] have explored the impact of lowering tariffs (and therefore increasing trade) on industrial networks within the affected countries. The main variables contributing to either losses or gains in welfare are traditionally industry and firm sizes, state of technology, costs of trade, etc. These models are then integrated into a game theory framework to inform whether countries have an interest in lowering tariffs and improve their bilateral relationship. Unsurprisingly in this side of the literature, the answer seems to always be a resounding yes with trade being seen as a positive-sum game for all actors in the countries, including consumers who do not actively participate in trade. Assuming low transaction costs, the negative externalities that might arise and cause losses for certain countries can therefore easily be fixed through a Coasean game of transfers from the winners to the losers [32].

(ii) Macro-economic models, especially in recent years, usually adopt a general equilibrium approach to studying externalities of trade derived from the gravity framework. In this framework, developed in the last decades by Eaton and Kortum [17], Anderson and Van Wincoop [16], Eaton et al. [15] or Melitz [20], among others, bilateral trade is viewed as a function of bilateral costs. From these frameworks, several predictions on micro-economic and welfare variables can then be derived. Compared to the micro-economic models, this approach has the advantage of predicting welfare and trade effects on countries that are not part of the bilateral relationship. Examples of applications in recent years include counterfactual analyses on various trade shocks such as WTO membership (Felbermayr et al. [34]) or the US-China trade war (Li et al. [36]). Just like in the micro-economic approach, on both these studies, trade is seen to have a positive relationship with welfare both in general and for the countries that engage in it (tariff wars influence negatively US and China welfare for instance). However, results differ when it comes to externalities, where some countries, most notably the smaller ones, will benefit from dwindling trade relationships between giants. The most commonly cited and observed reason for this outcome is trade diversion : the bilateral cost-reduction from a positive trade shock between two countries will lead to these countries trading more with each other and less with the rest of the world, although the trade creation effect is usually stronger, which explains the general positive relationship between trade and welfare globally.

Absent from these analyses are the environmental effects, since these are seen as much harder to quantify. While the macro-economic approach allows for the quantification of welfare effects on the whole, both in the short- and long-run, they neglect the effects stemming from environmental causes. There is a side of the literature that specifically looks at the environmental externalities of trade, but they tend to do so through a long-term, global approach by looking at CO2 emissions, which means that the conversion from environmental impacts to welfare losses is almost impossible to infer from these results. Examples of studies on the CO2-trade liberalization relationship are plentiful and contradictory : some like Sbia et al. [13] find that trade liberalization leads to decreased levels of CO2 emissions, whereas Rasoulinezhad and Saboori [26] find a positive relationship between CO2 emissions and openness. Channels explaining the former include technology improvements and economic growth, which, in a Kuznets framework, would lead to decreased pollution once a specific threshold of development is reached. Channels for the latter mostly encompass increased transportation, as well as a less efficient sharing of production when it comes to environmental outcomes (goods are produced in developing countries with less environmental regulation than the importing countries). On the other side of the equation, while some of these papers infer relationship between economic growth and CO2 emissions, they do not distinguish CO2 sources and how a specific economic activity can impact growth through its CO2 emissions. Furthermore, the economic impacts of CO2 are not disentangled between actual productivity losses and policy responses. This is not to say that this relationship has never been studied : Authors like Raffin and Seegmuller [27] or Dechezleprêtre et al. [28] use air pollution (PM concentrations) as proxy variables for emissions to show that they indeed have an impact on economic growth. For the former paper, the result found is massive: a 10% increase in PM concentration would lead to a reduction in GDP growth of 0.8% in the EU. However, it is not clear whether these results are a direct effect of air pollution, or a consequence of the policy response to it (which would necessarily hinder growth by restricting polluting economic activities).

The next sections of this paper covers some of the limits pointed in this literature review. Section 2 addresses the lack of estimates on recent trade data of the CHAFTA's general equilibrium impact in the South Pacific, section 3 refines this analysis by estimating the impact of the trade diversion channel, and section 4 uses fishing yields as a way to quantify the local environmental impacts of Australian trade, deviating from the CO2 analysis seen earlier.

1.2 General equilibrium impacts of the Chinese-Australian trade on SPIC

To our knowledge, the subject of Australia's and China's trade relationship and its impact on third countries has been remarkably scarcely studied. Nonetheless, there have been mentions in a few studies, although none of them were specifically looking at the problem. A study by Qi and Zhang [35] performed a general equilibrium analysis of the Chinese-Australian Trade Agreement on trade and welfare using a PPML regression and an expanded gravity model, and generally found negative, albeit very weak, impacts of the FTA on exports and industrial output in South East Asia and the Pacific. It is important to note that these results are derived from a counterfactual analysis using 2007 and 2011 data. In section 3 we will perform a similar analysis using more recent data. Another study by Timsina and Culas [9] analyses the impact of Australian trade agreements on agricultural trade and finds that CHAFTA has had a net creation effect on agricultural trade in the world, although some countries might lose SPIC are not singled out.

1.3 Shipping, trade and marine life

As seen previously, most of the literature on trade and the environment focuses on CO2 emissions which makes it hard to convert these effects into tangible economic impacts. The greenhouse effect, by definition, is a long-term and global phenomenon and attempts at quantifying exactly how much it impacts a specific countries are likely to result in insignificant results. However, pollution from trade also has many local impacts, especially in marine regions like the South Pacific. Shipping in particular has taken center place in many studies for its impacts on biodiversity. Some studies by Galil et al. [11] and Katsavenis et al. [6] show that the introduction of invasive species (transported on the shipping vessels) can lead to catastrophic implications in the long-run, however these impacts are a lot harder to spot in the short-run. Walter et al. [1] provide an overview of the different effects of marine transportation on fish ecosystems. They identify noise pollution and collision as the two biggest factors. Oil spills come third, and pollution from normal operation (CO2 emissions and waste emitted in the ocean) does not seem to play a major role. This information is critical as it shows that path-finding and route optimization are viable solutions to alleviate the issues surrounding trade and biodiversity.

All these studies do not offer a quantification of the effects of marine transportation, merely an explanation of the channels. Furthermore, they focus either on the Atlantic Ocean on the Mediterranean Sea. To our knowledge, there are no publicly available studies specifically on the effect of marine transportation on fish biodiversity or fishing yields in general.

2 Bilateral China-Australia trade and SPIC GDP

This section provides general estimation results of the effect of bilateral trade between China and Australia on welfare in the South Pacific, while the various channels through which this impact could take place will be analyzed in later sections. A panel data approach is first used to compute the bidirectional effects of Australia/China trade on SPIC GDP, followed by a robustness check by changing the outcome variables, and a counterfactual analysis of CHAFTA using the PPML framework,

Table 1: Summary statistics for section 1

	mean	p50	min	max	sd
GDP of SPIC countries	2.12e+09	3.66e+08	2.71e+07	2.47e+10	4.73e+09
Value added derived from agriculture (USD)	4.78e+08	7.08e+07	2452498	4.30e+09	1.11e+09
Value added derived from industry (USD)	7.42e+08	2.86e+07	1578922	9.07e+09	1.84e+09
Value added derived from services (USD)	1.16e+09	2.01e+08	1.95e+07	1.03e+10	2.27e+09
Sum of bilateral relationship between Australia and China	7.58e+07	7.34e+07	8354204	1.64e+08	5.13e+07
Exports from Australia to China (K USD)	4.68e+07	4.39e+07	3702288	1.11e+08	3.53e+07
Imports from China to Australia (K USD)	2.90e+07	3.04e+07	4651916	5.30e+07	1.63e+07
Share of Chinese imports in Australia	.1655846	.1733339	.0714304	.2566492	.0548057
Shares of Australian imports in China	.0317187	.0361336	.0147079	.0536504	.0128
Observations	240				

2.1 Data and descriptive statistics

For this section, the macroeconomic and trade data has been collected for 12 SPIC between 2000 and 2019 : Papua New Guinea, Fiji, Solomon Island, Palau, Samoa, Tonga, Tuvalu, Northern Marianna, Nauru, Micronesia, Kiribati and Marshall Islands.
Macroeconomic data (GDP and sectoral value added) come from the World Bank World Development Indicators databank [3], trade data for both the main and the counterfactual analyses has been collected using the CHELEM database hosted on DBnomics [7] by CEPII. Both the data sources are freely available online. Summary statistics for all these variables are provided in table 1.

Of note from these descriptive statistics is the heterogeneity of SPIC countries when it comes to GDP. While all the countries from the sample are classified as lower-income countries, their populations vary massively with Papua New Guinea having over 11 M inhabitants while Nauru only has 10 000. This heterogeneity confirms the need for fixed effects in the model, as well as the potential presence of heteroskedasticity, which is taken into account by using robust estimates.

2.2 Main results

In order to analyze the impact of bilateral trade between Australia and China on GDP, we have selected a panel data approach. This strategy allows for the inclusion of time-and spatial fixed effects, as well as different controls such as the value added intensities in the main sectors of the economy. We use log transformations to calculate elasticities, as is consistent with the literature on international trade. The main model can be written as follows :

$$ln(SPICWELFARE_{it}) = \alpha + \beta ln(AUSCNTRADE_t) + \theta_1 X_{it} + u_i + u_t + \epsilon_{it} \quad (1)$$

Where $SPICWELFARE_{it}$ is a welfare indicator of a SPIC country i in year t (total GDP in a first regression, then VA for each major sector), $AUSCNTRADE_t$ are bilateral trade flows in volume (constant 2015 USD), Xit is a vector of time- and space-varying control variables (SPIC value added in different industries and GDP when it is not the outcome variable), u_i u_t are spatial and temporal fixed effects, and ϵ_{it} is the error term.

We then disaggregate the explanatory variable to estimate whether the direction of flows matters :

$$\begin{aligned} ln(SPICWELFARE_{it}) = \alpha + \beta_1 ln(AUSexports_t) + \beta_2 ln(AUSimports_t) \\ + \theta_1 X_{it} + u_i + u_t + \epsilon_{it} \end{aligned} \quad (2)$$

Where $AUSexports_t$ and $AUSimports_t$ are respectively the shares of Australian exports in Chinese imports and the shares of Chinese exports in Australian imports.

The results of the estimation from equation (1) are presented in table 2. Total trade volume between Australia and China has a significant negative impact on SPIC GDP : for every 1% increase in trade volume, SPIC GDP goes down by 0.03%. More importantly, this effect seems to only be significant on the primary sector, where it triples, meaning that the elasticity of trade to value added is almost 0.1. The bilateral relationship also seems to have negative effects on the other sectors, although these are not significant.

Table 3 shows the results of equation (2) where direction of trade and economy shocks are taken into account through the use of share. Unsurprisingly, Australian shares in Chinese imports seem to have the most impact on GDP (both in terms of level and significance) : A 1% increase of Australian shares in Chinese imports leads to a 0.075% decrease in SPIC GDP. However, a smaller impact of Chinese shares in Australia in also reported, which suggests that the effect goes both ways (a 1% increase in Chinese shares in Australia reduces SPIC GDP by 0.049%). While the impact on agriculture is still there, it is far less significant which

Table 2: Main regression results for section 1 (equation 1)

VARIABLES	(1) Trade on GDP	(2) Trade on agriculture	(3) Trade on industry	(4) Trade on services
Total trade between China and Australia (ln)	-0.037***	-0.091**	-0.027	-0.034
	(0.008)	(0.040)	(0.059)	(0.035)
VA of agriculture (ln)	0.091***		0.406***	-0.280***
	(0.016)		(0.110)	(0.063)
VA of industry (ln)	0.096***	0.187***		0.096**
	(0.011)	(0.051)		(0.045)
VA of services (ln)	0.502***	-0.377***	0.283**	
	(0.018)	(0.085)	(0.132)	
Observations	179	179	179	179
R-squared	0.943	0.346	0.117	0.530
Number of w_id	10	10	10	10
Time FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

might be explained by the increased noise from separating imports and exports.

2.3 Robustness: Population shocks

While initial differences in country size are included in the country-fixed effects, these do not account for unilateral population shocks that might occur in the region. Especially in the South Pacific where migration crises and natural disasters are a frequent occurrence, it might therefore be reasonable to perform the regressions using an outcome resistant to these shocks : GDP per capita. Table 4 presents the results of both regressions with GDP per capita and VA per capita as outcomes.

Changing the outcome does not affect the results significantly. Total trade effects are still highly significant for GDP per capita and agriculture per capita (even more so than in the base regression with elasticities of 0.055 and 0.103 respectively). In terms of direction of trade, both directions strongly affect GDP per capita negatively, but this time imports from China to Australia seem to have a bigger effect. This is further verified in column 6 where only Chinese imports in Australia seem to have a strong negative and significant effect.

Table 3: Supplementary regression results for section 1 (equation 2)

VARIABLES	(1) Trade on GDP	(2) Trade on agriculture	(3) Trade on industry	(4) Trade on services
Shares of Australia in Chinese imports (ln)	-0.075***	-0.115	0.069	-0.086
	(0.015)	(0.077)	(0.114)	(0.067)
Share of Chinese imports in Australia (ln)	-0.049*	-0.234*	-0.279	0.022
	(0.028)	(0.140)	(0.206)	(0.121)
VA of agriculture (ln)	0.091***		0.398***	-0.276***
	(0.015)		(0.110)	(0.064)
VA of industry (ln)	0.098***	0.185***		0.101**
	(0.010)	(0.051)		(0.045)
VA of services (ln)	0.500***	-0.373***	0.294**	
	(0.018)	(0.086)	(0.131)	
Observations	179	179	179	179
R-squared	0.945	0.347	0.128	0.532
Number of w_id	10	10	10	10
Time FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

These results might be counter-intuitive, but can be explained by the labour mobility programs put in place in the region by Australia. These programs are aimed at encouraging short-term migration of agricultural workers in Australia, which would both increase Australian agricultural output and reduce population in SPIC (increasing agricultural value/capita). If such programs have a significant impact, then the competition of Australian agricultural exports when population is taken into account might be underestimated. Unfortunately there does not seem to be reliable per-country/year data on the extent of these programs readily available to test this hypothethis. While this section has proven that population shocks do not provide a significant bias to our estimations, for the rest of this paper, including the counterfactual analysis, we will stick to aggregate measures of value added.

2.4 Counterfactual analysis

Finally, we establish a counterfactual scenario : the CHAFTA has never been signed. We calculate the impact of these events on Chinese-Australian trade using an augmented gravity framework and a PPML estimation (without intra-national trade), as described in Yotov et al. [21]. We first estimate trade between Australia and China using the augmented gravity

Table 4: Robustness results for equations 1 and 2 with the dependant variables normalized by population

VARIABLES	(1) Trade on GDP	(2) Trade on agriculture	(3) Trade on industry	(4) Trade on services	(5) Trade on GDP	(6) Trade on agriculture	(7) Trade on industry	(8) Trade on services
Total trade between China and Australia (ln)	-0.055***	-0.103***	-0.043	-0.044				
	(0.012)	(0.038)	(0.055)	(0.028)				
Shares of Australia in Chinese imports (ln)					-0.081***	-0.114	0.057	-0.074
					(0.023)	(0.074)	(0.106)	(0.055)
Share of Chinese imports in Australia (ln)					-0.115***	-0.285**	-0.321*	-0.048
					(0.042)	(0.134)	(0.191)	(0.099)
VA of agriculture (ln)	0.030		0.311***	-0.281***	0.030		0.304***	-0.279***
	(0.023)		(0.102)	(0.052)	(0.023)		(0.102)	(0.052)
VA of industry (ln)	0.013	0.092*		-0.007	0.014	0.089*		-0.005
	(0.016)	(0.049)		(0.037)	(0.016)	(0.049)		(0.037)
VA of services (ln)	0.288***	-0.569***	0.045		0.288***	-0.563***	0.057	
	(0.027)	(0.082)	(0.122)		(0.027)	(0.082)	(0.121)	
Observations	179	179	179	179	179	179	179	179
R-squared	0.723	0.305	0.065	0.480	0.723	0.306	0.079	0.479
Number of w_id	10	10	10	10	10	10	10	10
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

framework :

$$trade_{ijt} = exp[ln(\alpha_0)+\beta_1 ln(GDP_{ijt})+\beta_2 ln(d_{ij})+\beta_3 ln(RTA_{ijt}+ln(R_{ij}+ln(Year_t)+\epsilon_{ijt}] \quad (3)$$

Where $trade_{ijt}$ is the trade relationship in volume between two countries, d_{ij} is the distance between the centroids of two countries, RTA is a dummy for the signature of an RTA (including CHAFTA), R_{ij} is the multilateral resistance term represented by pair fixed effetcts, and $Year_t$ is the year fixed effect.

From this equation, we predict $\widehat{share}_{AUSCN}$ and $\widehat{share}_{CNAUS}$, respectively the shares of Australia in Chinese imports and the share of China in Australian imports. The next step is to constrain the RTA variable and have it take the value 0 for Australia and China after 2015, then, using equation (3), calculate new predictions for bilateral shares : $\widehat{\widehat{share}}_{AUSCN}$ and $\widehat{\widehat{share}}_{CNAUS}$. Using these new predictions, we perform a means t-test :

$$\widehat{share}_{AUSCN} - \widehat{\widehat{share}}_{AUSCN} \quad (4)$$

$$\widehat{share}_{CNAUS} - \widehat{\widehat{share}}_{CNAUS} \quad (5)$$

We apply the differences found in equations 4 and 5 to $AUSexports_t$ and $AUSimports_t$ from equation (2), and, using their respective coefficients, compute a GDP difference for SPIC countries. To ensure that we take into account anticipation effects, the impact of the CHAFTA on GDP is calculated as a mean on the whole period, not just the years after it has been signed.

The counterfactual scenario provides estimations of the effect of the CHAFTA on SPIC GDP using first an augmented gravity framework to obtain estimates on trade, then the estimations developed in this paper to apply these estimates to welfare (as described in section 2.1). Table 5 presents the coefficients for the PPML estimation (equation 3) using the log of trade (real terms), while table 6 provides the ttest estimates for $\widehat{share}_{AUSCN}$, $\widehat{share}_{CNAUS}$, $\widehat{\widehat{share}}_{AUSCN}$ and $\widehat{\widehat{share}}_{CNAUS}$. Over the entire period, the RTA has had a significant positive effect on the trade relationship between Australia and China. The effects found are consistent with these found by Qi and Zhang [35], albeit slightly lower, which

Table 5: PPML general equilibrium regression with multilateral resistance term. Dependant variable : bilateral trade volumes

VARIABLES	(1) Trade with RTA	(2) Trade with no RTA
ln_DIST	-0.756***	-0.759***
	(0.028)	(0.028)
Exporter WTO membership	0.307***	0.308***
	(0.059)	(0.059)
Importer WTO membership	0.270***	0.271***
	(0.046)	(0.046)
Regional Trade Agreements (source: WTO)	0.420***	0.409***
	(0.054)	(0.056)
Observations	546,398	546,398
Exporter x Year FE	Yes	Yes
Importer x Year FE	Yes	Yes
Pseudo R^2	0.923	0.923
Number of pairs	37505	37505

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

might be due to the fact that Qi and Zhang estimated the effect on 2011 data, whereas we do it using data including 3 years after the signature of CHAFTA.

The final step of the counterfactual analysis is simply to apply the differences to the estimation of equation (2) on GDP. Doing so yields the following results : Through its effect on bilateral Australia-Chinese trade, CHAFTA has reduced SPIC regional GDP over the 2000-2019 period by 0.917% ($((0.075*0.07)+(0.049*0.08))*100$). Assuming most of these effects take place after the CHAFTA has been signed, this means that over the 4 years (2016-2019), growth in the South Pacific has been reduced by 8% (total cumulated multiplicative growth rate of 12% over the 4 years according to the World Bank [3].

Table 6: Ttest for the predicted trade shares of Australia and China with and without RTA

VARIABLES	Obs	Mean	se
$\widehat{share}_{AUSCN}$	240	-3.91	0.01
$\widehat{\widehat{share}}_{AUSCN}$	240	-3.99	0.01
Diff	240	0.08***	0.16
$\widehat{share}_{CNAUS}$	240	-1.84	0.02
$\widehat{\widehat{share}}_{CNAUS}$	240	-1.91	0.02
Diff	240	0.07***	0.01

3 Channel n°1 : Trade diversion

The next two sections of this paper will focus on analyzing specific channels through which the results of section 2 can be explained. In section 3, we focus on the trade diversion mechanism : the intuition is that Australian exports to China generate competition that hurt SPIC exports, and therefore reduces their GDP. We first use panel data analysis to provide estimates of how Australian shares in Chinese imports impact SPIC shares in Chinese imports, then link this loss of market share to GDP. Finally we perform a similar counterfactual analysis as in section 2.4. to estimate the effect of CHAFTA on GDP through the trade diversion channel.

3.1 Data and descriptive statistics

The data used in this section is the same as in section 2, with one notable exception : The Northern Mariana Islands have been taken out of the sample due to the fact that they have no trade relationship with China whatsoever during the period. The exact reason is unknown, seeing as even countries that recognize Taiwan (Tuvalu, Nauru, Palau), as well as the Marshall Islands (which are also a US commonwealth nation) still have a trade relationship with China. Table 8 shows the key statistics for the reduced sample (as described in section 3.1 : Fiji, Papua New Guinea, Samoa, Solomon Islands and Tonga).

Table 7: Summary statistics for section 2

	mean	p50	min	max	sd
GDP of SPIC countries	4.04e+09	1.08e+09	3.60e+08	2.47e+10	6.09e+09
Value added derived from agriculture (USD)	9.87e+08	2.67e+08	6.03e+07	4.30e+09	1.47e+09
Value added derived from industry (USD)	1.64e+09	4.19e+08	5.98e+07	9.07e+09	2.48e+09
Value added derived from services (USD)	2.43e+09	1.22e+09	1.79e+08	1.03e+10	2.95e+09
Share of Chinese imports in Australia	.1655846	.1733339	.0714304	.2566492	.0549207
Shares of Australia in Chinese imports	.0317187	.0361336	.0147079	.0536504	.0128269
Shares of Spic country in Chinese imports	1.33e-07	1.94e-09	0	1.36e-06	2.61e-07
Iron price (USD/t)	82.8825	70.75583	28.79	167.7542	44.08439
Observations	120				

3.2 Base estimations with full and reduced sample

We use the same panel data approach as in section 2.2. to analyze the trade diversion effects. This time, the first step consists in regressing trade shares of Australian imports in China on trade shares of SPIC imports in China :

$$ln(SPICTRADESHARE_{it}) = \alpha + \beta ln(AUSTRADESHARE_t) + \theta_1 X_{it} + u_i + u_t + \epsilon_{it} \quad (6)$$

Where $SPICTRADESHARE_{it}$ and $AUSTRADESHARE_t$ are respectively the exporting trade shares of SPIC countries and Australia in Chinese imports.

This regression is first tested on the full sample of countries, then on a reduced sample comprised of countries with similar export structures to Australia (meaning mostly mining commodities and wood). The 5 selected countries for the reduced sample are : Fiji, Papua New Guinea, Samoa, Solomon Islands and Tonga. In addition to being the country most exposed to Australian competition, they also make up most of the GDP and population of the region, and therefore reduce noise in the estimation.

The second step consists in making sure that the reduction in market shares in China leads to an actual GDP loss, and not just a recomposition of exports towards other countries. We therefore regress SPIC trade shares in China on GDP (again in the full and reduced samples). The reason GDP is selected over SPIC exports is because SPIC trade is highly volatile and

Table 8: Main regression results for section 2

VARIABLES	(1) Shares in China full sample	(2) Shares in China reduced sample	(3) GDP full sample	(4) GDP reduced sample
Shares of Australia in Chinese imports (ln)	-0.678	-1.585**		
	(0.933)	(0.674)		
Shares of Spic country in Chinese imports (ln)			-0.003	0.015*
			(0.004)	(0.009)
GDP (ln)	-0.904	1.842		
	(1.326)	(1.211)		
Observations	187	97	187	97
R-squared	0.195	0.168	0.607	0.787
Number of w_id	11	5	11	5
Time FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

impacted by many political variables that would be hard to control for (political relationship with China for instance). Using the results from equation 6 and 7, we finally compute the full effect, including substitution, of Australian exports to China on SPIC GDP.

$$ln(SPICGDP_{it}) = \alpha + \beta ln(SPICTRADESHARE_{it}) + \theta_1 X_{it} + u_i + u_t + \epsilon_{it} \tag{7}$$

Table 8 shows the results of the base estimations with the full and reduced samples. Columns 1 and 2 express the coefficients of equation (6), while columns 3 and 4 the ones from equation (7). The intuition that the sample is affected differently depending on its export structure seems to be verified. While there is no significant effect in the full sample, in the reduced sample an increase in 1% in Australian shares leads to a decrease of 1.6% in SPIC shares in Chinese imports. On the GDP side, while there seems to be almost no effect for the full sample, a reduction by 1% in Chinese shares seems to lead to a decrease 0.015% in GDP for the reduced sample. This means that whenever Australia gains 1% in Chinese import shares, countries in the reduced sample lose an average 0.024% of GDP through the trade channel alone. In 2019, this corresponds to about 2 M USD.

Furthermore, these results can be used to compute a substitution effect. In 2019, total exports from Australia to China amounted to 100 Bn USD, whereas combined exports to China in the reduced sample totalled 2.3 Bn USD. With the estimation results, this means that an increase in Australian exports to China by 1 bn USD leads to a loss in SPIC exports to China of 37 M USD. This effect is stronger than expected : assuming an increase in Chinese imports of Australian products leads to a proportional substitution effect, this means that a 1 bn USD increase should lead to a decrease in imports from SPIC countries of 23 M USD (1%). The fact that the effect is higher than the proportional substitution means that Australian and SPIC exports to China are close substitutes, which explains the welfare effect through the trade deflection channel.

3.3 IV estimations with full and reduced sample

One worry is that these estimations as specified might lead to reverse causality issues : Australia might increase its exports to China because of an external negative shock to SPIC productivity in the primary and secondary sectors. With natural disasters being so prevalent in the South Pacific, this option is far from being unrealistic. To account for this possibility, an instrumental variable approach is used as a robustness check. We use global iron prices to predict Australian trade shares in China (equation 8), then use the predicted trade shares to compute their effect on SPIC trade shares (equation 9).

$$ln(AUSTRA\widehat{DE}SHARE_t) = \alpha + \beta ln(iron_t) + \epsilon_{it} \tag{8}$$

$$ln(SPICTRADESHARE_{it}) = \alpha + \beta ln(AUSTRA\widehat{DE}SHARE_t) + \theta_1 X_{it} + u_i + u_t + \epsilon_{it} \tag{9}$$

Iron prices are one of the key drivers of Australian exports to China. In 2019, iron ore made up 62% of total exports to China. They are also completely exogenous to SPIC economies and exports for two reasons : First, none of the SPIC countries in our sample produce or export any iron, and second, the industrial, iron-consuming sectors are very poorly developed in the region. In Papua New Guinea, the most industralized SPIC, industrial exports make up less than 1% of total exports, being vastly supplanted by gas, copper and gold (which combined make up 60% of exports). There are two effects expected from a reduction in iron prices. First, a trade diversion effect: when iron prices go down, China should reduce its

Table 9: Effect of iron price on Australian shares in China for both samples

VARIABLES	(1) Shares in China full sample	(2) Shares in China reduced sample
Iron prices in USD (ln)	-0.581*	-0.434*
	(0.308)	(0.224)
Time	0.199***	0.079***
	(0.030)	(0.022)
Observations	187	97
R-squared	0.207	0.124
Number of w_id	11	5
Time FE	Yes	Yes
Country FE	Yes	Yes

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

imports of SPIC commodities and import more from Australia. Second, a revenue effect : China being richer from lower input prices means it could increase its imports altogether. As an additional reassurance, we provide in table 9 the regression results of iron prices on SPIC China shares on the full and reduced samples, and show that this is indeed the result. Both estimations yield mildly significant negative coefficients, as expected.

Table 10 shows the result of the IV estimation presented in section 3.1. for both samples, with the first step in column 1. With the IV, the negative effect of Australian shares actually becomes significant and stronger on the full sample than the reduced sample. This means that this strategy has brought to light a bias affecting the full sample downwards and the reduced sample upwards. Considering the main difference between the two samples is the export composition (mostly fishing products for the countries not included in the reduced sample, and mostly commodities for the countries in the reduced sample), it is not clear what such an effect could be, but it seems to be accounted for in the IV estimation. The fact that the results are still significant means that the effect found in the previous section still holds, and can even be applied to the full sample.

Table 10: IV regression results for section 2

	(1)	(2)	(3)
VARIABLES	Step 1	Step 2 - Shares in Chinese imports (full sample)	Step 2 - Shares in Chinese imports (reduced sample)
IV estimates of Australian shares in Chinese imports (ln)		-1.201*	-0.824*
		(0.614)	(0.439)
GDP (ln)		-1.078	2.027
		(1.315)	(1.219)
Iron prices in USD (ln)	0.505***		
	(0.030)		
Observations	240	187	97
R-squared	0.419	0.210	0.150
Time FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Number of w_id		11	5

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

3.4 Counterfactual analysis

The counterfactual analysis on CHAFTA uses the same base results as in section 2.4. to estimate the effect of CHAFTA on SPIC shares in China and welfare. Using the IV estimates of the previous section, we can conclude that the increase of 8% in Australian trade shares due to CHAFTA would reduce SPIC shares in China by 9.6% in average over the whole period for the whole sample, and 6.6% for the reduced sample. Using the base estimates, this means that the reduced sample would have suffered a loss of 0.1% of its GDP over the full period through trade diversion effects.

This contributes to about 10% of the overall effect found in section 1, which means that there must be other channels through which regional GDP is reduced by Australian/Chinese trade. Of note, we have not tested the diversion effects of Chinese competition in Australian imports, which might be an interesting avenue to explore. However, in the rest of this paper we will focus on non-trade related externalities, and most notably local environmental effects manifested in fishing yields.

4 Channel n°2 : Fishing yields

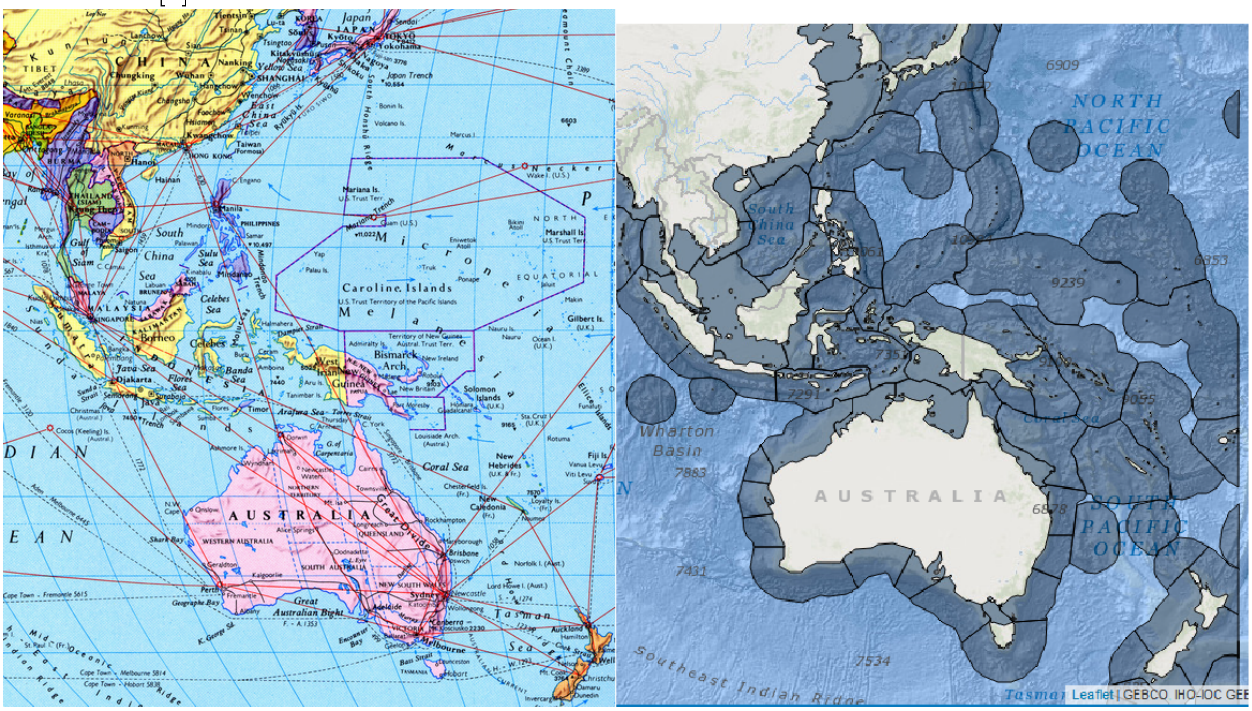
As seen in the literature review, trade in goods can lead to a disturbance of marine biodiversity, which in turn can impact fishing yields and therefore economic development in countries dependant from the blue economy. This section tests this hypothesis for Australian exports and imports (not just to and from China) in the South Pacific fishing zones, first using a fixed effects model, then an SDB spatial model with a queen contiguity matrix to take spatial autocorrelation into account. To identify the biodiversity channel, shipping variables are regressed on the mean trophic value (position on the food chain, from 1 to 5, 1 being primary producers and 5 carnivorous mammals)) of caught fishes in the marine ecosystems. Finally, a counterfactual analysis of the CHAFTA is performed to determine its effect on fishing yields, using a similar method as the previous sections.

4.1 Data and summary statistics

In order to establish whether ship passage affects fishing yields in the South Pacific, three methodological challenges have to be addressed to construct the dataset. First, a unit of observations needs to be selected, as fishing zones are divided according to several different nomenclatures by the FAO (EEZ, LME, etc.). After careful consideration, marine ecosystems have been selected. Marine ecosystems are defined as "major units of ecological function in the marine environment. Ecosystems are communities of organisms and their physical, chemical, and geological environment – distinct assemblages of species coevolved with a particular environment over long periods of evolutionary history." (Grassle [12]). This notably means that marine ecosystems are generally independant from each other (at least without human intervention). This eliminates issues of natural migration, which would otherwise arise at another disaggregated level (like exclusive economic zones for instance). Marine ecosystems also have the advantage of being the smallest level of aggregation when it comes to fishing zones, which creates more heterogeneity.

Secondly, shipping routes have to be matched to the marine ecosystems defined above, and, in the absence of accurate data on ship traffic in each ecosystem, these were constructed using Australian shipping data from the Australian Port Authority on origin and destination of goods. The method used is the following : ship route maps have been extracted from the World Atlas of Shipping [25] and the online resource Shipmap [18] for the 5 major Australian ports (Sydney, Melbourne, Brisbane, Fremantle and Adelaide) and their 5 main partners (China, ASEAN countries, Japan, United States, New Zealand) for a total of 25 routes. These routes have then been mapped to the 44 marine ecosystems in the South Pacific (a marine ecosystem is considered to host a route if the route goes through at least a part of it, regardless of actual distance in the ecosystem). The maps in figure 3 shows each marine ecosystem, and a complete list of routes matched with each ecosystem is available in the annex. From there, shipping data from the Australian Port Authority (both in number of ships and number of containers) is matched to each route and therefore attributed to marine ecosystems. For example, the Papua marine ecosystem lies to the northwest of Papua New Guinea and is traversed by all shipping routes from Australia (except Fremantle) to China and ASEAN countries. Adding up traffic for all these routes to and from Australia allows us to compute that Papua has been traversed in 2010 by 1784 ships transporting 3 566 925 twenty foot equivalent units (TEUs, the standard unit of measure for containers). Most standard containers measure 2 TEUs, so this means that in average, one of these ships transported 2000 containers (as a comparison example, the Evergreen vessel that blocked the Suez Canal in 2021 transported about 4000 containers [31]).

Figure 3: Shipping routes and marine ecosystems - Sources : Shipping Atlas [25] and Sea Around us [5]



Thirdly, the issue of marine resource depletion through both overfishing and climate change has to be addressed. If increased fishing yields in year t lead to decreased fishing yields in year t+1, then any attempt at analyzing the correlation between yields and another variable will be biased by temporal autocorrelation. Fortunately, two indices from the Sea Around Us resource (joint project from the University of British Columbia and University of Western Australia [5]) exist to remedy the problem.

The first is the ”Fishing in balance” index (fib), which uses the mean trophic level of fishes captured by fisheries to determine ”fishing down” effects which in turn inform us on whether the zone is victim of overfishing in a given year. The intuition stems from three hypotheses : 1/ Fishes with a higher trophic level (ie on top of the food chain) tend to live closer to the surface, 2/ These larger fishes are the most exposed to the dangers of overfishing and climate change, and 3/ Everything being equal, fisheries would rather catch lower higher levels. These three hypotheses mean that when mean trophic level decreases in catches

Table 11: Summary statistics for section 3

	mean	p50	min	max	sd
Fishing yields (tonnes)	198269.8	33824.22	177.9914	1714562	346770
Number of ships	911.6712	742.5168	28.41149	3001.563	604.273
Number of containers (TEUs)	1359606	1018510	18431.01	6372508	1192600
Average size (TEU/Ships)	1410.162	1426.538	220.3504	2739.173	512.1343
Fishing in balance index (0=balanced, 8=highly overfished)	2.850257	2.525	.08	7.96	1.621565
Expansion factor (average distance from the cost in nautical miles)	69.85074	12.49	1.08	2864.07	189.4103
Observations	1012				

faster than productivity, fisheries were likely forced to fish down because of fish depletion from the previous year. The fib index therefore indicates the differences in growth in mean trophic level from the previous year compared to productivity growth (fib=0 when the zone is considered to be ”in balance”, and increases up to 8 when overfishing occurs).

The second index is the expansion factor, which is more straightforward : this index measures how far from the coast the fisheries are located. Fishing farther from the coast means more yields but also proportionally higher costs, so fishers only tend to do it when resources closer from the coast are depleted. The expansion factor simply measures the average distance of fisheries from the coast in nautical miles for a given year.

These two indices, which, considering we do not measure costs, should be positively correlated with fishing yields for the following year, solve the temporal autocorrelation problem by identifying the effects linked to overfishing. Assuming the hypothesis that climate change affects all marine ecosystems in the region equally, this only leaves local pollution effects from shipping as a variable to explain the differences in fishing yields.

Overall, the data for this section comes from two distinct sources: the Sea Around Us project [5] for fishing data (including the overfishing indices) and the Australian Port Authority [14] for the shipping data, including number of ships, containers and average ship size. The dataset is comprised of observations on 44 marine ecosystems in the South Pacific region and shipping data for 25 routes (full lists in the annex) over the period 1996-2018. Table 11 provides summary statistics for all the data.

From these statistics, it is clear that the sample provides plenty of heterogeneity in terms of number and size of ships, as well as fishing yields. The eastern zones especially are isolated with very few islands, which means few fishing boats and few shipping routes (this variable is taken into account through fixed effects). On the whole, the fishing in balance index is very high (remembering that anything over 0 means the zone suffers from overfishing), which is consistent with the various reports on overfishing in the region.

4.2 Estimation results with panel data and SDM

This novel dataset allows for a base estimation strategy using a panel data, fixed effect model with control variables :

$$\begin{aligned} ln(fish_{it}) = \alpha + \beta_1 ln(ships_{it-1}) + \beta_2 \frac{ln(containers_{it-1})}{ln(ships_{it-1})}) + \beta_3 ln(containers_{it-1}) \\ + \theta_1 fib_{it} + \theta_2 expansion_{it} + u_i + u_t + \epsilon_{it} \end{aligned} \tag{10}$$

Where $fishingyields_{it}$ is the total catch recorded in ME i in year t in tonnes, $numberofships_{it}$, $numberofTEUs_{it}$ and their interaction are respectively the number of ships (absolute value), the number of containers (TEU) and the average ship size (interaction term), and fib_{it} and $l.expansion_{it}$ are the overfishing indices.

The use of interaction terms allows to take into account not only the total number of ships on the route, but also the average ship size, which might be a determining factor for local effects such as collisions and noise pollution.

There is however a worry that the base estimation suffers from spatial autocorrelation effects : if fishes, when confronted to ships, migrate to other zones (either by latching on to the ships or simply moving away), then this means that passage in zone i might affect fishing yields in adjacent zones. There is a class of models that can take spatial autocorrelation effects into account called spatial econometrics models. Of these, the Spatial Durbin Model (SDM) allows for spatial interactions of the independant variables with the dependant variable. In our case, this means that ship traffic in region i can impact fishing in region i+1. To account for these effects, a spatial matrix must be constructed using either queen contiguity rules (zones touching each other) or an inverse distance rule. For simplification reasons, we have selected a queen contiguity matrix. It is unlikely that fishes traverse more than one ecosystem when displaced by shipping, considering that this is a forced migration. The SDB estimation takes the following form :

$$\begin{aligned} ln(fish_{it}) = \rho WY + \alpha_i + +\beta_1 ln(ships_{it-1}) + \beta_2 \frac{ln(containers_{it-1})}{ln(ships_{it-1})}) \\ +\beta_3 ln(containers_{it-1}) + \theta_1 fib_{it} + \theta_2 expansion_{it} + W\rho_1 ln(ships_{it}) \\ +W\rho_2 \frac{ln(containers_{it-1})}{ln(ships_{it-1})}) + W\rho_3 ln(containers_{it-1}) + W\rho_4 fib_{it} + W\rho_5 expansion_{it} \\ +u_i + u_t + \epsilon'_{it} \end{aligned} \tag{11}$$

With W being the spatial matrix and ρ_n the spatial autocorrelation coefficents.

In addition to providing spatially unbiased estimates, this model also has the advantage of quantifying the spatial autocorrelation coefficients (although the exact effect size cannot be interpreted from this regression alone, the sign and significance are still useful).

Table 12 provides results for the base estimations presented in equations 10 and 11 (panel data and SDB). Column 1 presents results for the panel data estimation, and columns 2-3 results for the SDB model with respectively the direct and spatially lagged effects.

Both the panel data model and the spatially lagged model yield similar results for our variables of interest. The indirect (spatially lagged) effects are positive, which makes sense considering there are migration effects (a ship passing through an adjacent zone will displace fishes, which will increase yields in the zone of reference). However, these effects do not appear to be significant and their level is lower than the loss of biodiversity observed in the direct effects. Since number of ships, average size and number of containers are interaction terms, they cannot be interpreted as is and require the use of cumulated effects. Figure 5 sums up the cumulated effects for both size and number of ships at different combinations of containers and ships (by quartile), without taking migration effects into account.

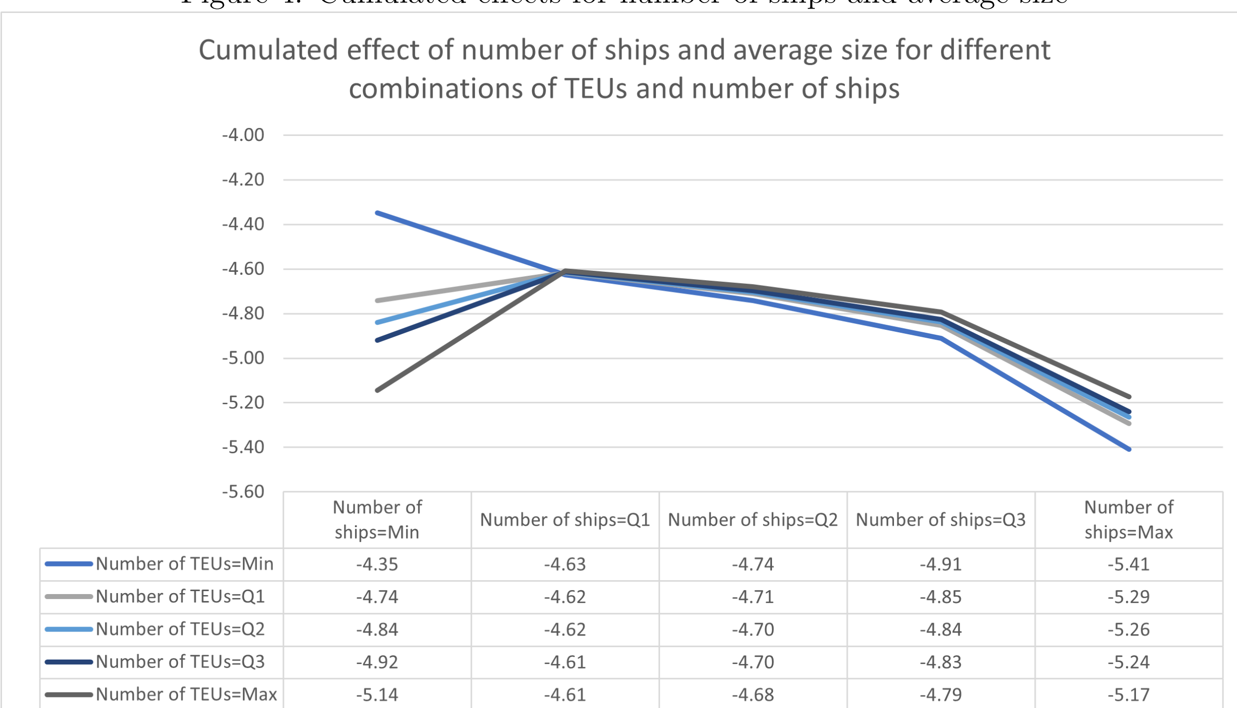
The graph in figure 4 can be interpreted the following way : When the number of containers and number of ships are at their median level, their cumulated effect on fishing yields is -4.7%. Marginal effects of going from a quartile to the next can also be easily computed : At the minimum number of containers, increasing the number of ships from its minimum to

Table 12: Main regression results for section 4, including panel data (column 1) and SDM (columns 2-3)

VARIABLES	(1) Panel data (Fishing yields)	(2) SDB direct effects (Fishing yields)	(3) SDB indirect effects (Fishing yields)
Lagged number of ships (ln)	-0.650***	-0.741***	0.138
	(0.154)	(0.287)	(0.234)
Lagged average size (TEU/ship) (ln)	-1.229***	-1.316***	0.435
	(0.449)	(0.480)	(0.586)
Total number of containers (ln)	0.358***	0.213	0.312*
	(0.082)	(0.163)	(0.188)
FIB index (ln)	-0.120***	-0.172*	0.218*
	(0.043)	(0.088)	(0.122)
Expansion factor (ln)	0.735***	0.748***	-0.267***
	(0.025)	(0.090)	(0.056)
rho		0.294***	0.294****
		(0.063)	(0.063)
Observations	1,012	1,012	1,012
R-squared	0.779	0.137	0.137
Number of X_ME	44	44	44
Time FE	Yes	Yes	Yes
ME FE	Yes	Yes	Yes
Number of w_id	44	44	44

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 4: Cumulated effects for number of ships and average size



its first quartile increases the negative effect by 0.28 points (4.63-4.35).

There are a few conclusions that can be drawn from these results : first, ship traffic has a net negative effect on fishing yields in the South Pacific over the period (even if migration effects were significant, their coefficients are much lower). This means that while fish displacement might be possible, ships actually cause a fishing loss, either via loss of biodiversity, or fisheries moving out of the way and losing productivity in the process. While at this stage it is impossible to say, section 4.4. tries to identify the biodiversity channel.
Second, increasing the number of ships seems to have a larger effect than increasing the number of containers at almost all levels, which means that the size of the fleet matters more than the size of individual vessels (increasing the number of containers while maintaing the number of ships constant means increasing average ship size). At higher levels of number of ships, increasing ship size even seems to decrease slightly the overall effect. It is not clear where this trend could come from, some hypotheses might be that larger vessels use less fish-dense routes, or are more closely regulated.

Third, while this is not the focus of this paper, conclusions on overfishing can be drawn from the coefficients of the two indices. Increasing the FIB index (which means increasing overfishing) seems to have a negative impact on fishing in the reference zone, but a positive impact on fishing in other zones. This seems to indicate that fisheries likely abandon zones that are overfished for a while to turn other more bountiful zones (this would be a similar mechanism to fallow on land).

4.3 Linking shipping and biodiversity

One criticism that could be addressed to the above conclusions is that the reduced fishing yields may not be due to fish migration, but to the fisheries themselves adapting to fishing routes and moving away on their own. While this would certainly be valid, there is a way to identify the biodiversity channel by looking at the average marine trophic level of catches as a dependant variable. The main advantage of doing so is that since this is an average, the channel of fisheries moving away from shipping routes is controlled for. This means that, if controlling for total catch, migration effects and over fishing indices, ships reduce the mean trophic levels in the region as a whole, we will have identified an actual biodiversity effect through which fishing yields might be affected.

Table 13: Supplementary regression results for section 4 with marine trophic index as a dependant variable, SDM

	(1)	(2)
VARIABLES	SDM Model direct effects (Mean trophic level)	SDM Model indirect effects (Mean trophic level)
l_ln_ship	-0.013**	0.011
	(0.006)	(0.007)
l_ln_avg_size	0.020	-0.020
	(0.020)	(0.020)
l_ln_fib	0.005	-0.001
	(0.004)	(0.003)
ln_expansion	0.049***	-0.015**
	(0.014)	(0.007)
Catch in tonnes (ln)	-0.040**	0.007
	(0.017)	(0.009)
rho	0.211***	
	(0.049)	
Observations	572	572
R-squared	0.198	0.198
Number of w_id	44	44
Time FE	Yes	Yes
ME FE	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 13 shows in columns 1 and 2 the direct and spatially lagged effects of the two shipping variables on mean trophic levels. The difference between both effects for the number of ships is positive and significant at the 5% level (0.0289). This means that there is indeed a mean trophic level loss of 0.0289% for each 1% increase in the number of ships (trophic levels vary on a scale of 1 to 5, so this means that an increase of about 700% in the number of ships leads to the loss of one trophic level on average). While this might not seem like much, it is important to keep in mind that over the 1996-2018 period, in some zones like the West Caroline Islands, the number of ships has increased by over 850%, and one trophic level is an entire level on the food chain (it can mean going from a herbivore to a carnivore). Combined with the results from section 4.3., while we cannot draw definitive conclusions, some trends start to appear : shipping reduces biodiversity and trophic levels when fishing levels are held constant. While with the available data it is impossible to quantitatively assess the effect of a loss in fishing yields on SPIC welfare, it is clear that for countries relying massively on fishing, the signature of a trade deal that increases ship traffic would have an impact on GDP through the biodiversity channel.

4.4 Counterfactual analysis

Using a similar method to subsections 3.4. and 2.4., we perform a counterfactual analysis of CHAFTA by considering a scenario where it has never been signed. We first use our PPML predictions of Australian and Chinese trade to predict new ship, container and ship sizes numbers, then compare predictions of catches in the spatial model between the predicted values with and without RTA. The final ttest results can be found in table 14. On average, over the whole period, the CHAFTA has reduced fishing yields by 0.32% in the South Pacific.

This result seems low but can be explained by a more detailed analysis : While the CHAFTA has increased both the number of ships and their average size, a ttest of both variables shows that the average size has increased significantly while the difference in the number of ships fails to be significant at the 10% level. This means that the CHAFTA has resulted in bigger ships, which, as we have seen in section 2.3., tend to reduce the overall effect of traffic on fish biodiversity (even though here the effect is still negative due to the extra traffic). Another point to consider is that our fishing data only goes as far as 2018, which means that, ignoring anticipation effects, there are only 3 years over which the CHAFTA could have had an impact over fishing yields (vs 5 years for the other counterfactual analyses on trade and GDP).

Table 14: Ttest for the predicted trade shares of Australia and China with and without RTA

VARIABLES	Obs	Mean	se
Log of catch with RTA	1012	7.68	1.52
Log of catch without RTA	1012	8.00	1.53
Diff	1012	-0.32***	0.004

Conclusion

The results provided in this paper are evidence that bilateral trade relationships cannot be simply understood by studying their effect on trade in a general equilibrium setting. While this analysis can be useful for trade predictions, as it was in determining the depth of the counterfactual effects in this paper, it needs to be paired with a more local approach to understand the exact negative externalities of such relationships. Our analysis of trade diversion effects has shown that these can only explain about 10% of the total welfare effect. While other macroeconomic channels like investment diversion, price making and exchange rate effects can be at play, there are also more original and less studied effects, like the one studied in section 4. While we cannot provide an exact welfare effect quantification of the loss of fishing yields, it is clear that these types of environmental local effects require further studies.

Politically, there is a need to put in place compensation mechanisms when signing free trade agreements treaty to take these externalities into account. It is entirely possible, and in fact likely, that trade agreements like these have a general positive effect on welfare on a global scale, but as international trade models have demonstrated in the last few years, these effects can be very unequally distributed, to the point that some countries might lose. This therefore requires a redistribution of the gains of trade that takes into account all the welfare effects, both local and global, both economic and environmental. While such a mechanism would be impossible to implement on the multilateral level, including environmental externalities in the signature of FTAs does not seem so far-fetched. Today, almost all EU RTAs include some form of environmental clauses (norms, environmental goods...) [4] and even regionally, the PACER Plus negotiations (RTA between Australia, New Zealand and 9 SPIC) stirred discussions on exactly that topic [2], although none of the proposed provisions actually made it into the final agreement [30].

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Annex

Table 15: List of all 25 routes for section 4, with legend number

Australian Port	International	Number
Brisbane	China	11
Brisbane	US	12
Brisbane	Japan	13
Brisbane	NZ	14
Brisbane	ASEAN	15
Sydney	China	21
Sydney	US	22
Sydney	Japan	23
Sydney	NZ	24
Sydney	ASEAN	25
Melbourne	China	31
Melbourne	US	32
Melbourne	Japan	33
Melbourne	NZ	34
Melbourne	ASEAN	35
Adelaide	China	41
Adelaide	US	42
Adelaide	Japan	43
Adelaide	NZ	44
Adelaide	ASEAN	45
Fremantle	China	51
Fremantle	US	52
Fremantle	Japan	53
Fremantle	NZ	54
Fremantle	ASEAN	55

Table 16: List of each ME with their associated route (2/2)

ME	Routes
Arafura Sea	15, 25, 35, 45
Banda Sea	15, 25, 35, 45, 51
Bassian	31, 32, 33, 34, 35, 41, 42, 43, 44
Bismarck Sea	11, 21, 31, 41
Bonaparte Coast	41, 51, 52, 53
Cape Howe	32, 33, 34, 42, 43, 44
Central New Zealand	14, 24, 34, 44, 54
Coral Sea	11, 12, 13, 15, 21, 23, 25, 31, 33, 35
East Caroline Islands	11, 21, 31, 33, 35
Eastern Philippines	11, 21, 31, 41
Exmouth to Broome	41, 45, 51, 52, 53, 55
Fiji Islands	12, 22, 32, 42
Gilbert/Ellis Islands	12, 22, 32, 42, 52
Great Australian Bight	41, 45, 52, 54
Halmahera	11; 15; 21; 31; 41; 51
Hawaii	12, 22, 32, 42, 52
Houtman	41, 45, 51, 52, 53, 54, 55
Kermadec Island	12, 22, 32, 42
Leeuwin	41, 45, 51, 52, 53, 54, 55
Lesser Sunda	15; 25; 35; 41; 45; 51; 55
Line Islands	12, 22, 32, 42, 52
Lord Howe and Northforlk Islands	12, 13, 14, 22, 23, 24, 32, 33, 42, 43, 52, 53
Manning-Hawkesbury	21, 22, 23, 24, 25, 32, 33, 42, 43
Mariana Islands	13, 23, 33, 43, 53
Marshall Islands	12, 22, 32, 42, 52
New Caledonia	12, 22, 32, 42
Ningaloo	41, 45, 51, 52, 53, 55
Palawan/North Borneo	15, 21, 25, 31, 35, 41, 45, 51, 55
Papua	11; 15; 21; 25; 31; 35; 41; 45
Phoenix/Tokelau/Northern Cook Islands	12, 22, 32, 42, 52
Samoa Islands	12, 22, 32, 42, 52, 55
Shark Bay	41, 45, 51, 52, 53, 55
Solomon Archipelago	12, 22, 32, 42, 52
Solomon Sea	12, 22, 32, 42, 52
South Australian Gulfs	41, 42, 43, 44, 45, 54
South New Zealand	14, 24, 34, 44, 54

ME	Routes
Southeast Papua New Guinea	15, 25, 35, 45
Sulawesi Sea/Makassar Trait	11, 15, 21, 25, 31, 35, 41, 45, 51, 55
Three Kings-North Cape	14,
Torres Strait Northern Great Barrier Reef	11, 15, 21, 25, 31, 35, 41, 45
Tweed-Moreton	11, 12, 13, 14, 15, 21, 22, 23, 25, 32, 33, 41, 42, 43, 45
Vanuatu	12, 22, 32, 42
West Caroline Islands	11, 21, 31, 41
Western Bassian	41, 42, 43, 53, 54