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Trade, Inequality, and Subjective Well-Being: Getting at the Roots of the Backlash Against Globalization

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Trade, Inequality, and Subjective Well-Being: Getting at the Roots of the Backlash Against Globalization

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Abstract Many countries in the Western hemisphere are currently experiencing a backlash against globalization. Most of the research examining the issue has concentrated on international specialization and within-country income inequality as main drivers of the backlash. Doing so, the discussion has primarily revolved around the question whether and to what extend the income distribution has widened and whether trade is responsible indeed. However, political trends may be more grounded in perceptions than facts, thus giving rise to inappropriate populist policies. The difference matters all the more as the former may be accentuated by (social) media. Drawing mainly on subjective well-being (SWB) data from the World Values Survey (WVS) and income statistics from the Luxembourg Income Study (LIS), this paper shows in an international cross-section analysis that income inequality is perceived very differently depending on openness to trade. The relevance of perceptions has wider politico-economic implications in that it carries the risk of costly anti-trade policies, without necessarily narrowing the income distribution.

JEL-Classification: F61, F13, D63, D31

Keywords: Subjective Well-Being, International Trade, Income Distribution, Inequality, Identity

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1. Introduction

Societal cleavages have now been on the agenda of politics as well as research for quite some time. Although cleavages may have many dimensions, those pertaining to income distributions are among those attracting the most attention. Fueled by marked shifts in income growth around the world and apparent implications as to the political landscape in a number of countries, the debate on income inequality has lately gained momentum. While the topic of income (and wealth) inequality has caught much attention, there is still a lack of consensus as to its dimension, its origins, and its implications (see, e.g., Alvaredo et al. 2017 versus Sutch 2017).

Contrary to popular beliefs, several measures of global income inequality actually indicate a narrowing of income gaps over the last three or so decades. Based on household surveys covering approx. 120 countries, Milanović & Roemer (2016), for instance, report that global income inequality decreased from 69 to 64 Gini points between 1988 and 2011 (income at purchasing power parties). The decrease has been mostly due to above-average growth rates in large, but, in terms of per-capita incomes, poorer countries, in particular China and India. While the lifting of a great many individuals out of poverty has been largely applauded, the process of old growth poles being driven out of the market by new ones raised concerns by those left behind. At the same time, spotlight shifted from income distributions between countries to those within countries, where the picture seems to point at a widening of income differences (World Bank 2016, Ch.4).

In the news, as well as in much of social media, and, recently, also in politics, international competition, in particular international trade, is frequently presented as *the* culprit in these developments (Nguyen 2017). The notion of trade as *the* culprit is in contrast to much of economic research, which finds some influence, but, empirically, considers trade not the primary driver in the observed income distributions. Adding to this clash of perceptions with reality is the fact that, most recently, international competition is more a question of tasks becoming tradable across all skill-levels, with the main driver advancements in ICT rather than simply cheap low-skilled labor from China or elsewhere. How international trade affects income distributions is thus less obvious than commonly assumed (Blinder & Krueger 2013; Baldwin 2016; Dluhosch & Hens 2016).

Three reasons may nevertheless contribute to nourishing the *belief* that competition from abroad is largely responsible for relative income positions. One reason may be the subjectively chosen reference norm as to income distributions. Depending on personal circumstances and one's own (perceived or de facto) position within income distributions as well as value judgments about both, impacts may be seen although there are none or minor impacts may be considered highly relevant. Secondly, public attention may differ across drivers: trade flows and foreign goods tend to be easily identifiable. They are often observed and tracked in the news, certainly more easily than other, more diffuse, developments such as those related to technical changes, which may take on many shapes. Thirdly, and somewhat related to the second channel, is the issue of "group identity". International trades may be more readily seen as a "them-versus-us issue" whereas domestic trades are less so. The implied notion of international trade as a zero-sum game may thus become widespread, despite being defied by many economists as erroneous. A survey experiment by Mutz & Kim (2017) based on data of 2,350 US citizens indeed holds complementary evidence of well-being displaying ingroup favoritism, which results in a preference for beggar-thy-neighbor policies. Because the corresponding group identity is so simple to observe, international trade may gain center stage, even if of minor importance compared to other reasons. Competition from abroad thus emerges as an easy scapegoat in popular discontent with income distributions. Perceptions about income inequality and trade may be even accentuated as (social) media serve as propagation mechanisms, regardless of whether sentiments are well grounded in facts or not (see, e.g., Garrett et al. 2016; Flynn et al. 2017).

The gap between perceptions and reality may trigger a backlash against globalization, thus promoting pro-nationalist and protectionist tendencies in the belief that they would contribute to a re-balancing of payoffs between "them" and "us", and, thereby, also to a more even income distribution, however measured.[1]

Drawing on subjective well-being (SWB) data from the 6th Wave (2010-14) of the World Values Survey (WVS), World Bank data on openness (WDI), and consistent household-income data from the Luxembourg Income Study (LIS), this paper shows in an international cross-section analysis that income inequality is indeed perceived very differently depending on international trade. Average adjusted predictions of probabilities tend to decrease at high(er) scores of SWB (and increase at lower scores) in response to a marginal increase in the disposable-income based Gini, with the downward effect on SWB stronger the more open the economy. Findings prove strikingly robust with respect to various measures of income inequality. With 19 countries and an implied number of 28,381 individual interviews, results are based on as comprehensive a data set as possible, taking account of the necessary country-wise overlapping of WVS and LIS data while also including a large number of controls with respect to individual characteristics, which may also shape SWB. In highlighting the role of perceptions, the paper thus opens up a novel perspective on the backlash against globalization.

Analyzing perceptions, we employ an ordered logistic regression model that factors in the ordinal nature of the dependent variable SWB and that is capable of tracing the interaction of income inequality and openness to trade in perceptions. Yet, non-linearity is an issue in logistic models to the effect that nailing down perceived interactions, here between inequality and trade, prove challenging. The paper manages to isolate and identify the role of percep-

[1] In light of the anti-trade, pro-nationalist, wave, Rodrik (2011) even concludes that democratic politics and national sovereignty are generally incompatible with the further deepening and widening of global integration. Political developments seem to prove him right: Brown (2016), for instance, sees the Brexit vote through this lens, as does Biden (2017), with reference to the political discussion on trade policies and agreements in the United States. Failure to address the anti-trade sentiments would contribute to an increasing divide of society, including an alienation of constituencies with their political representatives. Elsewhere, matters of income distribution raised the quest for "more inclusive trade" (e.g., World Economic Forum; Global Alliance for Trade Facilitation 2016, p.1).

tions by finely slicing primary results to get at the question how probabilities across ranks of subjective well-being are affected by changes in various measures of inequality at different levels of openness to trade. Dealing with the non-linearity issue in this manner substantiates the empirical finding of a conjoint effect of openness and income inequality on SWB in logistic regressions. The conjoint effect lends support to identity issues being at work in evaluating income distributions.

Research on how trade and distributional issues affect subjective well-being is surprisingly rare, despite a large body of research on the distributional impacts of globalization. Scheve & Slaughter (2001), for instance, were among the first to focus on attitudes with respect to trade policies, which, other than observed wages, contain more of a subjective element. Still, preferences over trade policies are ultimately traced back to how trade affects factor incomes and asset values rather than whether incomes and their distribution are perceived differently depending on trade (see also the surveys by Pew Research Center 2014 and Bluth 2016 on attitudes as to trade policy). As the authors themselves remark in Lü et al. (2012), the traditional factor-proportions explanation, according to which it is primarily the low-skilled at the bottom of the income-distribution in relatively skill-abundant countries who favor protectionist trade policies is also somewhat at odds with the fact that low-skill intensive industries in low-skill abundant countries also tend to receive protection – although they should tend to benefit from the opening up of markets. To reconcile the pattern of protection with the different distributional impacts of trade within countries, they discuss whether individual preferences differ from traditional assumptions in that they contain a strong element of inequity aversion. However, whether, and, if so, why, then, distributional issues are evaluated differently depending on trade with the bias apparently across the whole income spectrum remains to be explained.

Conventional factor proportions theory is also implicitly underlying the recent surge in research on whether voting behavior across regions or industries within countries can be explained by distributional effects of trade. With factor proportions theory and factor specificities in mind, Dippel et al. (2015) explore the role of trade exposure to Eastern Europe and China in German voting data, Feigenbaum & Hall (2015) to Chinese imports in roll-calls in U.S. congressional data, Autor et al. (2016) and Che et al. (2016) in U.S. congressional elections, Jensen et al. (2017) in U.S. presidential elections, and Colantone & Stanig (2017) in voting in Western European countries. Guiso et al. (2017) explain recent political developments in a great many places since 2008 by heightened economic insecurity affecting voter turnout negatively. Those still going to the polls would favor populism, to the effect that populist parties are strengthened. While compatible with the fact that policy shifts go well beyond those affected negatively via the distributional effects of trade, their analysis focuses on objective indicators of economic insecurity rather than subjective well-being and perceptions about what is responsible in income distributions.

However, all of these contributions find some evidence for the distributional impacts of trade, as does research that examines more closely indicators on the regional and sectoral distribution of trade exposure and well-being. According to Pierce & Schott (2016), post-2000 U.S.-China trade liberalization went in tandem with an increase in suicide deaths in U.S. counties and by workers specialized in manufacturing. Results are in line with empirical studies for the U.S. by Case & Deaton (2015), and Graham & Pinto (2017), who find evidence that the various societal strata show much heterogeneity as to socio-psychological indicators such as all-cause deaths and perceptions of stress, insecurity, and in particular, hope and confidence in the future. Accordingly, poorer rural whites in their middle ages are the least optimistic as to their personal outlook. The socio-geographic pattern suggests again a relationship to shifts in the demand for labor because of trade as it was presumably these strata, which were affected the most by import competition from abroad. Khun et al. (2015), as well, focus on the broader concept of well-being, and in particular on life satisfaction. Still, their set up and their results follow the Stolper-Samuelson theorem according to which the relatively abundant factor reports higher life satisfaction with openness whereas the other factor suffers from lower life satisfaction.

While also finding empirical evidence for trade attitudes as predicted by traditional factor-endowments and specific factor models, research by Mayda & Rodrik (2005), suggests that other socio-economic aspects may be of even greater importance in the formation of attitudes as to trade. In particular nation-centered questions about feeling locally attached or about being proud of the Home countries' social and political institutions or economic achievements turned out to be important in explaining the variation in attitudes over trade (similarly, Mansfield & Mutz 2013). Likewise, Schalembier (2016) identifies national characteristics such as per-capita incomes (that is, measures of comparative performance vis-à-vis other countries) to become more important for SWB as international exposure increases. On a similar account, Inglehart & Norris (2016), in analyzing European Social Survey data, find evidence that it is much more cultural values across a wide range of social groups rather than just the low-skilled low-income groups forming the backbone of the backlash against globalization.[2] Much like Inglehart & Norris, research based on US panel data by Mutz (2018) adds to the evidence of perceived status threat by previously dominant groups as main drivers in political attitudes, and not the more narrow economic losses of the (primarily) low-skilled.

The paper shares in those perspectives in that the backlash is rooted in a much broader sentiment, here, in income inequality being perceived differently depending on trade, independent of one's own position in the income distribution. Notably, this is not to say that the traditional channels of trade-related income distribution are not relevant in SWB and the formation of preferences over trade. Rather, it is to be understood to widen the perspective to an additional channel, thus offering an explanation of the widespread surge in anti-globalization sentiments that can be observed across the board rather than being confined to low-skilled income strata.

In the following empirical sections, we will thus leave the discussion about how the income distribution relates to trade somewhat aside and concentrate on its relation to the anti-trade

[2] However, see Ballard-Rosa et al. (2017) for an effort in reconciling both perspectives based on British data.

climate more deeply. To this end, we will take the following two Hypotheses to the data in Sections 4 to 6:

> HYPOTHESIS 1: Income inequality is perceived differently depending on trade.
>
> HYPOTHESIS 2: Marginal effects on life satisfaction of the nexus between inequality and trade depend on the level of satisfaction: the higher the level, the stronger is the (negative) effect on the probability of reporting to the level.

Hypothesis 1 indicates whether trade affects how individuals think about inequality; Hypothesis 2 looks at whether individuals tend to report lower scores of life satisfaction for any marginal increase of inequality when the economy is more open to trade. Notably, the marginal increase in the inequality index is in any case assumed to refer to the same observed value of the index. Taken together, both results are evidence of conjoint effects of trade and inequality on SWB. As such, they are consistent with a bias in perceptions according to which inequality is particularly considered an issue in open economies. The fact that marginal changes in income inequality are evaluated differently alludes to an identity-explanation as to the discontent with globalization, in any case a channel that operates separately from any winner-loser impacts of trade.

However, before examining how perceptions contribute to the explanation of the backlash, we will first present in Section 2 the data and some descriptive statistics on openness to trade and the income distribution and how both are correlated with subjective well-being in the data set. The descriptive statistics already suggest that some popular beliefs as to the nexus require more detailed analysis, how to proceed methodologically and how to appropriately handle challenges in the analysis, which will be the subject of Section 3. In Sections 4 to 6, we will carefully slice estimations thus squeezing out information on whether changes in the observed income distributions are perceived more negatively at higher levels of trade exposure. Section 7 concludes.

2. Data and Descriptive Statistics

Both hypotheses require data on SWB and income inequality, which is collected by different sources. Data availability and data consistency requires us to adopt a cross-section perspective with the most comprehensive data set for the year 2010. We thus merge a number of 2010 data sets, giving us in the end 28,381 individual observations originating from 19 countries. SWB data stems from the World Values Survey (WVS). The WVS asks individuals to position themselves according to their "satisfaction with life" along an ordinal (Likert) scale ranging from 1 ("dissatisfied") to 10 ("satisfied"). Ferrer-i-Carbonell & Frijters (2004), have shown that problems in filtering out how micro data (such as data on SWB) depend on macro circumstances (such a country-level indicators in which we are interested) can be kept at a minimum by including an extensive set of micro variables.[3] We will account for the micro-macro issue by including a substantial number of additional individual data from the WVS as controls in the analysis. The WVS provides survey information on individual circumstances of the same set of individuals that was asked about their SWB. We will include those circumstances that have been identified as potentially relevant by the previous micro-oriented literature: age, gender, education, health, religion, employment status, martial status, number of children, and sense of self on an income scale ranging from the lowest to the highest decile within the income distribution (e.g., Scheve & Slaughter 2001; Bjørnskov et al. 2008; Geishecker et al. 2012; Dluhosch & Horgos 2013). However, in some instances, we will deviate from the purely micro-oriented work based on raw WVS data by regrouping and coding the information in a slightly different manner so as to cater better to our focus.

The micro data are supplemented by macro variables of the countries according to residence, namely income inequality and openness. Our primary source of cross-national data on income inequality is the Luxembourg Income Study (LIS), which admittedly provides the largest available harmonized and thus most consistent micro-data set on market and dis-

[3]Bryan & Jenkins (2016) discuss various approaches in dealing with the issue, however, with the focus on extracting proper country-level information in the estimation.

posable incomes. Matters of consistency are sort of a limiting factor in the analysis. There are surely more comprehensive data sets available out there. One of which is, for example, the World Income Inequality Database (WIID), currently in version 3.4 published by UNU-Wider.[4] Those data sets, however, are not the result of studies having prepared the data themselves but summarize information from various sources, thus lacking consistency because of conceptual differences rooted already in the income data.

In addition, both of the LIS income concepts, market and disposable income, are measured at the household level which is more informative for SWB across all age groups within the WVS than purely individual data. Both concepts summarize information on total monetary and non-monetary current income. Disposable income differs from market income by net income taxes and social security contributions, and will turn out the more relevant one in shaping perceptions. For matters of consistency with WVS data, our LIS data also refers to 2010, that is, in this case, the eighth wave of the income survey. The eighth wave has covered 40 countries, with more countries and revised information continuously being added. However, because of the necessary country-wise overlapping with WVS data of the sixth wave, our data set includes 19 countries after merging with the micro data, with an implied number of WVS interviews of 28,381 individuals.[5]

Measures of inequality based on income information differ in terms of their weighting of different income strata. The difference in weighting raises a number of issues. One of which is that cross-country comparisons do not necessarily yield the same ranking, even if income data are carefully harmonized, as is the case with LIS data. The ambiguity is compounded by the fact that any cross-country analysis aggregates the data further thus probably introducing additional differences. A second issue is that choosing a particular indicator already reflects

[4] See `https://www.wider.unu.edu/database/world-income-inequality-database-wiid34` (accessed Dec 30, 2017), and the SWIID data set prepared and maintained by Fredrick Solt `https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/11992`, which is based on both sources, LIS and WIID, and which is currently in version 6.1 (as of Oct 2017).

[5] As to countries, the sample covers Australia, Brazil, Colombia, Estonia, Georgia, Germany, India, Mexico, the Netherlands, Peru, Poland, Russia, Slovenia, South Africa, South Korea, Spain, Taiwan, the United States, and Uruguay.

either implicitly or explicitly some value judgment, which may bias results substantially (see Dluhosch 1997 for EU regional income data). Hence, even the most popular indicator may not reflect perceptions particularly well. To account for these possibilities, we will start out with the most commonly used indicator, which is the Gini coefficient, and then proceed in the robustness analysis to other popular indicators such as the Theil- and Atkinson-indices containing various levels of inequality aversion. By means of their different properties, we try to deal with the sensitivity as to the weighting. Nevertheless, we will be able to narrow down the range of results.

As to openness, we concentrate on the most common indicator, that is trade (exports plus imports) over GDP, retrieved from the Word Development Indicator (WDI) database of the World Bank. The only exception is Taiwan with the data taken directly from national accounts.[6] However, in robustness checks, we will also allow for the possibility that trade intensity is evaluated differently as to imports and exports by considering each variably separately.

To accommodate a trade freedom channel on SWB, we include variables for trade freedom besides traditional openness indicators, with the most widely used the one supplied by the Heritage Foundation. However, because trade freedom is more of a policy indicator, that is the result of perceptions in the policy sphere (e.g. Lü et al. 2012), we will consider it a control rather than the main variable in the conjoint effect of actual trade exposure and income inequality. In fact, work by Dluhosch and Horgos (2013) established that trade flows and trade policies should be treated as two separate dimensions with trade policies capturing more of an option value of trade rather than trade itself. As data originating from think tanks are not undisputed, we will also run a robustness analysis with data provided by the Fraser Institute. Both institutes evaluate annually the trade freedom of countries by a composite indicator that merges information on trade policy, including tariff- and non-tariff measures,

[6]See `https://portal.sw.nat.gov.tw/APGA/GA05E` for trade and `https://eng.stat.gov.tw/public/data/dgbas03/bs2/yearbook_eng/y044.pdf` for income data (accessed Mar 17, 2017).

with the resulting trade freedom index ranging from 1 (least) to 10 (most) open (or 1 to 100 respectively).

With a difference of 258.461, the Bayesian Information Criterion (BIC) in the final model provides very strong support for trade freedom having an impact on SWB independent from measures of actual trade. The BIC also calls for including the interaction term when compared to trade and income distribution per se (BIC difference of 686.197), and, for including the log of per capita incomes (BIC difference of 143.534). The seemingly minor importance of per-capita incomes in fitting the model may be because of the combined effect of distribution and individual variables dominating or partially also accounting for these variables and thus outperforming those influences. Tables A1 and A2 in the Appendix provide an overview of the data sources and the variables used in the empirical analysis.

Figures 1 and 2 give a first impression of the aggregate data. Figure 1 displays the mean of self-reported well-being of individuals in 19 countries within the sixth wave of the WVS paired with the respective trade-to-GDP ratios and Gini coefficients (here: based on disposable incomes) of these countries. Although aggregates are fairly spread out, overall, the data in the LHS panel, which displays openness and SWB, suggest a downward sloping nexus. The negative slope supports the notion that SWB is on average lower in countries, which are more open according to their trade-to-GDP ratios. In the RHS panel, by contrast, which summarizes distributional and SWB data, it is much harder to identify either a downward or an upward pattern. The minuscule downward sloping summary of the income distribution data is even more flattened when being based on market incomes (not shown). This lack of SWB-impact of the income distribution may surprise at first as it is contrary to popular belief. However, it has to be kept in mind that this is a first (suggestive) overview, showing the unconditional correlation, and containing highly aggregate data. The aggregation may mask patterns in the disaggregated data underneath. The caveat applies in particular to SWB, which, by its ordinal and subjective nature, cannot be that easily aggregated and thus compared across individuals or even internationally as individuals may find themselves at different points within a subjectively perceived income distribution.

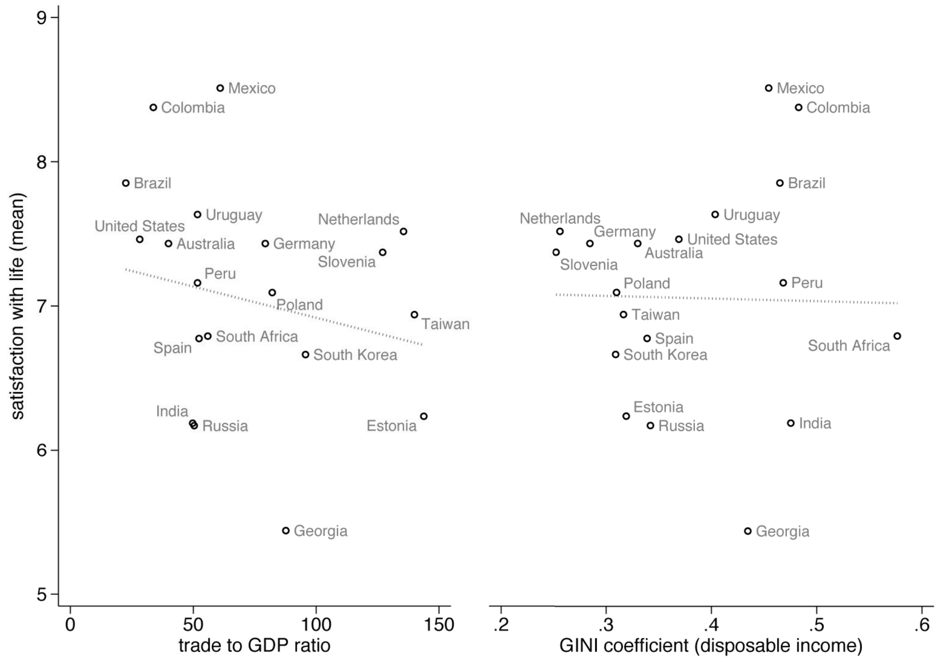

Figure 1: SWB, Trade and Inequality: Aggregate Data

Issues of interpretation also arise because of the non-linearity in the probability of reporting a particular level of SWB and the subsequent aggregation of the data. We will come back to this issue in a moment. Nevertheless, by challenging conventional beliefs, observations call for a deeper investigation as to why those patterns differ from the widespread conjecture that directly runs from trade to income distribution and to SWB.

Figure 2 casts even more doubts on traditional understanding. Accordingly, countries, which are more open display lower income inequality as measured by the Gini. Notably, the negative relationship is not confined to disposable incomes (as shown on the RHS), but also applies to market incomes (shown on the LHS). This clashes with the hypothesis (for instance, advanced by Mayda & Rodrik 2005) that redistribution allows individuals to accept higher (perceived) income risk in a more open economy. The similarities across income

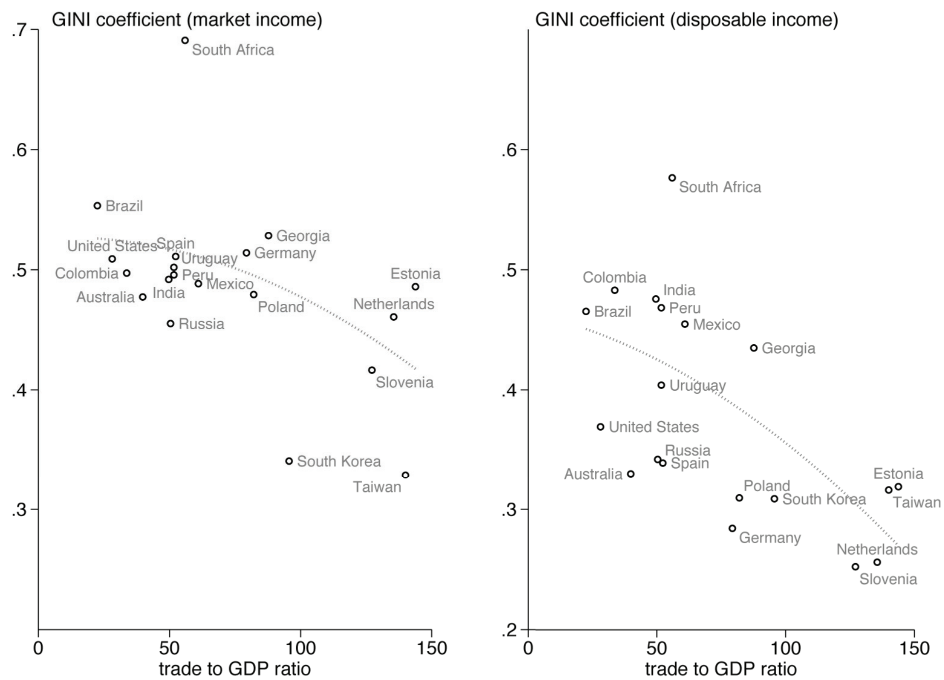

Figure 2: SWB, Trade and Inequality

concepts might be compatible though with more homogeneous countries in terms of income distribution allowing for a higher degree of trade exposure.

3. Empirical Methodology

Because of the challenges in aggregating SWB data, the following section aims at a disaggregated perspective that is capable of identifying, segmenting, and quantifying the contribution of various exogenous variables as well as their interaction on the endogenous variable SWB. As to methods, the analysis requires an ordered logistic regression model that factors in the ordinal nature of the dependent variable SWB and that is capable of tracing the interaction of income inequality and openness to trade in perceptions. The logistic regression accounts for the fact that probabilities as well as marginal effects cannot be constant across all levels of SWB with SWB covering a limited range scoring from 1 (bottommost) to 10 (topmost). Because of the limited range, changes in probabilities tend to be lower as probabilities converge at the upper part of the scale than those in the mid-scale. Similar reasoning applies with respect to the lower end of the SWB spectrum.

Because our research question focuses on the leverage effect of trade on income distributions in perceptions, an interaction variable approach supposedly capturing explicitly the conjoint effect is the natural way to empirically approach the question. However, while data requires a logistic approach, interpretation of this type of model is not straight forward, in particular when trying to track down effects of changes in continuous variables interacting. We will come back to this issue in a moment. To capture the nexus between SWB and the distributional impact of trade as perceived, we employ the following ordered logistic regression model

$$SWB_{ij} = \beta_1 Ineq_j^m + \beta_2 Open_j + \beta_3(Ineq_j^m \cdot Open_j) + \beta_4 TF_j^k + \beta_5 GDPpc_j + \beta_6 IndC_{ij} + \epsilon_{ij} \quad (1)$$

with SWB_{ij} the ordinal information on (subjective) well-being of individual i in country j and with ten ordered categories ranging from 1 (lowest) to 10 (highest level of SWB). As to the independent variables, $Ineq$ refers to the income distribution, $Open$ to trade over GDP (so that $Ineq_j^m \cdot Open_j^n$ measures the conjoint impact), TF the trade freedom, $GDPpc$ income per capita, and $IndC$ individual controls relating to socio-demographic characteristics as previously mentioned and listed in Table A2 in the Appendix. ϵ_{ij} is, as usual, the error term. To capture country-specific differences in variables, we cluster the errors at the country level.

Whereas, in the main analysis, we use the Gini coefficient when scaling income distributions, we also consider different measures m of income inequality besides the Gini in the robustness analysis (Theil-index; Atkinson-index at various levels of inequality aversion). Likewise, we check for robustness by applying variants k of the trade freedom index, which are supplied by different institutions. To achieve robust standard errors, the Huber/White sandwich estimator is applied in the regression.

4. First Results: Trade Matters in How Inequality Is Perceived

Table 1 shows the probability distribution derived by estimating the model in eq.(1) with the data. It summarizes probabilities at all levels of SWB with all variables as observed (1st row) or at their means (2nd row).

Table 1: Predicted Probabilities (PP), distribution over SWB scores 1 (lowest) to 10 (highest)

PP	SWB 1	SWB 2	SWB 3	SWB 4	SWB 5	SWB 6	SWB 7	SWB 8	SWB 9	SWB 10
PP (as observed)	0.0232	0.0202	0.0328	0.0450	0.1151	0.1085	0.1725	0.2293	0.1151	0.1384
PP (at means)	0.0262	0.0235	0.0395	0.0560	0.1481	0.1382	0.2005	0.2116	0.0807	0.0757

The probability distribution in Table 1 is the starting point for examining how predicted probabilities are affected by distributional and/or openness variables. While the pattern of predicted probabilities with both model variants is similar, predictions as to the various levels differ slightly because of the non-linearity of the underlying model.

Which of these assumptions, as observed (i.e., average adjusted predictions or short AAPs) or at means (i.e., adjusted predictions at the means or short APMs) is considered more suitable is very much disputed. While APMs may be considered the result of a "representative" individual (although in purely statistical terms), this very fact is also cited as disadvantage, because, in reality, there is no such individual (Karaca-Mandic et al. 2012, p.568; Bornmann & Williams 2013, p.568). In what follows, we thus go with the data as observed, that is, we start out from the first row in Table 1. Notwithstanding variation in detail, major results of our analysis stand up to both variants, AAP and APM.

Table 2 has aggregate (averaged) results for how each of the covariates in the model enters the probability distribution over SWB scores. According to these preliminary results, income distribution clearly matters, as does openness, with the conjoint effect of an increase in either variable implying a highly significant decrease in SWB. Thus, income inequality is considered an issue with trade but not necessarily separately from trade.

Table 2: Perceptions of distribution and openness as to life satisfaction

endogenous variable: satisfaction with life; distribution: Gini-coeff. (with min=0 to max=100); openness: trade-to-GDP ratio

Variables	Coef.
distribution (Gini)	.1145***
	(.0295)
openness	.0470***
	(.0157)
distribution x openness	-.0016***
	(.00054)
trade freedom	.0304***
	(.0088)
gdp pc (log)	.7861
	(.6490)
age	-.0509***
	(.0097)
age2	.0005***
	(7.45e-05)
male	-.0867
	(.0606)
income categories	
reference: income category 5	
inc1	-.2531
	(.4482)
inc2	-.504**
	(.253)
inc3	-.428***
	(.100)
inc4	-.173***
	(.0483)
inc6	.169***
	(.0455)
inc7	.386***
	(.0709)
inc8	.577***
	(.104)
inc9	.851***
	(.170)
inc10	1.113***
	(.281)
level of education	
reference: university degree	
no edu	-.221*
	(.130)
incomplete primary	.340
	(.236)
complete primary	.0134
	(.200)
incomplete secondary	-.0697
	(.129)
complete secondary	.0495
	(.105)
incomplete univ prep	-.192
	(.120)
complete univ prep	-.140*
	(.0846)
univ drop out	-.220***
	(.0801)
number of children	
reference: 2 children	
no children	-.111**
	(.0488)
1 child	-.0681**
	(.0304)
$\geqslant$ 3 children	.120*
	(.0627)
employment status	
reference: employed (full/part)	
self employed	.0675
	(.106)
retired	-.00223
	(.0780)
house	.136
	(.104)
student	-.00997
	(.0788)
unemployed	-.458***
	(.106)
other	-.302***
	(.100)
marital status	
reference: married/partner	
sep., div., wid.	-.378***
	(.0524)
single	-.191**
	(.0841)
other (dummy variables)	
not religious	-.246***
	(0.0594)
not good health	-.813***
	(0.117)
union member	-.223**
	(0.0943)
Observations	28,381
Pseudo R-squared	0.0468
Clustered errors	YES

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

The finding that inequality per se enters the equation with a positive coefficient corresponds with psychological research (see Starmans et al. 2017 for details as to the psychological foundations, Schneider 2016 on potential explanations, and Fattore & Fitzpatrick 2016 for evidence from Latin America), according to which inequality is not met with concern, if regarded as fair.[7] Data suggest that this differs with trade.[8]

Table A3 in the Appendix performs some robustness checks on results, showing that results as to the conjoint effect hold for different measures of inequality and trade freedom. However, the non-linearity in logistic models is an issue, as are (consequently) measures of goodness-of-fit. In cross-national studies of political economy measures are generally low. This is also the reason why any measures similar to those used in linear models are often met with skepticism and therefore are sometimes not even reported. The non-linear nature in the nexus implies that because of the averaging, which underlies aggregate results, one-for-all regressions are not generally informative of quantitative effects but have to be interpreted with care. Rather, coefficients may obfuscate vastly different impacts, depending on actual values of variables.

The very fact that coefficients amalgamate impacts comes on top of another, although somewhat related, problem: as pointed out by Ai & Norton (2003) and Norton et al. (2004), estimating and interpreting interaction terms in non-linear models is not trivial because properties of linear models, in particular the independence of marginal effects of covariates, do not carry over to non-linear models. Because of the non-linearity, the main variables of interest are not independent of the covariates. Despite these difficulties, many of the

[7]Rodrik (2017) also draws on this explanation. Accordingly, the discontent with globalization is at least partially driven by considerations of (unfair) competition clashing with domestic norms (such as those referring to child labor and inhumane working conditions).

[8]Performing a Wald test, we can reject the hypothesis that the effects of income inequality and openness (and thus also of the interaction term) are simultaneously zero (χ^2=18.35; df=3; p=0.0004), similarly with respect to the interaction term only (χ^2=9.14; df=1; p=0.025). While it is tempting to compare models w/out interaction terms in an attempt to see how large the effect is, we refrain from reporting details of a such a baseline. The motivation for deviating from this OLS-rooted practice lies again in the model's non-linearity: the error variance becomes smaller as the number of independent covariates increases, to the effect that odds ratios become larger, which makes sound comparisons with different covariates difficult (see, for instance, Mood 2010, Greene 2010, and Norton & Dowd 2018 on this matter). This is also the reason why, for instance, studies on SWB across U.S. regions and socio-demographic strata (e.g. Graham & Pinto 2017) are reluctant to report on the magnitude but instead concentrate on the sign.

properties of the logistic approach turn out to be actually informative on probabilities of the dependent variable when carefully set up and interpreted (see Rainey 2016 and Buis 2016). Accordingly, results provide a first approximation as to the impact of predictors, but need to be substantiated by subsequently slicing them at interesting, e.g. representative, values of variables.[9] In the special case under investigation here, the slicing of the variables also addresses the issue that the interaction term cannot vary independently from its components.

5. Slicing at Different SWB Scores, Trade-to-GDP Ratios and Gini Coefficients

There are basically two ways to slice results and thus to cope with the issue of "plasticity" of the nexus conditional on the covariates. One approach looks at the (log) odds with reference to a baseline model with the covariates centered on the mean; the other explores adjusted predictions of probabilities and calculates marginal effects on those probabilities at representative values of variables. The first procedure looks at the ratio, the second at the numbers per se by which the dependent variable (here: SWB) changes in case of a one unit variation in the independent variable of interest. Both of these approaches have their strengths and weaknesses (see Buis 2010 for advocating the first, Williams 2012 for advocating the second). Because our research question requires to track down a multitude of constellations with respect to income inequality and openness on SWB, the second approach is particularly suitable for the purpose of our analysis. In fact, it is also the approach which is applied in recent logit studies exploring interaction effects of exposure in medical research, as for instance, is demonstrated in Karaca-Mandic et al. (2012), VanderWeele & Knol (2014), and Norton & Dowd (2018).

[9]Shying away from these challenges, studies often sacrifice the proper ordered logit in favor of a simple linear OLS approach (e.g. Hessami 2010, Bjørnskov et al. 2013). However, the price tag is hefty, for two reasons: first, in a linear regression model, SWB is assumed to be cardinal, adding up across individuals, which does not account for the subjective nature of SWB, which is at the very heart of any analysis exploring the role of perceptions in politics; secondly, the effect of any independent variable on the probability of a particular level of SWB (and thus with SWB covering a limited range of values) cannot be linear, as implicitly assumed in OLS, thus injecting a substantial bias into the analysis. Figure 5 demonstrates that marginal effects are anything but constant, as assumed in OLS. See also Wiggins (2013) on the particular challenge of interaction terms in logit models.

Figure 3 shows how average adjusted probabilities (AAPs) vary with openness, disaggregated at SWB scores, again with 1 (lowest) to 10 (highest).

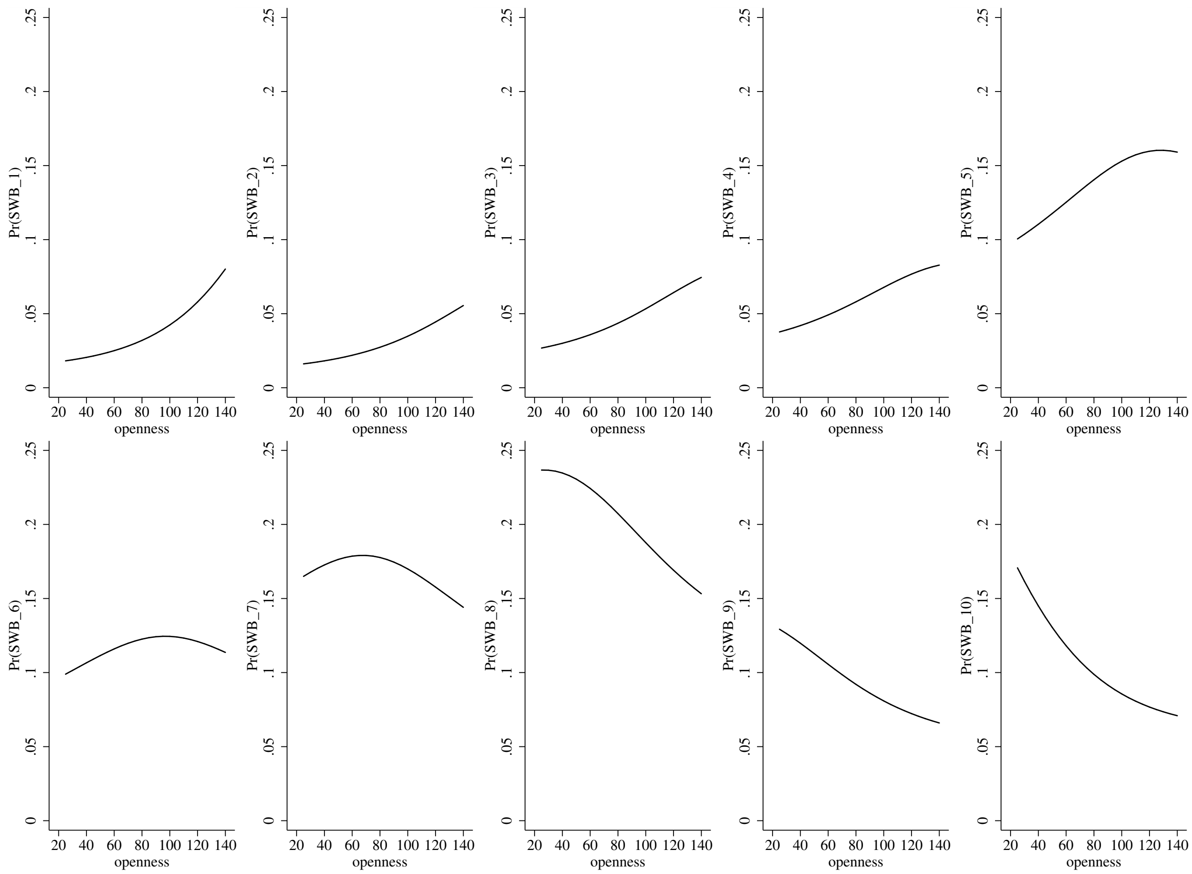

Figure 3: Average adjusted predictions (AAPs) of probabilities over SWB scores 1-10 at various degrees of openness

The probability distribution over SWB scores as displayed on the y-axis is derived by supposing that trade-to-GDP ratios were in any case 20, 40, 80, 140, or any ratio in between, rather than those actually observed. As shown, AAPs at the higher end of the SWB spectrum tend to be lower the higher the trade-to-GDP ratio and those at the lower end the reverse.

Hence, there is considerable variation underneath the averages of SWB scores in Table 2, which is highly informative as to perceptions.[10] The shift in AAPs indicates that, on average, and, given everything else, individuals tend to be less content with life at higher

[10]These results already show that an OLS approach assuming linearity falls short of capturing the diversity in effects of openness in conjunction with income inequality.

levels of openness (with all other variables as observed). The pattern at both ends of the SWB spectrum clearly reflects a negative impact, while movements in the middle are more difficult to disentangle.

However, Fig. 3 assumes changes in trade intensity while keeping the income distribution unchanged at observed values. Yet, perceptions may be different for each level of actual trade, depending on the level of income inequality. Figure 4 therefore has results for each degree of (presumed) openness with the Gini qua assumption at 35, 40, and 45 percent, and the rest of the variables again as observed. The variation in the Gini covers approx. the mean in the underlying data (39.43 percent) and one standard deviation below and above (-/+ 9.37 percentage points).

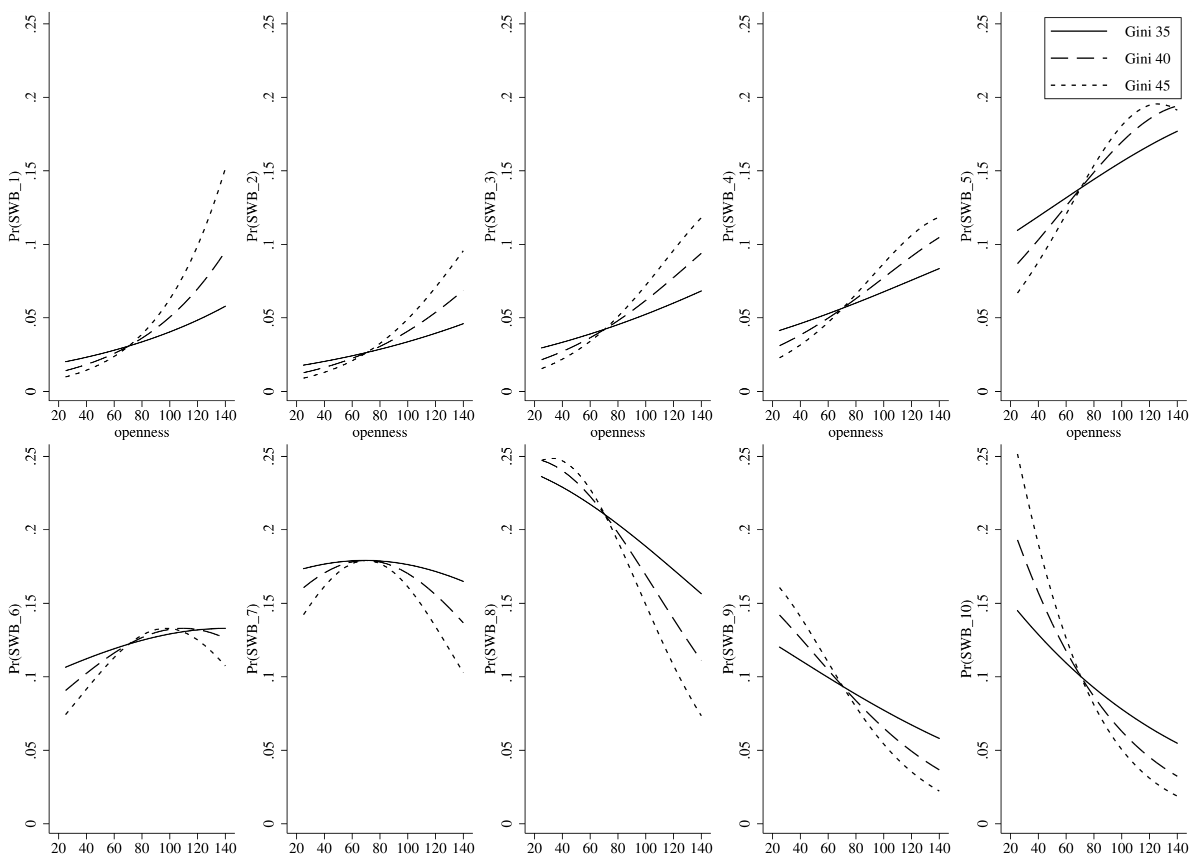

Figure 4: Average adjusted predictions (AAPs) at various degrees of openness & income inequality

Accordingly, income distributions matter in perceptions about (actual) trade intensity. Once the trade-to-GDP ratio has surpassed a pivotal ratio,[11] a higher Gini requires a lower degree of openness to yield the same AAP at each rank of SWB. Conversely, higher trade-to-GDP ratios accentuate negative perceptions as to income inequality. Taken together, Figs. 3 and 4 thus lend support to Hypothesis 1, namely that income inequality is perceived differently, depending on trade. While these results may also be considered partly reconcilable with the notion of individuals seeing themselves at a higher risk of falling into the lower end of the spectrum of the income distribution at higher levels of inequality for any given level of trade, marginal effects of the actually observed income inequality on SWB at various levels of trade cater more directly to a trade-sensitivity in perceptions about income distributions. Therefore, the estimating of marginal effects is a natural extension of the previous analysis.

6. Dissecting Results Further: Marginal Effects of Income Inequality

Marginal effects of variations in the Gini (from its observed value) do indeed further substantiate previous findings. We thus dissect results further by calculating the marginal effect of a one percentage point increase in the Gini from its observed value at different degrees of openness with the other covariates held constant as observed. Figure 5 summarizes the resulting effects on predicted probabilities for all ranks on the SWB scale, including the respective confidence interval (95 percent). Notably, all panels of Fig. 5 display marginal effects, that is, the difference in the predicted probability in case of a (marginal) change in the inequality measure. Because of referring to differences, the marginal effects can be positive as well as negative, with a positive sign indicating an increase in the probability of reporting to the respective rank on the SWB scale and a negative sign the opposite. They are average marginal effects (AMEs) as they are based on an averaging of the impact of all other covariates across individuals, even with the values as observed.

[11] The pivotal point at a trade-to-GDP ratio of approx. 70 is not a bug, but a feature: at this point, both effects (openness, income inequality) just compensate each other's impact on SWB at the margin (similar, though with respect to a completely different research question and data: Greene 2010: p.295, Fig.4.)

The panels referring to SWB scores 1 and 10 have an unambiguous interpretation has they solely correspond with the upper (in case of a SWB score of 10) and the lower (in case of a SWB score of 1) ranks of satisfaction. In case of the 1st rank, a negative sign thus implies that, on balance, individuals move up the ranks, a positive sign implies that, on balance, individuals with the assumed characteristics as to the covariates fall down the ranks and into the 1st rank.

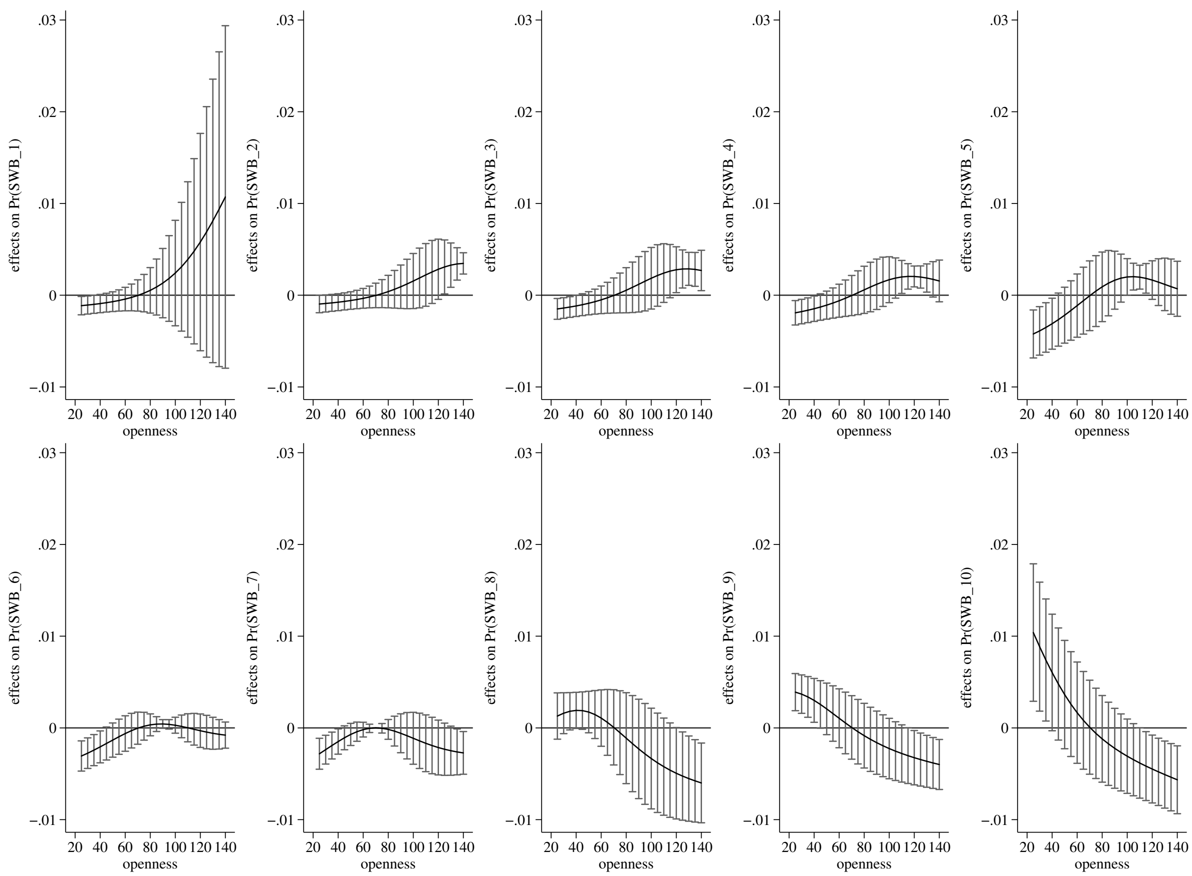

Figure 5: Marginal effects of an increase in the Gini (based on disposable household income) from its observed value on the probability of a particular level of subjective well-being (SWB), at various degrees of openness

However, according to the leftmost panel in the top row of Fig. 5, individuals become more satisfied with their lives even if the Gini increases by one percentage point, provided that openness is still low, whereas at higher levels of openness (beyond a pivotal trade-to-GDP ratio of approx. 70) no such effect can be identified for sure. Although the AMEs in this case are for the most part positive at higher levels of openness, probabilities are generally low (with few individuals seeing themselves in this category), and with some of them falling out of the positive range (as indicated by the vertical confidence interval), so that the positive impact cannot be considered significant.

Results for the upper scores differ though, both with respect to the sign and the significance. As to the upmost SWB scores, results show that, at high(er) degrees of openness to trade, the marginal effect is negative and significantly so at the 5 percent level. Consider, for example, the 10th rank, shown in the rightmost panel of the bottom row. Here, individuals clearly drop out of the rank at high levels of openness, indicating a discontent with a marginal increase in inequality as measured by the Gini. Probabilities of reporting to the 10th rank increase though with the sign again significant if openness is sufficiently low.[12]

In the middle of the SWB domain, marginal effects are more difficult to disentangle because a positive sign may be due to movements down as well as up, with both of the movements into the respective rank. However, at high(er) degrees of openness, (marginal) changes in income inequality still exert a significant (negative) effect on high(er) levels of SWB and (positive) effects on low(er) levels of SWB (SWB scores 7, 8, 9 experience a decrease in predicted probabilities at the margin, SWB scores 2 and 3 an increase).

In any case, results back Hypothesis 2, according to which marginal effects on life satisfaction of the nexus between inequality and trade differ across SWB-levels. While results show some variation, income inequality is obviously considered more of an issue the more open the economy. Openness thus changes how matters of income distribution are being seen. This is quite different from any discontent with globalization because of its distributional impact. Perceptions are more compatible with issues of group-identity and a "them-versus-us perspective" on trade. That being so, it is susceptible to populist policies and costly protectionism, even more so than the discontent because of any distributional impacts of trade.

[12]At lower degrees of openness, the "option value" of openness for climbing the SWB ladder seems to dominate whereas at higher levels of SWB it is the fear of losing out.

7. Conclusions

The backlash against globalization, and international trade in particular, is usually seen as an outcome of the distributional impact of trade. While generally associated with welfare gains, not all stand to benefit from trade. Rather, foreign competition also drives out industries, with specialized labor and production factors losing out. This winner-loser perspective has some truth to it, as for instance research on voting behavior has shown.

However, the fact that the backlash has gained political leverage across a broad range of countries and sectors so as to shape policies in a great many countries is much harder to explain by simply referring to a winner-loser divide. This paper thus goes beyond traditional winner-loser explanations in that it focuses on whether there is also a broader anti-trade sentiment underneath, a sentiment that is rooted in group-identity and a "them versus us" understanding of trade. Results of a logit analysis based on subjective well-being, openness and income distribution data indeed cater to this explanation. Accordingly, marginal effects of a one-percentage change in the observed income inequality as measured by the Gini coefficient tend to lower self-reported scores of satisfaction with life, with the adverse effect accentuated at higher degrees of openness.

The analysis lends itself to a number of extensions. As in the winner-loser debate, income redistribution, if not a roll-back of globalization, is often considered an appropriate answer. While popular, it is not clear whether this holds true. Further research may tell.

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Appendix

Table A1: Data sources

Variable	Source	Webpage	Edition
Dependent variable			
satisfaction with life (SWB)	World Values Survey	http://www.worldvaluessurvey.org	Jan 01, 2017 (Wave 6)
Independent variables: main indicators			
income distribution (Gini, Atkinson, Theil)	Luxembourg Income Study	http://www.lisdatacenter.org	Feb 09, 2017 (Wave 8)
openness	World Bank	http://wits.worldbank.org	Jan 20, 2017
income per capita at ppp	World Bank	http://databank.worldbank.org/data/home.aspx	
trade freedom	Heritage Foundation	http://www.heritage.org/index/download	Jan 19, 2017
	Fraser Institute	http://www.fraserinstitute.org/economic-freedom/	Jan 19, 2017
Independent variables: individual controls			
gender	World Values Survey (as above)		
age			
income category			
education level			
number of children			
employment status			
marital status			
dummies (religion, health, union member)			

Table A2: Description of the dependent and independent variables (n=28,381 interviews; N=19 countries)

Variable	Percentage/Mean (Median)	Standard Deviation	Min	Max
Dependent variable				
satisfaction with life / SWB	(7)		1	10
SWB1	2.35			
SWB2	2.04			
SWB3	3.28			
SWB4	4.45			
SWB5	11.30			
SWB6	10.58			
SWB7	16.94			
SWB8	23.10			
SWB9	11.90			
SWB10	14.07			
Independent variable				
distribution				
Gini	.39(.32)	.09	.25	.58
Atkinson (.5)	.13(.11)	.06	.05	.27
Atkinson (1) for marginal effects: x 100	.25(.22)	.11	.10	.48
Atkinson (2)	.57(.59)	.17	.22	.82
Theil	.28(.23)	.14	.11	.59
openness (trade to GDP)	69.09(55.99)	36.37	22.52	143.80
trade freedom				
Heritage	79.87(82.80)	8.11	67.90	89.10
Fraser	7.39(7.60)	0.82	5.80	8.63
gdp pc (USD @ PPP)	22,256.06(20,497.93)	13,937.48	4,315.60	48,373.88
age	43.96(42)	16.93	16	99
female (ref.cat)	50.97			
income	4.64(5)		1	10
inc1	8.23			
inc2	8.40			
inc3	13.26			
inc4	15.24			
inc5 (ref.cat)	21.71			
inc6	14.47			
inc7	10.57			
inc8	5.53			
inc9	1.45			
inc10	1.14			
level of education				
no education	.81			
incomplete primary	5.89			
complete primary	11.43			
incomplete secondary	7.97			
complete secondary	18.55			
incomplete univ. prep	8.04			
complete univ. prep	18.83			
univ. drop out	8.73			
univ. degree (ref.cat)	19.75			
number of children	1.51(2)	1.13	0	3+(8)
0 children	26.87			
1 child	19.01			
2 children (ref.cat)	30.11			
3+ children	24.02			
employment status				
full/part employed (ref.cat)	42.83			
self employed	10.48			
retired	15.87			
house	11.77			
student	5.52			
unemployed	10.73			
other	2.81			
marital status				
married/partner (ref.cat)	63.63			
separated, divorced, widowed	13.58			
single	22.79			
religious (ref.cat)	63.02			
good health (ref.cat)	70.66			
not union member (ref.cat)	83.44			

Table A3: Robustness with respect to trade, inequality & freedom indices

endogenous variable: satisfaction with life

distribution (disposable household income; original index numbers times 100): Gini index, Atkinson index, Theil index;

trade intensity / ratios: (i) openness: trade-to-GDP, (ii) ex: exports-to-GDP, (iii) im: imports-to-GDP;

trade freedom: Heritage Foundation, Fraser Institute

Variables	Coef.
distribution (Gini)	.1056***
	(.0282)
im	.0906***
	(.0286)
distribution x im	-.00320***
	(.001)
trade freedom (Heritage)	.0372***
	(.01)
gdp pc (log)	.427
	(.703)
⋮	⋮
Pseudo R-squared	0.0472

Variables	Coef.
distribution (Gini)	.1128***
	(.0325)
ex	.0859***
	(.0322)
distribution x ex	-.0029***
	(.0011)
trade freedom (Heritage)	.0222**
	(.0107)
gdp pc (log)	1.167*
	(.635)
⋮	⋮
Pseudo R-squared	0.0458

Variables	Coef.
distribution (Atkinson ϵ=05)	.1926***
	(.0526)
openness	.0203**
	(.00848)
distribution x openness	-.00302***
	(.00108)
trade freedom (Heritage)	.0332***
	(.0084)
gdp pc (log)	.618
	(.558)
⋮	⋮
Pseudo R-squared	0.0470

Variables	Coef.
distribution (Atkinson ϵ=1)	.1013***
	(.0289)
openness	.0214**
	(.0090)
distribution x openness	-.00159***
	(.0006)
trade freedom (Heritage)	.0306***
	(.0085)
gdp pc (log)	.593
	(.581)
⋮	⋮
Pseudo R-squared	0.0465

Variables	Coef.
distribution (Theil)	.08979***
	(.02389)
openness	.0190**
	(.0080)
distribution x openness	-.00138***
	(.0005)
trade freedom (Heritage)	.0344***
	(.0085)
gdp pc (log)	.680
	(.557)
⋮	⋮
Pseudo R-squared	0.0473

Variables	Coef.
distribution (Gini)	.0972***
	(.0315)
openness	.0382**
	(.0166)
distribution x openness	-.00131**
	(.0006)
trade freedom (Fraser)	.131
	(.139)
gdp pc (log)	1.099
	(.776)
⋮	⋮
Pseudo R-squared	0.0452

Observations 28.381; clustered errors YES

Robust standard errors in parentheses

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