Heterogeneous Effects of Tariff and Non-tariff Trade-Policy Barriers in Quantitative General Equilibrium

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Abstract

Structural quantitative work in international economics typically models trade costs as a log-linear function of exogenous trade-policy variables. We propose a structural approach that allows for a non-parametric relationship and for treating tariff and non-tariff trade-policy variables as potentially endogenous. The data reject the assumption of log-linearity of trade costs in both tariff- and non-tariff-policy variables. We assess the effects of a unilateral increase of US tariffs on Chinese imports by 10 percentage points and document that the estimated effects on real bilateral trade-flow changes would be substantially underestimated by standard approaches.

Keywords: Trade policy; Gravity models; Semi-parametric methods; Non-parametric methods; Generalized propensity scores.

JEL classification: C14; F14; F13.

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1 Introduction

Virtually every announcement of a trade-policy intervention is followed by an attempt to quantify its economic consequences. Economists achieve this by employing parameterizations of structural models, predominantly general-equilibrium models, which formalize the impact of trade-policy shocks. Countless studies have aimed at quantifying the effect of trade liberalizations in this spirit.[1] One important insight gained from this work is that the economic outcome responses to a uniform trade-policy shock differ across countries due to their distinct fundamentals. However, despite incorporating rich mechanisms that produce heterogeneous responses across countries, conventional quantitative general-equilibrium models often impose at least three important restrictive assumptions.

First, they impose a homogeneous and log-linear relationship between trade-policy variables and ad-valorem trade costs and a log-linear *direct* relationship between ad-valorem trade costs and trade flows.[2] Heterogeneous trade-cost effects emerge only indirectly, and mainly through general-equilibrium repercussions, i.e., through effects on consumer and producer prices (see, e.g., Eaton and Kortum, 2002; Anderson and van Wincoop, 2003; Arkolakis et al., 2012). This paper demonstrates that the data appear to reject a log-linear direct relationship between trade policy and trade flows and illustrates that assuming it depresses the heterogeneity of equilibrium responses to trade-policy changes.[3]

A second customary restriction lies in the focus on trade policy through tariffs alone.[4] Non-tariff barriers to trade are associated with the application of specific checking routines at borders and the implementation of standards and procedures with an intent to protect domestic suppliers (see Anderson, 2016). Non-tariff policy regulations have

[1]See, e.g., recent work on Brexit by Breinlich et al. (2016), the Transatlantic Trade and Investment Partnership (TTIP) by Felbermayr et al. (2016), or the 2018 trade war between the US and China by Fajgelbaum et al. (2019).

[2]Eaton and Kortum (2002) and Henderson and Millimet (2008) consider non-parametric direct effects of geography on trade costs and trade flows, but the results do not point to any strong non-log-linearity of the direct effects at large geographical distance. The findings of Hillberry and Hummels (2008) suggest, however, that geography induces non-log-linear effects over short distances.

[3]In a recent study Adão et al. (2017) emphasize the importance of relaxing functional form restrictions in general-equilibrium models of trade but do not consider non-parametric trade costs.

[4]See, e.g., Romalis (2007) or Caliendo and Parro (2015).

become extremely important since the Uruguay Trade Round (see, Horn et al., 2010). They have garnered attention and become the focus of interest in the context of the "new" protectionism since the beginning of the Economic and Financial Crisis (Bown, 2011; Baldwin and Evenett, 2012; Bown and Crowley, 2013). The use of non-tariff measures is relevant if tariffs and non-tariff barriers are set jointly and not independently by policy makers, and if their partial effects depend on each other. We will allow for the latter and document that responses to tariff changes tend to depend on non-tariff provisions and vice versa.[5]

A final customary but restrictive assumption is that trade-policy measures are treated as randomly assigned to countries rather than chosen with an economic rationale.[6] Economic theory hypothesizes that countries choose tariffs based on their fundamentals (see Bond, 1990; Bond and Syropoulos, 1996; Bagwell and Staiger, 1999, 2004; Ossa, 2011, 2014; Felbermayr et al., 2013; Caliendo et al., 2015).

The present paper puts forward a quantitative framework and analysis of trade-policy effects on trade costs and trade flows in a unified framework to relax the aforementioned three assumptions. It builds on a multi-country-multi-sector quantitative framework that is consistent with a wide range of trade models (compare Arkolakis et al., 2012; Costinot and Rodriguez-Clare, 2014). To address the aforementioned concerns, the paper suggests implementing the following multi-step approach.

First, trade data – here, for 115 countries and 128 sectors – are decomposed to extract information on exogenous producer-country-sector fundamentals as well as total ad-valorem trade frictions. Second, machine-learning algorithms are used to decompose tariff and non-tariff policy barriers into their deterministic (predicted) and residual (random) parts. In line with the literature on optimal trade policy (Bond and Syropoulos, 1996; Ossa, 2011, 2014; Felbermayr et al., 2013), we impose that trade policy and trade

[5]Related to this, Caliendo et al. (2021) suggest that, in quantitative models of migration, it is insufficient to control for direct migration costs alone, but other policy domains need to be be considered, too.

[6]See, e.g., Eaton and Kortum (2002) or Caliendo and Parro (2015). If at all, endogeneity of trade policy is mostly considered through the (binary) membership of countries in preferential trade agreements (see Baier and Bergstrand, 2007, 2009). With the exception of Egger and Larch (2011) and Egger et al. (2011), related work on endogenous trade agreements is concerned with the direct (partial) rather than the *total* (direct plus indirect) effects on economic outcome.

flows depend on the same fundamentals in their reduced form. Third, we estimate the link function of ad-valorem trade costs on tariff and non-tariff barriers, using the joint density of their random components. This approach is a multivariate generalization of the dose-response-function estimation in Flores et al. (2012). We present evidence of a non-log-linear mapping of the trade-policy variables with ad-valorem trade costs.

We find that the marginal effect of an increase in tariffs is very strong for very low and medium tariff barriers, while it is much weaker and even close to zero for very high tariff barriers, especially, when non-tariff barriers are high. Non-tariff barriers increase trade costs, in particular, for very low initial levels of non-tariff barriers. For medium levels of non-tariff barriers, marginal effects on trade costs can actually be trade-cost-reducing which is owed to the beneficial effects of some technical barriers to trade. These patterns are consistent with tariff and non-tariff avoidance at high levels of these costs (see Fisman and Wei, 2004, Javorcik and Narciso, 2008, Sequeira, 2016, and Demir and Javorcik, 2017), and with a lacking usage of granted preferential tariffs at low most-favored-nation tariff levels (see Herin, 1986, Francois et al., 2006, Estevadeordal et al., 2008, Fugazza and Nicita, 2013, Krishna et al., 2021).

To demonstrate the importance of these non-linearities we feed the estimated trade-policy gradients into a quantitative multi-country, multi-sector general-equilibrium model of trade and evaluate the effect of a unilateral increase in US tariffs on Chinese imports of 10 percentage points. The effects of this particular policy change would be severely underestimated by a customary modeling of trade costs as log-linear in tariffs compared to the flexible-gradient approach proposed in this paper. The average reduction across all treated sector-level US import shares from China is about 7 percentage points larger with the flexible-gradient approach and total US imports from China (evaluated at benchmark income levels) fall by 6% as compared to only 3% under an ad-valorem specification.

2 The effect of trade policy in gravity models of international trade

Quantitative work in international economics on the effect of trade-policy changes is almost exclusively based on gravity models for at least three reasons: (i) the empirical success of structural gravity estimation (Head and Mayer, 2014), (ii) the wide range of theoretical general-equilibrium trade models leading to a gravity equation including models with appealing micro-foundations (Costinot and Rodriguez-Clare, 2014), and (iii) the parsimonious nature that allows researchers to quantify the (welfare) consequences of changes in fundamentals relying on only very few key parameters – in particular estimates of the so called trade elasticity – while still being able to take into account general-equilibrium effects.[7]

Consider the simplest case of such a gravity model – a single-sector Armington model where different countries are endowed with a fixed quantity, Q_i, of distinct goods and each country is populated by a representative consumer with constant-elasticity-of-substitution (CES) preferences over these goods. Bilateral trade flows, X_{ij}, between an exporter i and an importer j will be given by the well-known CES demand for the exporter's good which is a function of the good's price (mill price, P_{ii}, times ad-valorem trade costs, D_{ij}), the price index in j, P_j, and the importer's total expenditure (which equals income), Y_j. The elasticity α is a linear function of the elasticity of substitution specified in the CES preferences:

$$X_{ij} = (P_{ii}D_{ij})^{\alpha}\,\frac{Y_j}{P_j} \tag{1}$$

Note that bilateral sales consist of an exporter-specific part, an importer-specific component and bilateral trade costs. The mill price of exporter i's good, P_{ii}, is the total value of the good country i is endowed with, Y_i, divided by total endowment Q_i, $P_{ii} = Y_i/Q_i$. While the quantity is exogenously given, the price of the good is endogenously deter-

[7] We provide details on the general equilibrium formulation of the specific parsimonious trade model outlined in this paper in an online appendix to this paper.

mined in general equilibrium. The importer-specific part consists of total expenditure of partner country j, Y_j, divided by the price index prevailing in that country, P_j.[8] The price index itself is a function of mill prices P_{kk} of all countries, $k = 1...J$, and trade costs D_{kj} between all countries $k = 1...J$ and j.

Using this model for trade policy analysis, it is customary to assume that ad-valorem trade costs, D_{ij}, are proportional to ad-valorem tariffs. Then, the direct effect of tariffs on trade – the effect before general-equilibrium adjustments of prices and income – is log-linear and governed by α. Note that this direct effect is uniform for all countries and irrespective of their fundamentals. Hence, a reduction in tariffs would have the same direct effect in a country irrespective of its previous tariff level, its implementation of non-tariff barriers or how hard it is to actually apply preferential market access formalities. Only once general-equilibrium adjustments are taken into account, heterogeneous effects of trade policy can emerge through the endogenous adjustment of mill prices.

While the Armington model is admittedly stylized, the general structure of bilateral trade flows outlined above holds for a wide range of models some of them incorporating sophisticated micro-theoretical mechanisms. In these so-called gravity models, trade flows, X_{ij}^s, between an exporter i and an importer j within a sector s depend multiplicatively on three components: supply-potential factors that are exporter-sector specific, A_i^s, demand-potential factors that are importer-sector specific, B_j^s, and friction factors that vary at the sector-country-pair level, D_{ij}^s, and whose impact on trade-flows is governed by the trade elasticity, α_s:

$$X_{ij}^s = A_i^s B_j^s \left(D_{ij}^s\right)^{\alpha_s}. \tag{2}$$

Theoretical models resulting in a gravity-type model for international trade flows differ mainly with respect to the structural interpretation of the exporter-sector-specific component, A_i^s, and the importer-sector-specific component, B_j^s, but not with respect to the bilateral component, D_{ij}^s.[9] This bilateral component is typically simply referred to as

[8] Note that we abstract from tariff revenues here, this is relaxed later.

[9] In the simple Armington model above, for instance, $A_i = (Y_i/Q_i)^\alpha$ and $B_j = Y_j/P_j$.

"iceberg-type" trade costs and assumed to encompass all potential frictions to trade in some unspecified way.[10] Absent any theoretical guidance, most empirical work assumes a log-linear trade-cost function. Just as above, modeling changes in ad-valorem tariffs will lead to the same restrictive, uniform direct effects on trade flows irrespective of the underlying complex micro-theoretical mechanisms.

How can we better understand how bilateral trade costs D_{ij}^s and trade policy are related?

To begin, we can obtain an estimate of these costs in logs, $\widehat{d}_{ij}^s$,[11], by decomposing product-level bilateral exports (in logs) into their product-level importer and exporter-specific components:

$$x_{ij}^s = a_i^s + b_j^s + \alpha_s d_{ij}^s, \tag{3}$$

estimating a linear fixed-effects regression to obtain estimates of a_i^s and b_j^s and using trade elasticities from the literature (Kee et al., 2008) to back out an estimate of bilateral sector-specific trade costs:

$$\widehat{d}_{ij}^s = \frac{1}{\alpha^s}\left(x_{ij}^s - \widehat{a}_i^s - \widehat{b}_j^s\right). \tag{4}$$

Our objective is to comprehend the nature of trade costs further. To this end, we will extend the notion of trade policy beyond its focus on tariffs taking into account non-tariff barriers and allow for potentially non-linear effects of trade policy on trade costs.

On the one hand, non-tariff policy regulations have become extremely important since the Uruguay Trade Round (see, Horn et al., 2010) and they have recently become the focus of interest in the context of the "new" protectionism since the beginning of the Economic and Financial Crisis (Bown, 2011; Baldwin and Evenett, 2012; Bown and Crowley, 2013). Non-tariff barriers to trade are associated with the application of specific checking routines at borders and the implementation of standards and procedures with an

[10]Note that we restrict our analysis to trade models featuring a constant trade elasticity and that this assumption has consequences, e.g., for welfare.

[11]Throughout the paper, hats will indicate estimates and lower-case letters, x, will refer to the log of a variable, X.

intent to protect domestic suppliers (see Anderson, 2016). In contrast to tariffs, certain non-tariff barriers might also have trade-enhancing effects, e.g., by establishing trust in products through standards or decreasing transaction costs (WTO, 2012).

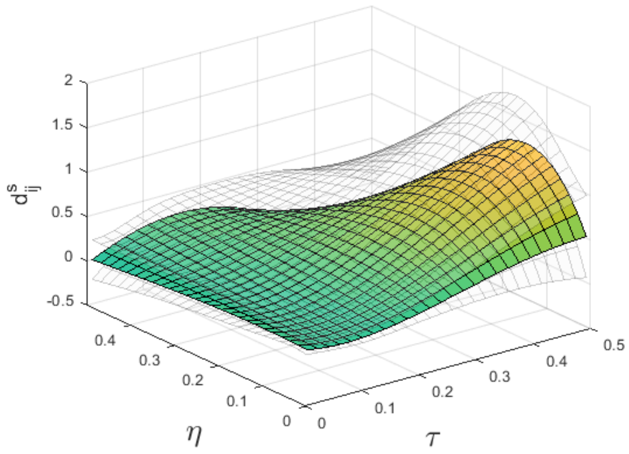
On the other hand, several studies question the assumption of log-linear trade costs based on at least five arguments. First, the nexus between tariff and non-tariff barriers and trade costs is affected by mis-declarations at customs (see, e.g., Demir and Javorcik, 2017; Fisman and Wei, 2004; Javorcik and Narciso, 2008; Sequeira, 2016). Second, a non-log-linear relationship between trade-policy variables and trade costs emerges once some trade-policy measures alter prices non-proportionately (as is the case with specific tariffs) rather than proportionately (see, e.g.,Hummels and Skiba, 2004; Irarrazabal et al., 2015). Third, work on the size and role of preference margins suggests that available preferential market access is under-used (see, e.g., Herin, 1986, Francois et al., 2006, Estevadeordal et al., 2008, Fugazza and Nicita, 2013, Krishna et al., 2021). Fourth, the uncertainty about expected applied tariff and non-tariff barriers may induce non-log-linear effects of trade policy on trade costs (see, e.g., Handley and Limao, 2017, Handley and Limao, 2015, Pierce and Schott, 2016, and Crowley et al., 2016). Finally, nonlinearities in the relationship between trade-policy instruments and effective trade costs may relate to the incomplete but trade-cost-dependent penetration of consumer markets (see, e.g., Arkolakis, 2010).[12]

In a first step, we will evaluate how trade costs, $\widehat{d}_{ij}^s$, vary along the dimensions of two measures of trade policy: tariffs, $\tau_{ij}^s = \ln(1+t_{ij}^s)$, and non-tariff barriers, $\eta_{ij}^s = \ln(1+n_{ij}^s)$, each expressed in ad-valorem terms, in a potentially non-linear way using a higher-order polynomial approximation while controlling for customary exogenous trade barriers and 4-digit sector fixed effects.[13] In this exercise, we treat τ_{ij}^s and η_{ij}^s as exogenous determinants of $\widehat{d}_{ij}^s$.

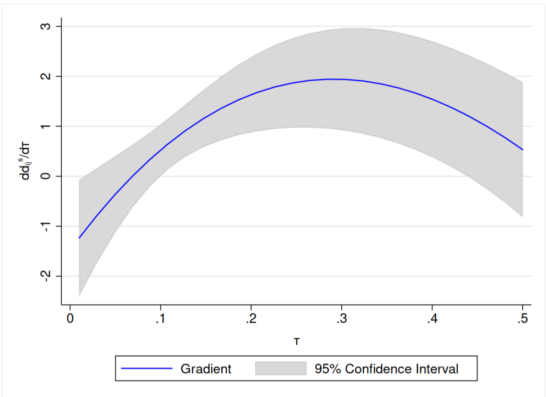
[12] That the trade-cost function may be non-linear in its arguments finds also strong support in the literature assessing distance effects on trade (Hillberry and Hummels, 2008).

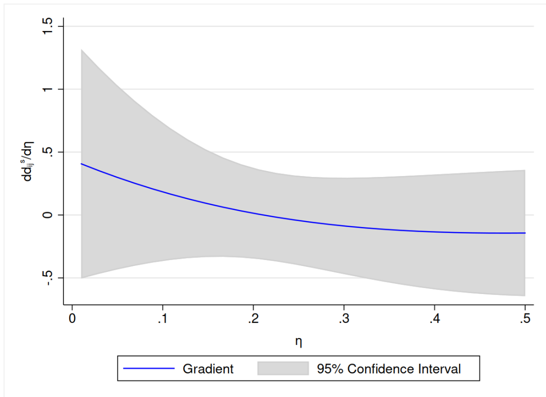
[13] Data on 4-digit sectoral trade flows, x_{ij}^s, to back out $\widehat{d}_{ij}^s$ and applied tariffs, t_{ij}^s, at the country-pair-sector level for the year 2011 are taken from the Trade Analysis Information System (TRAINS) Database contained in the World Bank's WITS Database. Data on ad-valorem equivalents of non-tariff barriers, n_{ij}^s, are available from Kee and Nicita (2016). For more details, see the respective data description in Section 4.

Figure 1: Trade costs as a flexible polynomial function of trade policy.



Dose-response function





Average gradient w.r.t τ Average gradient w.r.t η

We illustrate the results graphically in Figure 1. The upper panel illustrates a so-called dose-response function: it states how log statutory applied tarriff- and non-tariff-barrier ad-valorem rates map into effective log ad-valorem trade costs d^s_{ij}. The two lower panels represent the two-dimensional average gradient of the dose-response function with respect to the two policy variables averaging over the respective other trade-policy variable. The gradient function corresponds to the marginal effects of tariff and non-tariff trade policy at different levels of trade policy. What these figures suggest is that, for tariffs, the gradient is flatter at the lower and the higher end of the support, and for non-tariff barriers it also flattens out at the higher end. This is consistent with the evasion/avoidance as well as the under-usage arguments from earlier work.

However, this evidence must be taken with a grain of salt as (i) it makes an ad-hoc (polynomial) functional form assumption and (ii) it treats the trade-policy measures τ_{ij}^s and η_{ij}^s as exogenous. While the latter is true for many empirical studies on the effects of trade policy in quantitative trade models, earlier work considers their endogeneity in theory as well as in empirical analyses (see Bond and Syropoulos, 1996; Ossa, 2011, 2014; Felbermayr et al., 2013; Caliendo et al., 2015). The next section proposes an approach towards modeling trade costs as a flexible function of trade-policy variables that are jointly determined with trade flows by the same exogenous fundamentals as in the just-mentioned earlier work.

3 Econometric methodology

In modeling the dependence of trade costs on tariff and non-tariff trade-policy barriers we want to permit a sufficiently flexible functional form and to control for the fundamentals which jointly determine trade flows and trade policy (see Bond, 1990; Bond and Syropoulos, 1996; Ossa, 2011, 2014; Felbermayr et al., 2013; Caliendo et al., 2015).[14]

In this context, it is important to note that structural trade models in the quantitative literature we wish to speak to do not only permit decomposing trade flows into their supply, demand, and friction components as outlined in Equation (2). They also identify measures of the endogenous components in supply factors, and, hence, they permit identifying composite measures of the exogenous fundamentals of trade flows and policy. Specifically, in customary quantitative trade models, there is a fundamental driver of trade at the exporter-sector level which we will denote by F_i^s. This could be an exogenous endowment as in the simple Armington model, a supply-side parameter such as productivity (see Eaton and Kortum, 2002) or a demand-side parameter like preferences for this particular country-sector's good (see Anderson and van Wincoop, 2003). This compo-

[14]The endogeneity of trade-policy barriers can be addressed by either instrumental-variable (IV) estimation or approaches relying on an assumption of conditional mean independence (CMI). IV estimation in the present context would require that shifters of trade policy could be found which are independent of any other measurable or unmeasurable trade-cost factors. CMI, by contrast, requires us to model the endogenous component of trade-policy variables observed in the data. Using outside instruments in a multi-country quantitative general-equilibrium setting appears unnatural while the literature suggests that trade-policy variables are conditionally – on the fundamentals determining the endogenous model outcomes jointly with policy – mean independent.

nent is exogenous to the model. Moreover, in gravity-type general equilibrium models, endogenous factor prices ensure that markets clear. We denote this endogenous component by W_i^s. The sensitivity of trade flows to these country-sector specific factor prices is governed by an elasticity which is typically identical to (or at least, co-determined by) the trade elasticity α_s. Note that all three components of the export-sector-specific component of trade flows in Equation (2) are log-additive in endogenous (W_i^s) and exogenous determinants (F_i^s) of exporter potential:[15]

$$A_i^s = F_i^s (W_i^s)^{\alpha_s}. \tag{5}$$

This structural decomposition is important, as a large body of work on endogenous trade policy considers the fundamentals behind the (optimal) choice of trade-policy parameters to be the same as the ones behind the endogenous factor and output prices which co-determine supply and demand, and, hence, trade flows (see Bond and Syropoulos, 1996; Baier and Bergstrand, 2004; Bond et al., 2004; Ossa, 2011, 2014; Felbermayr et al., 2013; Caliendo et al., 2015). According to this literature all that matters for the systematic determination of trade policy are the sector-country-pair *natural trade costs*, the sector-country *fundamental drivers of supply potential*, and the sector-level *trade elasticities*. Conditional on these factors, trade policy is stochastically independent of or random to trade flows. The reason is that, upon a complete decomposition of trade flows in a generic general-equilibrium setting as considered here, there are no other systematic determinants of these flows beyond the mentioned ones.[16]

Hence, in order to tackle the endogeneity concerns in the present context, invoking an assumption of conditional mean independence (CMI) of trade policy appears attractive. After invoking the CMI assumption regarding the relationship between trade-policy barriers and trade costs, the potential endogeneity of trade-policy barriers in the trade-

[15] Adão et al. (2017) establish a quantitative trade model supporting non-parametric effects of preferences and technology – both of which are ingredients of F_i^s – on trade flows in s from i to j. The interest here is on a non-parametric link between endogenous trade policy and overall trade costs on the one hand and trade flows on the other hand, an issue which is not addressed in Adão et al. (2017). Hence, the two approaches appear complementary to each other.

[16] Note that all endogenous variables such as prices are fully characterized by the aforementioned exogenous determinants.

cost function mainly roots in two types of unknown functional forms, the one of how trade-policy variables map into trade costs, and the one how the deterministic part of trade-policy measures is determined by a large set of known exogenous fundamentals. In line with that argument, log ad-valorem trade costs, d^s_{ij}, are a function of a policy vector of two endogenous elements $m^s_{ij} = (\tau^s_{ij}, \eta^s_{ij})$ and a vector of (exogenous) remainder, natural other trade costs u^s_{ij}, $d^s_{ij}(m^s_{ij}, u^s_{ij})$. Moreover, the simultaneous determination of trade flows and trade policy by the same fundamentals suggests that log exports, x^s_{ij}, and the vector of log statutory trade-policy barriers, m^s_{ij}, can both be modeled as a function of country-specific fundamentals in logs, f^s_i and f^s_j, third-country-fundamentals in logs, $f^s_{-i,-j}$, country-pair natural trade costs in logs, u^s_{ij}, third-country-pair natural trade costs in logs, $u^s_{-i,-j}$, and the trade-elasticity parameter, α_s. We subsume these exogenous factors in the vector $q^s_{ij} = \{f^s_i, f^s_j, f^s_{-i,-j}, u^s_{ij}, u^s_{-i,-j}, \alpha_s\}$ and, regarding trade policy, specify the ex ante unknown functional relationship as:[17]

$$m^s_{ij} = g_m(q^s_{ij}) + \nu^s_{m,ij}, \tag{6}$$

where $\nu^s_{m,ij} = (\nu^s_{\tau,ij}, \nu^s_{\eta,ij})$ is a 1×2 vector of stochastic components of the tariff and non-tariff components in m^s_{ij}, τ^s_{ij} and η^s_{ij}, conditional on the flexible function of country-pair and third-country exogenous observables in q^s_{ij}.

In pursuit of establishing conditional mean independence of trade policy, we build on the idea of conditioning on the joint country-sector and country-pair-sector fundamentals of bilateral trade costs and trade flows, q^s_{ij}, through a compact metric, referred to as the generalized propensity score (GPS) (see Hirano and Imbens, 2004; Imai and Van Dyk, 2004; Flores et al., 2012). The corresponding approach proceeds in three steps.

Let us use indexed m^s_{ij}, unindexed m, and $\mathscr{M}$ to refer to actual (observed), potential, and the set of all potential levels of the two trade-policy variables of interest, respectively. First, m^s_{ij} is decomposed into the part which is explained flexibly by the joint exogenous drivers of trade policy and trade flows as well as the residual part which is conditionally random. Second, the joint density of the random component $\nu^s_{m,ij}$ in tariff and non-tariff

[17] A similar function exists for log exports, x^s_{ij}.

barriers, $r(m, q_{ij}^s)$, is estimated in a flexible way. Third, the partial relationship between effective log ad-valorem trade costs d_{ij}^s and the two statutory trade-policy variables in logs in m_{ij}^s is estimated by conditioning on the joint density $r(m, q_{ij}^s)$.

Let us define potential (unobserved) bilateral trade costs in logs that are associated with any potential trade-policy treatment $m \in \mathscr{M}$ as $d_{ij}^s(m)$. For identification of the causal partial effect of tariff and non-tariff trade policy on trade costs and trade flows, we rely on two assumptions (see Hirano and Imbens, 2004; Imai and Van Dyk, 2004):

Assumption 1 (Stable unit treatment value assumption) *Conditional on the vector of observed covariates, q_{ij}^s, which contains all joint exogenous drivers of trade policy and trade flows, the distribution of potential outcomes (trade costs and trade flows) for one (country-pair-sector) unit is independent of the (potential) trade-policy treatment level of any other unit.*

Assumption 2 (Weak unconfoundedness assumption) *Any potential level of bilateral trade costs is independent of the actual trade-policy treatment conditional on the vector of all joint determinants of trade policy, trade costs, and trade flows, q_{ij}^s:*

$$d_{ij}^s(m) \perp m_{ij}^s | q_{ij}^s \ \forall \ m \in \mathscr{M}. \tag{7}$$

Assumption 1 implies that, conditional on the observables included in the treatment and the outcome equations, the treatment effects of trade policy on trade costs are independent between the country pairs within a sector. This does not preclude that trade costs induce effects on trade through general equilibrium effects on third countries. Note also that we implicitly condition on the impact of other countries' trade policy by allowing their fundamentals (that are co-determining their trade policy) to enter the equation. This is also true for other endogenous variables such as prices and quantities.

Assumption 2 relies elementarily on the suitability of the vector of joint determinants of trade policy, trade costs, and trade flows, q_{ij}^s. While doing so may be difficult elsewhere, the setting within a generic quantitative trade model is invaluable here, as it illustrates that the elements of q_{ij}^s together make an exhaustive set of joint determinants of trade policy, trade costs, and trade flows.[18]

It can be shown that, under the adopted assumptions (see Theorem 3.1 in Hirano and Imbens, 2004, for a proof)[19],

$$E(d_{ij}^s(m)|r_{ij}^s = r, m_{ij}^s = m) = E(d_{ij}^s(m)|r(m, q_{ij}^s) = r) = k(m, r(m, q_{ij}^s)), \tag{8}$$

$$E(d_{ij}^s(m)) = E(k(m, r(m, q_{ij}^s))). \tag{9}$$

Hence, conditioning on the generalized propensity score removes any bias associated with the joint determination of trade-policy variables and trade costs. We obtain a consistent estimate of the average causal partial effect of a change in trade-policy variables on trade costs as follows:

The function $k(\cdot)$ in Equation (8) is a *unit dose-response* function and reflects the link between observed trade-policy variables along with their associated joint conditional density for each tuple $\{ijs\}$. This function can be estimated in a flexible way using observed trade-policy variables and their associated generalized propensity score.

In order to obtain the average treatment effect of a particular trade-policy treatment m, we evaluate the *unit dose-response* for all potential trade-policy treatment levels m and average across all units. This leads to the *average dose-response* function $E(k(\cdot))$ in Equation (9), which relates potential levels of trade policy in logs, m, to the corresponding levels of effective log ad-valorem trade costs, d.

[18] Note that the true functional form of aggregation of individual third-country fundamentals is non-linear. Using the average attaches equal weights to the individual fundamentals. It turns out that the proposed approach produces estimates with a relatively high explanatory power suggesting that the source of endogeneity is reduced substantially.

[19] As before, let us use q_{ij}^s and q to refer to actual and potential values of each of the elements in q_{ij}^s, and let r_{ij}^s and r denote the actual and hypothetical conditional (on q_{ij}^s and q) densities of trade-policy treatments m_{ij}^s and m, respectively. The two values $r(m, q)$ and r_{ij}^s may be referred to as potential and actual generalized propensity scores, respectively.

4 Data

4.1 Bilateral exports

In order to obtain estimates of the log sales potential per country and sector, a_i^s, and of log scaled ad-valorem trade costs, c_{ij}^s, we collect data on bilateral imports at the 4-digit ISIC Rev. 3.1 sector level for the year 2011 from the World Bank's World Integrated Trade Solution (WITS) Database. Apart from data on sector-specific trade volumes, we use free-on-board unit values (i.e., the total value of exports of country i in sector s divided by the corresponding tonnage of exports) as reported in WITS. These values are proportional to exporter-sector-level costs of the factor bundle, W_i^s, according to the structural quantitative trade models used as a reference point in this paper.

4.2 Trade-policy variables and import-demand elasticities

Data on ad-valorem tariff and non-tariff barriers to trade are collected from the following sources. First, data on applied tariffs, t_{ij}^s, at the country-pair-sector level for the year 2011 are reported in and taken from the Trade Analysis Information System (TRAINS) Database contained in the World Bank's WITS Database.[20] Second, data on ad-valorem equivalents of non-tariff barriers, n_{ij}^s, are available from Kee and Nicita (2016). Finally, data on sector-level import-demand elasticities, α_s, are available from Kee et al. (2008).[21]

4.3 Trade-cost and sales-potential fundamentals

Data on a host of *natural* (non-policy) trade barriers – i.e., the elements of u_{ij}^s – are taken from the Centre d'Études Prospectives et d'Informations Internationales' (CEPII's) database on geographical and historical trade-cost variables (Conte et al., 2022). The corresponding variables are log(Distance$_{ij}$) (log of the geographical distance between the

[20] We use effectively applied tariff rates. In case data for 2011 are not available, we take the information from the closest year with the earlier year winning ties.

[21] While these data come at the 6-digit HS96 level, we aggregate them to the 4-digit ISIC Rev. 3.1 level in a way that is consistent with their estimation methodology. See their Online Appendix for more details. Conversion tables are taken from WITS. Note that Kee et al. (2008) estimate quantity elasticities that can be adjusted to price elasticities by adding unity.

main economic centers of countries i and j; continuous), Contiguity$_{ij}$ (land adjacency between countries i and j; binary), Common official language$_{ij}$ (whether countries i and j have at least one official language in common; binary), Common ethnological language$_{ij}$ (whether countries i and j have at least one language in common that is spoken by at least 20% of the population; binary), Colony$_{ij}$ (whether one country in i and j was the colonizer of the other one in history; binary), Colony (1945)$_{ij}$ (whether one country in i and j was the colonizer of the other one after 1945; binary), Common colonizer$_{ij}$ (whether the two countries i and j had the same colonizer in common at some point in history; binary), Current colony$_{ij}$ (whether the two countries i and j are currently in a colonial relationship; binary), Same country$_{ij}$ (whether one country in i and j formed part of the other one in history and was or is simply a territory rather than an independent country; binary).

In order to obtain estimates of country-sector-specific fundamentals of the model in logs, f_i^s, we use the estimate of exporter-sector fixed effects obtained from estimating Equation (3) and back out log country-sector sales fundamentals using Equation (5), where factor costs W_i^s are obtained from the proportionality with log country-sector (free-on-board) unit values and data on the latter.

4.4 Summary statistics

Since mass points pose a challenge to the econometric methodology used in this paper, all estimates of the treatment effects will be based on an estimation sample, where both tariff and non-tariff trade-policy barriers are non-zero. Hence, the estimated effects should be interpreted as *treatment effects on the (trade-policy) treated.*[22]

Nonetheless, it is pivotal to base our estimates of exporter fundamentals f_i^s and trade costs d_{ij}^s on the universe of trade flows. For this reason, we use two samples of data: the *total sample* of 746,902 country-pair-sector trade flows – based on 237 exporters, 127 importers, and 136 sectors – is used for the estimation of the components of log trade

[22]This is the case in order to avoid the results to be driven by a mass point of the treatment data (e.g., at zero). Compare Flores et al. (2012) for this suggestion and a discussion in a different context.

flows.[23] The *treatment sample* (for non-zero trade-policy variables) is used in order to obtain estimates of the average dose-response function $E(k(m, r(m, q_{ij}^s)))$ in Equation (9) as well as the treatment effect functions of log trade costs with respect to log tariff and non-tariff trade-policy variables.

The treatment sample is much smaller than the total sample for several reasons. First, data on policy barriers, τ_{ij}^s and η_{ij}^s, all covariates used to estimate the sales fundamentals in logs, f_i^s, as well as natural trade costs in logs, u_{ij}^s, have to be observed, which reduces the sample size to 187,815 country-pair-sector observations. Second, for every country-pair-sector-level import flow, we need an estimate of the fundamentals for both the exporter and the importer, f_i^s and f_j^s, the requirement of both further reduces the data-set to 181,732 observations.[24] Third, we exclude two sectors, namely *Manufacture of macaroni, noodles, couscous and similar farinaceous products* (ISIC Rev. 3.1: 1544) and *Manufacture of rubber tyres and tubes* (ISIC Rev. 3.1: 2511), since the obtained α_s for these sectors are positive for the former and very close to zero for the latter.[25] Finally, as mentioned above, we exclude all observations $\{ijs\}$ for which anyone of the two trade-policy variables is zero. Altogether, this leads to a treatment sample of 92,830 observations, which includes 115 exporters, 56 importers, and 128 sectors. Table 1 summarizes the key variables entering the analysis. Tables 4-6 in the Appendix provide an overview of the sectors and countries used in the analysis.

Clearly, average tariff and non-tariff barriers are higher in the treatment sample where all zero-barrier observations have been dropped. Also, average bilateral trade flows are higher in the treatment sample pointing to the fact that many flows that are dropped pertain to exports to rather small countries that do not report any exports themselves in the respective sector or where data on covariates are missing. For the remainder of the covariates the summary statistics do not vary substantially across the two samples.

At the bottom of Table 1 we summarize two moments of the distribution of the ex-

[23]Note that we do not consider zero trade flows, hence, we assume the outcome positive versus zero trade flows is fixed or random conditional on all the observables.

[24]Since the estimation of fundamentals is based on the exporter-sector specific effect, we obtain this value only for those bilateral trade flows where an importing country exports output of the respective sector to at least one foreign country.

[25]The results are not sensitive to this choice.

Table 1: Summary statistics.

Variable	Total sample (gravity) Mean	Total sample (gravity) Std. dev.	Treatment sample (dose-response) Mean	Treatment sample (dose-response) Std. dev.
Outcome (log imports):				
x_{ij^s}	4.328	3.850	5.977	3.498
Trade-policy-treatment variables in m_{ij}^s:				
τ_{ij}^s	0.056	0.081	0.070	0.109
η_{ij}^s	0.050	0.132	0.072	0.159
Natural trade-cost variables in u_{ij}^s:				
log(Distance$_{ij}$)	8.679	0.830	8.793	0.795
Contiguity$_{ij}$	0.020	0.139	0.022	0.145
Common off. lang.$_{ij}$	0.146	0.353	0.104	0.306
Common ethn. lang.$_{ij}$	0.150	0.357	0.116	0.320
Colony$_{ij}$	0.016	0.125	0.017	0.129
Common colonizer$_{ij}$	0.082	0.275	0.024	0.153
Current colony$_{ij}$	0.001	0.039	0.001	0.024
Colony$_{ij}$ (after 1945)	0.010	0.102	0.011	0.102
Same country$_{ij}$	0.010	0.099	0.006	0.079
Variables needed for fundamentals:				
f.o.b. price in logs (w_i^s)	-4.513	3.010	-4.501	2.768
Trade elasticity (α_s)	-1.607	1.569	-1.539	1.223
Implied country-sector-specific log sales fundamentals:				
$\hat{f}_i^s$			-6.684	7.159
Observations	746,902		92,830	

Note that for non-triple-indexed variables weighted means are reported to account for their multiple occurrence in the data. The total sample is used to estimate the gravity-model fixed-effects regression (3), while the treatment sample in the right panel is used to estimate the bilateral-trade-cost dose-response function. The number of observations in the total sample refers to the total number of trade flows, since the fixed effects regression does not rely on any further covariates. The summary statistics within the total sample for some covariates are based on less than 746,902 observations and are reported to compare the sample compositions of covariates across samples. The summary statistics of the treatment sample are all based on 92,830 observations.

Table 2: Examples of estimated country-sector sales fundamentals versus estimated country-sector fixed effects in the data.

	Sector			
	Structural metal	Motor vehicles	Structural metal	Motor vehicles
Country	$\hat{f}_i^s$		$\hat{a}_i^s$	
China	-22.86	6.30	5.38	5.22
Germany	-20.74	11.21	3.99	7.60
Japan	-23.21	10.90	0.39	7.66
United States	-21.14	9.95	3.66	6.44
Mexico	-27.19	6.89	-0.26	3.92
India	-27.13	6.36	1.73	4.24
Brazil	-25.61	5.15	-0.31	2.49

ogenous country-sector-specific sales fundamentals, $\hat{f}_i^s$. Table 2 provides some illustrative examples of the estimated country-sector fixed effects, $\hat{a}_i^s$, and the associated derived log sales fundamentals, $\hat{f}_i^s$. What is particularly interesting about the table is the relative ranking of the fixed effects and the fundamentals across countries and sectors. For instance, the estimates for Germany suggest that the country has a larger sales (or supply) potential, $\hat{a}_i^s$, than China in the *Motor vehicles* sector, while the opposite is true for *Structural metals*. However, the latter is due to exogenous (fundamental) as well as endogenous factors (factor costs). Net of costs – i.e., focusing on the exogenous factors in $\hat{f}_i^s$ – suggests that Germany is more productive than China in either of the two sectors. However, Germany's comparative advantage in terms of $\hat{f}_i^s$ is more than undone by the sector-specific factor cost differences in *Structural metals* but not in *Motor vehicles*. A similar reversal is observed, e.g., when comparing the United States with China in that table.

5 Empirical analysis

5.1 Estimating the joint conditional density of tariff and non-tariff trade-policy barriers

In a first step, we aim at estimating the joint conditional density of $m_{ij}^s|q_{ij}^s$. We use machine learning in order to specify the set of relevant exogenous factors influencing tariff and non-tariff trade-policy variables.[26] We know the set of the exogenous candidate factors, q_{ij}^s, and can extract them by invoking quantitative trade models. Machine learning helps us learning the subset of relevant (polynomial and interaction) terms of these factors which are numerous for every sector and country pair. This part of the analysis is interested in separating the conditional mean of tariff and non-tariff policy measures from the stochastic part, $\nu_{\tau,ij}^s$ and $\nu_{\eta,ij}^s$:

$$\tau_{ij}^s = g_\tau(q_{ij}^s) + \nu_{\tau,ij}^s, \quad \eta_{ij}^s = g_\eta(q_{ij}^s) + \nu_{\eta,ij}^s. \tag{10}$$

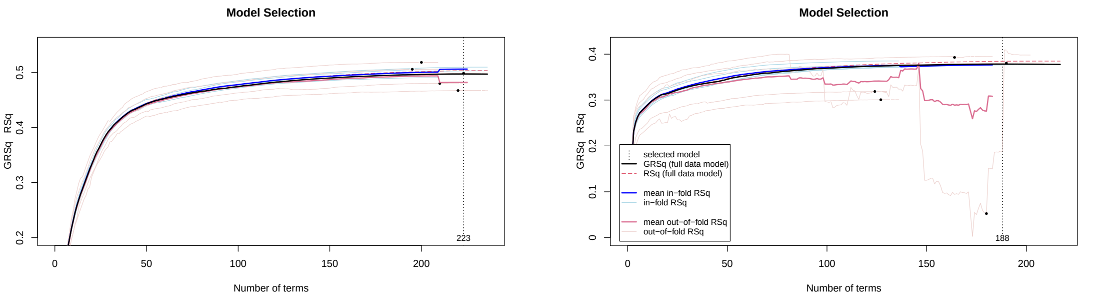
It is crucial to allow for a high degree of flexibility in estimating $g_m(\cdot)$. We achieve this by applying a powerful approach that estimates the relationship non-parametrically using multivariate adaptive regression splines (MARS) following Friedman (1991). In order to account for any country-specific characteristics in policy formation, we allow for fixed effects across importing countries j and exporting countries i.[27]

The model selection of the MARS model along with cross-validation statistics is presented in Figure 2. The selected model is able to explain 50% of the variation in τ_{ij}^s and 39% of the variation in η_{ij}^s. Up to almost one-half of the basic variables in q_{ij}^s as well as the importing-country and exporting-country fixed effects are chosen as predictors and enter

[26]Note that the purpose of machine learning here is to achieve the best possible prediction of the trade-policy variables as a flexible function of instruments in order to cleanse the residuals of these observables. These residuals as measures of the stochastic components of trade policy are key ingredients in the second step of the procedure, where the treatment effect of the trade-policy variables on trade costs is the focus of the analysis. Hence, machine learning is not yielding causality here as such.

[27]The MARS algorithm applied in this context has two steps. Forward passage: After estimating an intercept, piecewise-linear basis functions of the covariates are added iteratively (allowing for interactions). Backward passage: In order to avoid over-fitting, a subset of the previously selected terms is deleted, and the final model is selected based on the minimization of the generalized cross-validation (GCV) score.

Figure 2: Model selection of $g_\tau(\cdot)$ and $g_\eta(\cdot)$.



(a) Determinants of log ad-valorem tariff barriers τ_{ij}^s: The optimization process selected 223 of 236 terms, and 138 of 313 predictors. The selected model yields na R^2 (RSq) of 0.503. The mean of out-of-fold R^2s (depicted by black dots) is 0.494 with a standard deviation of 0.020.

(b) Determinants of log ad-valorem non-tariff barriers η_{ij}^s: The optimization process selected 188 of 218 terms, and 96 of 313 predictors. The selected model yields an R^2 (RSq) of 0.385. The mean of out-of-fold R^2s (depicted by black dots) is 0.289 with a standard deviation of 0.138.

the model in a total of 223 and 188 terms (such as interactions or powers), respectively.

A fundamental concern with respect to machine-learning algorithms is over-fitting.[28] Note that the employed algorithm contains a backward passage in which a subset of previously selected regressors (e.g., polynomial terms or interaction terms) is deleted to avoid over-fitting. We can assess the degree of over-fitting by means of cross-validation. Specifically, in the present context we generate 5-fold cross-validated models for tariff and non-tariff trade barriers. For each fold, the algorithm builds a MARS model with the in-fold data (90% of the complete data) and uses this model to measure the R^2 from predictions made on the out-of-fold data (10% of the complete data). The mean of these out-of-fold R^2 statistics amounts to 0.494 (with a standard deviation of 0.0.20) for the tariff model ($g_\tau(q_{ij}^s)$) and 0.289 (with a standard deviation of 0.138) for the non-tariff model ($g_\eta(q_{ij}^s)$). These statistics are quite close to the R^2 statistics of the model estimated on the full data, in particular, for tariffs. While we abstain from an in-depth analysis of the reduced-form models for the two trade-policy variables τ_{ij}^s and η_{ij}^s here, we discuss some relationships in an online appendix to this paper.

The residuals $\nu_{ij}^s = (\nu_{\tau,ij}^s, \nu_{\eta,ij}^s)$ of the regressions in Equation (10) serve as estimates of the two conditional (quasi-randomized) tariff and non-tariff trade-policy-treatment

[28] In fact, under-fitting would be much more of a concern economically than over-fitting here, because what is key is that the residual is not systematically informed by the exogenous fundamentals. However, statistically, one may still care about over-fitting.

variables whose joint density has to be estimated. For most of the subsequent analysis, we estimate the joint density of the latter assuming a bivariate normal distribution and estimate the parameters of the distribution by maximum likelihood (see, e.g., Imai and Van Dyk, 2004; Hirano and Imbens, 2004; Kluve et al., 2012, for the assumption of normal densities in the context of univariate-continuous-treatment-effects estimation). We conduct an alternative non-parametric estimation that allows for a maximum degree of flexibility following Li and Racine (2006).

The estimated bivariate density by one of the aforementioned methods serves as an estimate of the propensity of getting randomly assigned to a specific tuple of tariff and non-tariff-barrier levels for any country pair and sector. The density as a compact (propensity) score can be obtained not only for observed but even for potential (hypothetical) trade-policy treatment levels. We will refer to this density as generalized propensity score. However, this compact score is only meaningful, if the covariates in q_{ij}^s are similar for all units $\{ijs\}$ with a similar level of the estimated joint density. Towards an assessment of the latter, we enforce a common support and discard observations with extreme joint-density-score values. Specifically, we follow Flores et al. (2012) in defining the common support and extend their methodology to multivariate treatments.[29]

Besides ensuring common support, we will test if for any observation with the same GPS the probability of a specific level of trade-policy treatment is independent of the observable determinants q_{ij}^s following Hirano and Imbens (2004). For each covariate in q_{ij}^s, we may conduct a t-test under the null hypothesis that the mean of the covariate is the same across groups that correspond to different levels of trade policy. Specifically, we perform such a test unconditionally versus conditionally on the GPS. The respective test statistics are reported in the online appendix. We show that conditioning on the GPS improves the share of balanced covariates (at the 5% level) from 31% to 96%.

We use the stochastic component of the two trade-policy measures in a control function which is employed in a second step, where the functional form of the causal relationship between the trade-policy measures and overall sector-country-pair trade costs are in the

[29]Details regarding the definition of the common support can be found in the online appendix.

limelight. This step determines what we will call the dose-response function.

5.2 Estimating partial (direct) effects of trade policy on trade costs and trade flows

In this subsection, we estimate the effect of tariff and non-tariff trade-policy variables on bilateral trade costs, d_{ij}^s, as obtained from the procedure in Equation (3). The corresponding model to estimate the so-called unit-level dose-response of derived trade costs $\hat{d}_{ij}^s$ to the trade-policy barriers in m_{ij}^s reads

$$\hat{d}_{ij}^s = k(m_{ij}^s, r(m_{ij}^s)) + \text{controls}_{ij}^s \theta + \xi_{ij}^s. \tag{11}$$

We additionally condition on a linear function of all covariates in this step of the analysis through the inclusion of controls_{ij}^s in Equation (11), as suggested by Imai and Van Dyk (2004). Note that this is not the same as assuming a linear relationship between natural trade barriers and trade costs – in fact we are agnostic about their impact on trade costs beyond their (potentially non-linear) relationship and interaction with endogenous trade policy. We then estimate the functional form of $k(\cdot)$ in Equation (11) by a polynomial approximation whose order is chosen based on the Aikake information criterion (AIC). We allow for both policy variables, their interaction, the GPS as well as any interaction with the GPS to enter the unit-level dose-response function up to a polynomial of order 10.

The estimated coefficients do not have any economic meaning. However, the polynomial model provides us with a functional form of $k(\cdot)$ in Equation (11) that allows for evaluating the average causal effect of changes in tariff and non-tariff trade-policy variables on trade costs at any potential level of the policy variables in the outset. Hence, we can define a grid of trade-policy levels for which we are interested in the level of trade costs and estimate the latter using the functional form of Equation (11). Figure 3 plots the bivariate distribution of the trade-policy data on the such-defined grid of $m = (\tau, \eta)$ and shows that the majority of the data is located at relatively low levels of

Figure 3: Distribution of the data across the 25×25 grid.

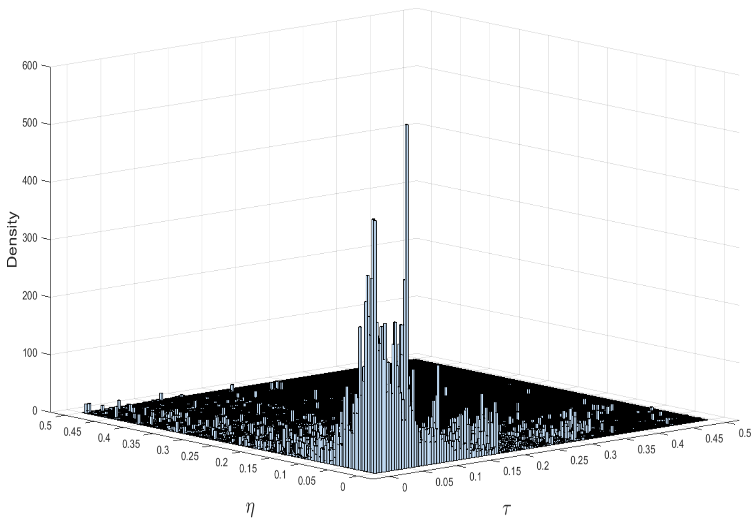
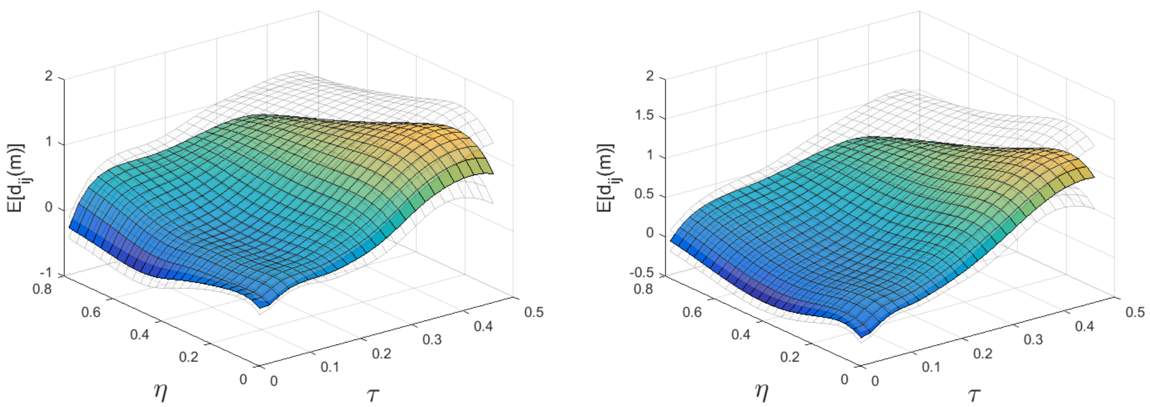


Figure 4: Average dose-response function of log trade costs and log trade-policy variables with 95% confidence bounds.



Average dose-response (normal density). Average dose-response (non-parametric density).

policy trade barriers but that there is variation in the tariff and as well as the non-tariff barrier dimension.

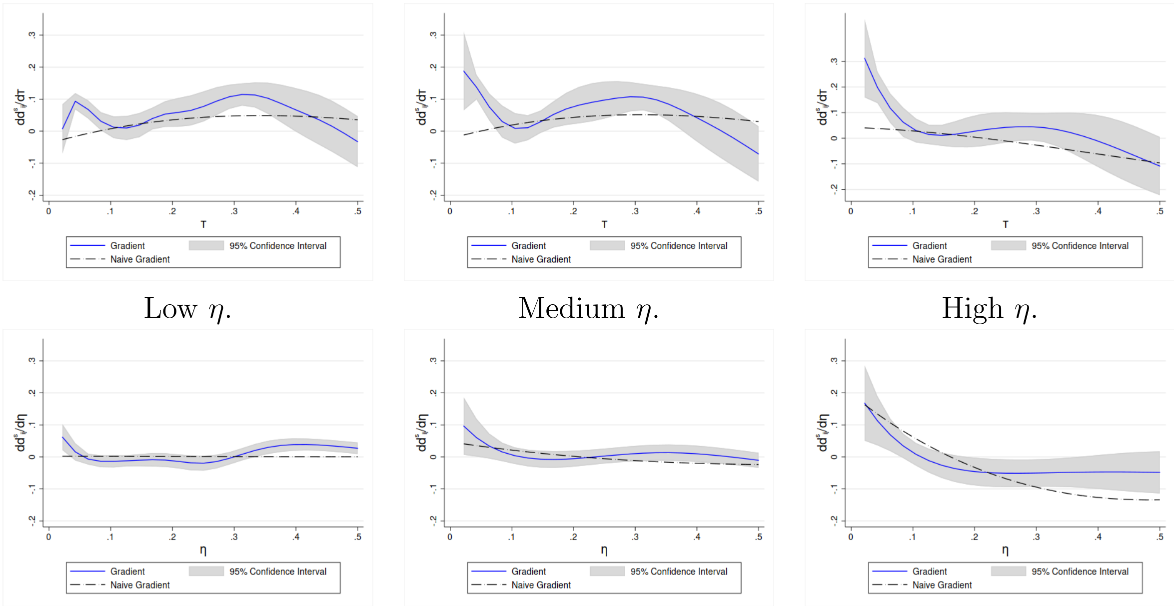
We evaluate the *expected conditional dose-response function*, $k(m) = E\left[k\left(m, r(m, q_{ij}^s)\right)\right]$, as an average from the size-n sample through

$$\hat{k}(m) = \frac{1}{n} \sum_{i \in \mathscr{J}} \sum_{j \in \mathscr{J}} \sum_{s \in \mathscr{S}} \hat{k}(m, \hat{r}(m, q_{ij}^s)), \tag{12}$$

where $\mathscr{J}$ and $\mathscr{S}$ denote the sets of countries and sectors in the data.

Figure 4 displays the average dose-response function (12) as well as the 95% confidence

Figure 5: Gradients w.r.t τ and w.r.t. η with 95% confidence bounds for different levels of trade policy (normal density).



Low η. Medium η. High η.

Low τ. Medium τ. High τ.

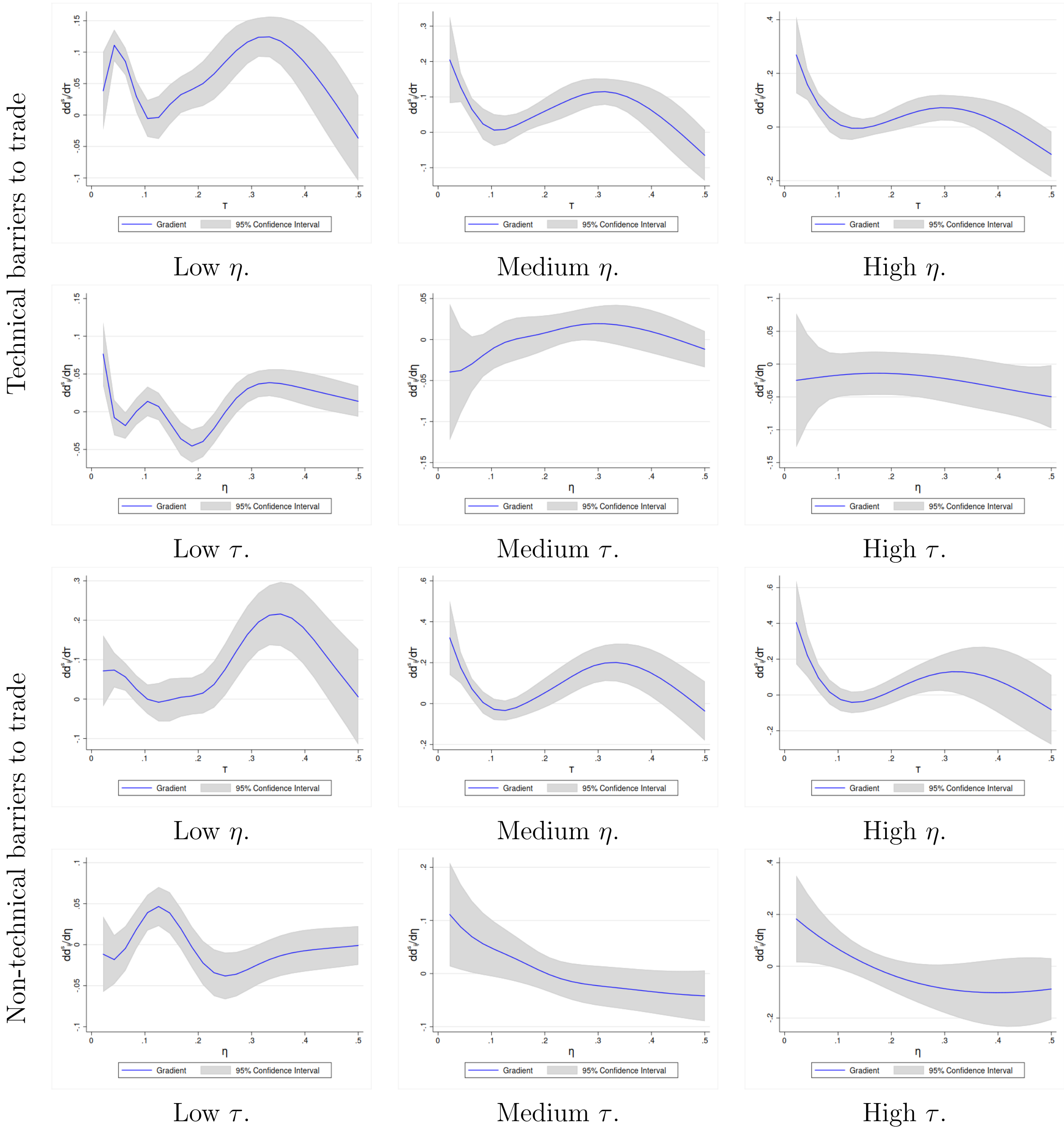
bounds that are based on 100 bootstrap samples for the estimation based on a normally distributed GPS in the left panel and the estimation based on a non-parametrically distributed GPS in the right panel.[30] The two variants of the GPS estimation are of minor importance for the overall shape of the dose-response function.

As expected, trade costs are generally increasing in the two trade-policy variables. The effect is, however, strongly nonlinear and depends on the level of trade policy in the outset. In order to investigate the non-linearities in more detail we present the gradient of the average dose-response function with respect to τ and η in Figure 5. For a better illustration, we present three slices of the gradient in each dimension. Each slice corresponds to either low (grid points 1–5), medium (grid points 11–15), or high (grid points 21–25) levels of tariff or non-tariff barriers, respectively.

Note that the gradient is referring to the change in log trade costs, $\hat{d}^s_{ij}$, in response to a change in policy barriers by one grid-point difference in the dose-response function,

[30] The bootstrap was conducted as follows. 100 bootstrap samples of the total sample (see Table 1) were drawn ensuring that all importer-sector combinations exist in each bootstrap sample. This corresponds to importer-sector block-bootstrapping, and all steps of the procedure are estimated for each bootstrap sample. This leads to differently-sized bootstrap samples that are then used in the subsequent steps. This procedure accounts for the imprecision in the measurement of estimated (derived) variables that are used in later stages, such as log sales fundamentals, $\hat{f}^s_i$, or trade costs, $\hat{d}^s_{ij}$.

Figure 6: Gradients w.r.t τ and w.r.t. η with 95% confidence bounds for different levels of trade policy – technical versus non-technical trade barriers (normal density).



which amounts to 0.02. To put the gradient into context, recall that the customary assumption in most general equilibrium models of trade is that trade policy enter trade costs log-linearly in an ad-valorem fashion. Hence, ad-valorem tariffs increase trade costs one for one. Translated to the grid defined in this exercise, a one-grid-point change in tariffs should increase log trade costs by 0.02 at any point on the grid. This is far below the maximum gradient of 0.3 obtained in this exercise pointing to a role of tariffs beyond the pure ad-valorem effect. At the same time, the gradient is effectively zero for some parts of the grid and a substantial share of the observations is placed in exactly those parts of the grid. The results suggest that trade policy is rather ineffective in these cases. For reference, we also plot the gradient of the 'naive' regression underlying Figure 1 for different slices and adjusted to the scaling such that the gradient refers to the change in log trade costs w.r.t. a one-grid-point change. We refer to this as 'naive gradient' in Figure 5. The reference illustrates that this approach entails a poor approximation for the marginal effect of changes in trade policy, in particular, in tariffs, both in terms of effect size and shape as a function of tariff levels.

The different panels in Figure 5 illustrate nicely that a given change in trade policy has a very different effect depending on where in the outset trade policy lies at the moment of evaluation and that these differences are particularly stark when considering large-scale trade-policy changes. A change in tariff policy has a very strong positive effect on trade costs for very low levels of tariff barriers when non-tariff barriers are medium to high. This marginal effect is substantially smaller for very low levels of tariff and non-tariff barriers which might be explained by unused preference margins (see Herin, 1986, Francois et al., 2006, Estevadeordal et al., 2008, Fugazza and Nicita, 2013). The effort to comply with any requirements in order to obtain a preferential tariff treatment might be simply too burdensome, especially, when the gains from compliance are rather low, leading to an unused preference margin and to a less pronounced marginal impact of tariffs on trade costs and trade flows. In contrast, there is virtually no marginal effect of a change in tariffs when tariffs are around 10%. The marginal effect of a change in tariffs remains zero also beyond a tariff level of 15% for high levels of non-tariff barriers.

However, the marginal effect becomes strongly positive for low and medium levels of non-tariff barriers as we move beyond 15% and fades slowly out as we approach a level of 40%. The result that the marginal effect of a change in tariffs fades out for high tariff levels and, in particular, in case of high non-tariff barriers, is well in line with the literature on avoidance strategies for high barriers to trade (see Fisman and Wei, 2004; Javorcik and Narciso, 2008; Sequeira, 2016; Demir and Javorcik, 2017).

The pattern is rather different when considering the marginal effect with respect to non-tariff barriers. We observe a very strong effect for low levels of non-tariff barriers, in particular, when tariffs are high. By contrast, we observe basically no or even negative marginal effects for intermediate levels of η across all levels of tariff barriers and a strong marginal increase in trade costs for high levels of non-tariff trade barriers when tariffs are low. As mentioned in the introduction, in contrast to tariffs, non-tariff barriers might entail a decrease in trade costs, in particular, in the case of non-technical measures. Since, the data on the ad-valorem equivalents of non-tariff barriers allow for differentiating between technical and non-technical barriers to trade, we analyze their differential effects in Figure 6. While the gradient of tariff-barriers is basically unchanged in the two sub-analyses, we see that the negative gradient in the non-tariff-barrier dimension is almost entirely driven by technical barriers to trade (compare WTO, 2012). Figure 6 suggests that technical barriers to trade have a strong marginal impact on trade costs for low policy barriers, but a negative effect for intermediate levels of technical barriers in place. We take this result as support for the notion that, while non-tariff measures are costly on average, there exists an intermediate level of, particularly, non-technical barriers to trade where a higher level may actually be trade-enhancing.

5.3 Putting the estimated trade-policy gradients in context

The non-linear relationship of trade costs and trade policy might stem from various sources (cf. Section 2). We cannot include measures of these sources in the regressions explicitly, because they are partly functions of trade policy and, hence, endogenous just like trade policy itself.[31] However, putting these measures in context with the gradient may shed light on the roots of the variation in trade-cost responses to trade policy. We do so in Figure 7.

We start with the role of trade-policy uncertainty. Earlier work has demonstrated that such uncertainty is an important factor in determining the actual effect of trade policy. For instance, the findings in Handley and Limao (2015) and Pierce and Schott (2016) suggest that trade-policy changes contain a signal about future trade-policy uncertainty. We hypothesize that trade-policy uncertainty affects the shape of the trade-cost function and it varies across tariff levels. In order to proxy for uncertainty, we use the unexplained variation from a first-order-autoregressive regression, where we regress the annual applied tariff level for any country pair and sector on its lagged value in all years between 2001 and 2011 for each tariff cell using TRAINS data. The left panel of Figure 7 suggests that a lower level of tariff predictability,i.e., a higher tariff uncertainty, is associated with higher applied tariff levels. In particular, the measure of tariff uncertainty rises substantially more strongly for tariff levels beyond 10-20%. The latter is exactly where the gradient of trade costs with respect to tariffs τ is strongly positive.

Further potential rationales for a heterogeneous impact of tariffs on trade costs are avoidance strategies at high tariffs on the one hand and the non-use of available tariff preferences at low most-favored nation tariffs on the other hand (see Herin, 1986, Francois et al., 2006, Estevadeordal et al., 2008, Fugazza and Nicita, 2013). We would assume tariff avoidance strategies to be more prevalent in countries with high levels of corruption (see Fisman and Wei, 2004; Javorcik and Narciso, 2008; Sequeira, 2016; Demir and Javorcik, 2017). We proxy for the lack of corruption by taking a measure of transparency at the country-level for 2006 from Transparency International as an inverse measure of corruption. We map the latter to tariffs by the respective countries' densities at different products and levels of tariffs. In order to proxy for the non-use of available tariff preferences, we use the preference margin (the difference between the most-favored-nation

[31] E.g., the "tariff water", the gap between bound and applied tariffs, or the correlation between lagged and contemporaneous tariffs as a measure of tariff variation in time or tariff uncertainty are both functions of applied tariffs.

tariff and the principally-available minimum tariff in a trade agreement). The results in Figure 7 suggest the following. First, the gradient is positively correlated with a greater transparency in the low- and high-tariff range, while at medium tariffs, transparency is negatively related to a higher gradient of trade costs w.r.t. tariffs. This is consistent with avoidance being negatively correlated with transparency. Second, the tariff gradient is relatively independent of the preference margin at low tariff levels. The latter is consistent with an under-exploitation of tariff preferences at low tariff levels.

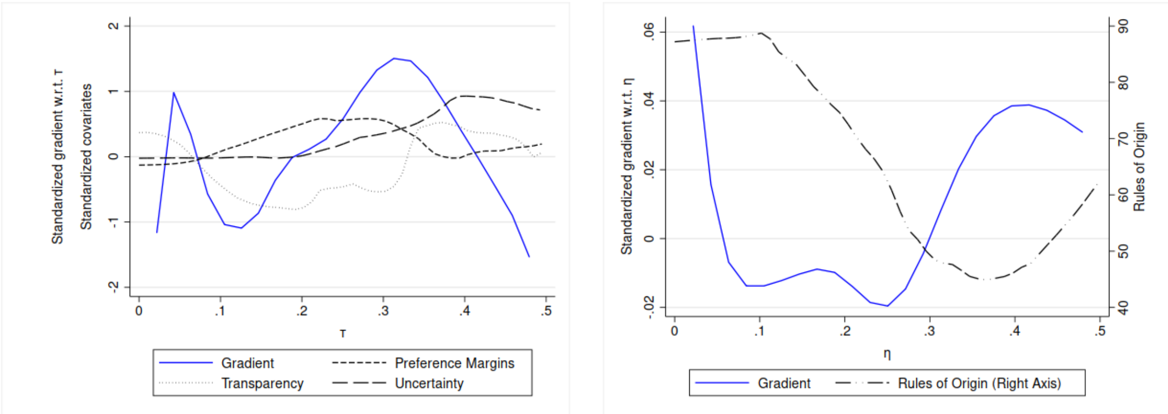
A further important determinant of the effectiveness of trade policy is the presence of rules of origin, which impose more restrictions and costs on the access to preferential treatment in trade agreements, in particular, regarding non-tariff barriers. Krishna et al. (2021) show that the fixed costs of meeting rules of origin decrease with the experience of the firm in obtaining preferential tariffs. Generally, we would expect that the impact of changes in trade policy is stronger, whenever fewer rules of origins are in place. We assess the role of rules of origin for the trade-cost gradient with respect to trade policy using the product-level incidence of rules of origin in the North American Free Trade Area (NAFTA) based on data compiled by Conconi et al. (2018). We summarize the associated findings in the right panel of Figure 7. The figure suggests that the gradient of trade costs w.r.t. non-tariff barriers is negatively associated with the prevalence of rules-of-origin provisions at different non-tariff barrier levels.

Overall, the relationship between trade policy and trade costs identified in this paper is well aligned with evidence in the literature on trade-policy setting and uncertainty as well as corruption, tariff avoidance, and trade-policy stringency.

5.4 Quantification of total (general-equilibrium) effects of trade policy on trade flows

A key insight of quantitative trade models is that even homogeneous partial effects of tariff and non-tariff barriers on trade costs materialize in heterogeneous responses of economic outcomes through general-equilibrium responses. However, heterogeneous partial treatment effects of trade-policy variables as portrayed in Figure 5 will add to and amplify the

Figure 7: Gradients and potential covariates.



(a) Tariff policy gradient. (b) Non-tariff policy gradient.

heterogeneity of total trade-cost treatment effects in general equilibrium. This subsection is concerned with a quantification of this amplification of the total trade-policy-treatment effects.[32]

To illustrate the relevance of our estimates, we will analyze the effect of a unilateral increase of US tariffs on all Chinese imports by 10 percentage points – a policy change that was discussed and partly implemented in a similar vein over the last years. In particular, we are interested in comparing the estimated outcomes based on a homogeneous gradient of trade costs with respect to tariffs (assuming a one-for-one response of log trade costs, d_{ij}^s, to a change in τ_{ij}^s) and the one corresponding to the flexible gradient as estimated above. Throughout the analysis, we keep the deficit share in terms of total spending constant for any country.[33] Details on the computation of the general equilibrium are delegated to the online appendix.

In the context of the experiment – an increase of US tariffs on Chinese imports – the actual change in trade costs resulting from the increase in tariffs is on average 19% and thus 9 percentage points higher than the pure ad-valorem effect of tariffs alone (which is 10%). This implies that the majority of affected trade flows between China and the US

[32]For this analysis, it is necessary to focus on a somewhat more aggregated sample of the data used above. The reason is that a general-equilibrium analysis needs to rely on a full data-set for all country pairs and sectors covered, while this was not necessary with the analysis of partial trade-policy treatment effects on the treated. Therefore, we focus on a subset of 41 individual countries and one rest of the world (ROW) for 97 sectors in the respective analysis.

[33]Note that trade imbalances do not affect the key insights regarding the response function of trade costs and trade-policy variables. The reason is that trade imbalances are indexed by (product and) importer but not by (product and) country pair.

lies in an area of the gradient where the response of trade costs to a change in tariffs is particularly strong. Indeed, the average tariffs levied on these flows in the benchmark economy lie at 5%, which is exactly the domain featuring strong marginal responses in Figure 5.

The share of US spending on Chinese goods drops by roughly one percentage point due to this policy change. Holding total US spending at the benchmark level, this amounts to a decrease of Chinese imports by more than 6% (95% confidence interval ranging from 7.2% to 4.8%). An effect that is substantially larger than the one implied by the customary ad-valorem specification in which the drop in imports is less than 3%.[34] The share of US income generated through tariffs increases by 50% in the nonparametric exercise whereas the increase is 54% in the ad-valorem specification, which illustrates the additional impact of tariffs in increasing trade costs beyond the pure ad-valorem effect. These aggregate numbers hide, however, substantial heterogeneity across import shares from different Chinese sectors as illustrated in the left panel of Figure 8. On average, for treated sectors – sectors that were subject to non-zero tariffs in the benchmark – the change in import flows (at US benchmark income levels) is 7 percentage points lower (significant at the 5% level) in the nonparametric specification compared to the ad-valorem specification. In some sectors, the import shares drop by more than 50% in the nonparametric case illustrating the wide range of responses under the nonparametric specification as compared to the ad-valorem exercise which exhibits substantially less variation. Note that for 92% of all bilateral trade share changes the differences between the nonparametric specification and the ad-valorem specification is significant at the 5% level.

The experiment of a unilateral increase in tariffs by the US towards Chinese imports reveals that customary (ad-valorem) approaches of evaluating the policy change would severely underestimate the implied effects of this particular policy change. How far the two different specifications diverge depends on the respective status quo of trade policy

[34]Note that since the estimation strategy is to be interpreted as a treatment effect on the treated, the counterfactual trade-policy change applies only to those trade flows that are subject to tariffs in the benchmark.

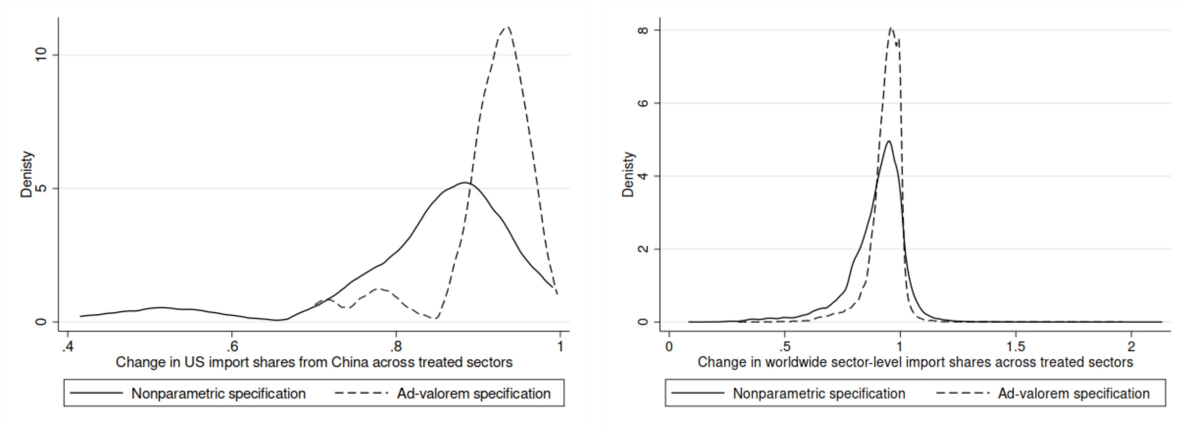
which differs across countries and sectors. To illustrate how large the divergence is on average, let us consider an alternative experiment that implies a change in trade costs for all tariff-treated trade flows in the data and not only Chinese imports to the US. We likewise consider an increase in tariffs of 10 percentage points for all trade flows that are currently subject to tariffs (roughly 50% in our data). On average, among the 42 countries, the share of total income spent on imports falls by 1.2 percentage points in the nonparametric specification compared to only 0.8 percentage points in the ad-valorem specification. Note that only flows that have been subject to tariffs in the benchmark are treated. Again, for individual (treated) flows the change in import shares varies substantially as depicted in the right panel of Figure 8. As before, the effect on import shares is downward-biased compared to the ad-valorem specification albeit on average to a smaller extent, namely by 4 percentage points (significant at the 5% level). The responses of the import shares in the nonparametric specification are significantly different from the ones in the linear specification in 80% of cases. As before, it stands out that the variation of the responses is substantially larger in the nonparametric specification compared to the ad-valorem specification.

We conclude that a misspecification of the effect of trade policy on trade costs leads to large deviations in predicted effect sizes on outcomes. For the average real bilateral trade flow in the dataset underlying the general-equilibrium analysis of this section, an ad-valorem specification underestimates the effect of trade-policy changes. Generally, it is, however, a matter of the status-quo and the type and magnitude of policy change considered whether the customary parametric ad-valorem approach under- or over-estimates the economic consequences of a policy change.

5.5 Robustness

We conducted several robustness checks of the aforementioned results. We relegate a detailed documentation of them to the Appendix and only briefly summarize the most important insights here. In particular, we assessed the robustness along five lines: (i) the assumed functional form of the first stage; (ii) using sector-country fixed effects

Figure 8: Counterfactual change in import shares for treated sectors and countries.



(a) 10-percentage-point-increase by US on China (b) 10-percentage-point-increase by all countries

to estimate fundamentals; (iii) relying on elasticities obtained from an alternative data source (Fontagné et al., 2022); (iv) taking into account potentially endogenous transport costs; (v) taking into account the imprecision of the elasticity estimates when calculating confidence bounds.

It turns out that strategies (i) to (iv) have little bearing for neither the qualitative nor the quantitative analysis. With respect to (v) we see that mainly the tariff effects display significant effects, where the density of observations is large enough. However, we should be careful in over-interpreting these results. After all, the standard errors of the respective elasticities are obtained from data sets that differ substantially from the one on trade flows used here. Note that in other quantitative work, where parameters from elsewhere are incorporated, the imprecision of those parameters is typically not taken into account.

Finally, in an Online Appendix we present additional results that are based on subsets of the data that impose stricter balancing rules than are applied in the baseline specification. Also those results point to the robustness of the findings in this paper.

6 Conclusions

This paper conducts an analysis which is focused on the nature and extent of effect heterogeneity of endogenous tariff and non-tariff policy barriers on trade costs. We document that the customary assumption of the homogeneity of partial effects of ad-valorem log tariff and non-tariff rates on trade costs is clearly rejected by the data. In order to demonstrate the importance of these non-linearities we feed the estimated trade-policy gradients into a quantitative multi-country, multi-sector general equilibrium model of trade and evaluate the effect of a unilateral increase in US tariffs on Chinese imports of 10 percentage points. We document that the effects of this particular policy change are severely underestimated by a customary ad-valorem approach of modeling trade costs compared to the flexible-gradient approach developed in this paper. The average reduction across all treated sector-level US import shares from China is about 7 percentage points larger with the flexible-gradient approach and total US imports from China (evaluated at benchmark income levels) fall by 6% as compared to only 3% under an ad-valorem specification.

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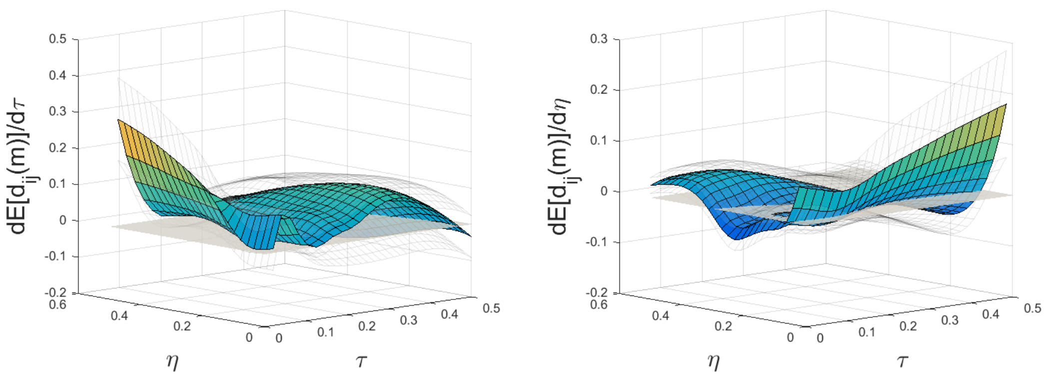
Appendix

In this section, we assess the sensitivity of the results along five lines: the assumed functional form of the first stage; using sector-country fixed effects to estimate fundamentals; relying on elasticities obtained from an alternative data source; taking into account potentially endogenous transport costs; taking into account the imprecision of the elasticity estimates when calculating confidence bounds.

Functional form of the first stage:

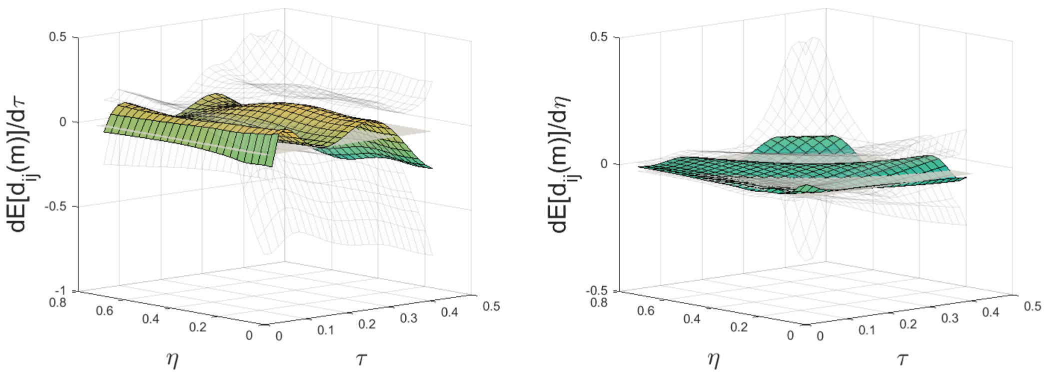
Figure 9: Gradients w.r.t τ and w.r.t. η with the underlying first-stage being estimated using OLS.



Gradient w.r.t τ (normal density). Gradient w.r.t η (normal density).

We estimate the first stage regression using OLS. The depicted relationships are very close to the ones predicted from the machine-learning algorithm in the main specification.

Figure 10: Gradients w.r.t τ and w.r.t. η with the fundamentals being estimated from fixed effects.



Gradient w.r.t τ (normal density). Gradient w.r.t η (normal density).

We depict the gradient function for tariff- and non-tariff trade-policy barriers in Figure 9. The estimated gradients are virtually identical to those of the main specification. We can conclude from this that the main insights in the paper regarding the nature and quantitative importance of the heterogeneity of the trade-cost and trade-flow responses to tariff and non-tariff trade-policy barriers are not driven by the assumptions about the functional form of the first stage.

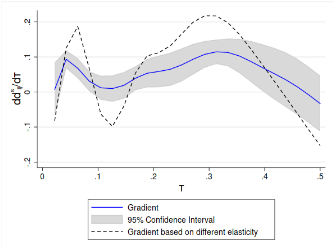
Using sector-country fixed effects to estimate fundamentals:

An important assumption underlying our empirical strategy is that country-sector fundamentals can be extracted from the fixed effects of a standard gravity equations using information on factor costs and elasticities. In this exercise, we reestimate the gradients without relying on this assumption. In particular, we estimate the first stage using sector-importing-country and sector-exporting-country fixed effects instead of the calculated fundamentals. While this specification results in larger standard errors, the overall shape of the gradients is remarkably similar to the main specification as can be seen from Figure 10. This robustness exercise demonstrates that the results persist even without relying on the decomposition of the gravity fixed effects.

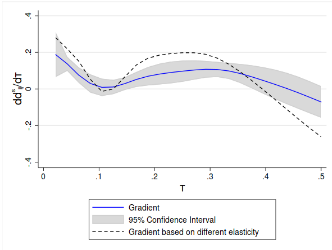
Relying on elasticities obtained from an alternative data source:

The trade elasticity is an important parameter to this study, as it scales the direct sensitivity of trade flows with respect to prices and, hence, ad-valorem trade costs. In the main text, we rely on a single source regarding trade elasticities, non-tariff barriers and tariff

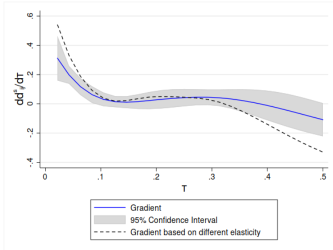
Figure 11: Gradients w.r.t τ and w.r.t. η with 95% confidence bounds for different levels of trade policy based on elasticities by Fontagné et al. (2022) (normal density).



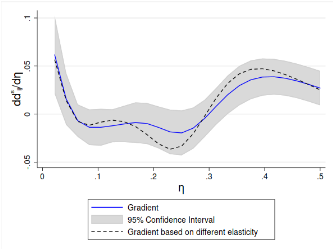
Low η.



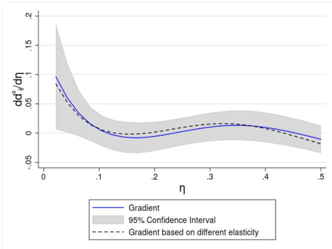
Medium η.



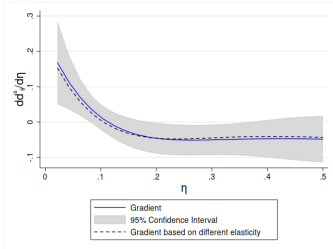
High η.



Low τ.



Medium τ.



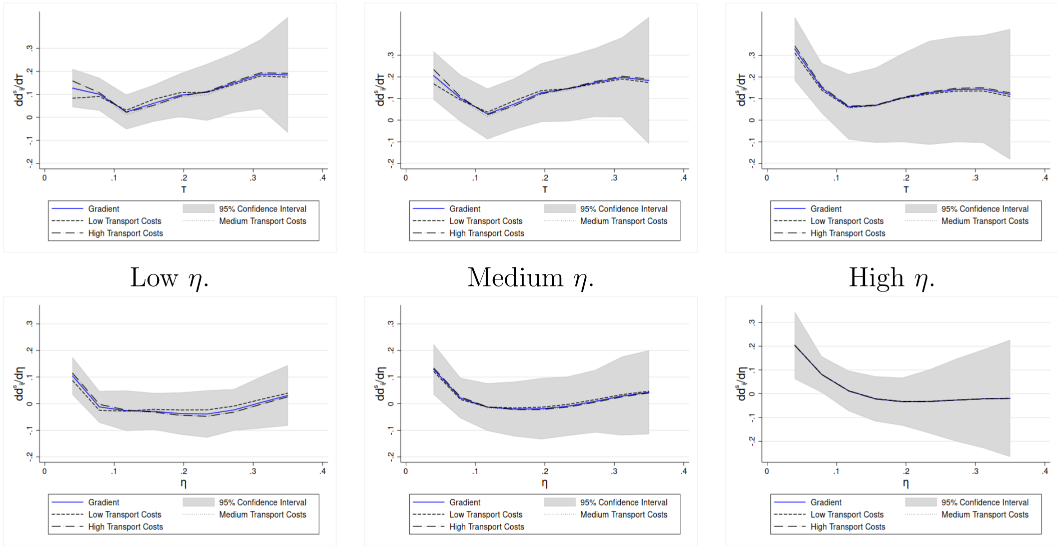
High τ.

barriers to trade for reasons of data coherency. However, we would hope that the shape of the gradient of trade costs with respect to the underlying tariff and non-tariff trade-policy measures τ and η is relatively robust to using a set of alternative trade-elasticity estimates. We assess the latter here in Figure 11, using trade elasticities recently published by Fontagné et al. (2022). Specifically, in the figure we display the gradient estimates with respect to τ and η together with the 95% confidence interval around them along with the one based on the alternative elasticities. The figure suggests that the amplitudes of the response heterogeneity are somewhat more pronounced but, generally, the patterns in terms of rising and falling gradients throughout the support of τ and η are aligned in a reassuring way.

Taking into account potentially endogenous transport costs:

In the main text, we consider tariff and non-tariff barriers τ and η as the only source of endogeneity in trade costs. One could put forward that costs related to insurance and freight are a third component that is endogenous. There is a long-standing literature in international economics that proposes measuring the insurance and freight costs of trade from the so called cif/fob ratio – imports including expenses on costs of insurance and freight over exports measured without those expenses (see Hummels, 2007). One of the challenges when considering endogenous cif/fob costs on top of tariff and non-

Figure 12: Gradients w.r.t τ and w.r.t. η with 95% confidence bounds for different levels of trade policy taking into account cif/fob transport costs as a third endogenous trade-cost component (assuming a normal density).

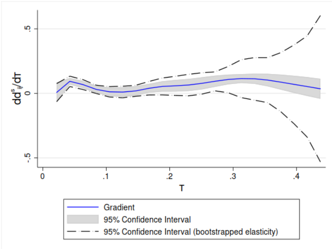


Low η. Medium η. High η.

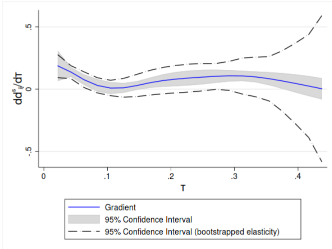
Low τ. Medium τ. High τ.

tariff barriers is that the analysis becomes higher-dimensional. Moreover, when adding more endogenous variables to the analysis, one would expect the precision of the results to decline. Here we present findings from an analysis where not only τ and η but also cif/fob (based on data by UNCTAD) are endogenous determinants of trade costs. Consistent with the selection-on-observables approach adopted throughout the paper, the latter are specified as a (possibly different) nonparametric function of the same observables as τ and η. Relative to the analysis here, the one in the main text can be viewed a reduced form, where cif/fob trade-cost interactions with τ and η are captured by a nonparametric function of the fundamentals in $g_\tau(\cdot)$ and $g_\eta(\cdot)$. We present the results regarding the trade-cost gradients with regard to τ and η evaluated at three different levels of cif/fob trade costs – one low, one medium, and one high – in Figure 12. Overall, what the figure suggests is that the gradients of interest do not vary systematically with alternative levels of underlying cif/fob trade costs. Hence, a focus on just τ and η as in the main text appears sufficient for the purpose of the present paper.

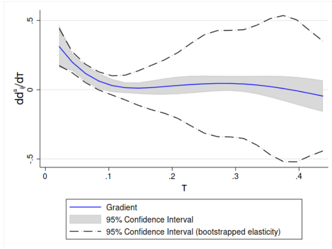
Figure 13: Gradients w.r.t τ and w.r.t. η with 95% confidence bounds (taking into account imprecision of elasticity estimates) for different levels of trade policy (normal density).



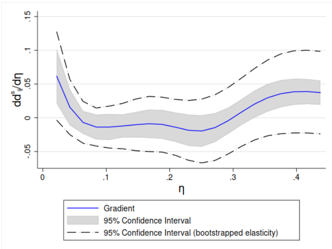
Low η.



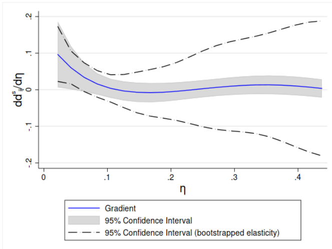
Medium η.



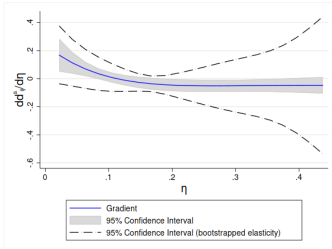
High η.



Low τ.



Medium τ.



High τ.

Taking into account the imprecision of the elasticity estimates when calculating confidence bounds:

Note that the trade elasticities in Kee et al. (2008) are estimated with some imprecision. It is customary to ignore such imprecision in quantitative work (see, e.g., Eaton and Kortum, 2002, Costinot and Rodriguez-Clare, 2014, or Caliendo et al., 2015). However, we assess it here by sampling simultaneously from the data as well as from the (assumed to be asymptotically normal) trade elasticities. The latter is possible, as not only the elasticity point estimates but also their standard errors are provided by Kee et al. (2008).

We display the results in Figure 13. The figure suggests that the confidence bounds around the gradient are wider than before, and they are particularly wider at extreme values of the policy variables, as the data support is low there. Moreover, there are significant gradient parts particularly for tariffs at lower values of τ and for η at medium levels of τ. However, overall we need to be cautious with the respective results, as the considered uncertainty in this analysis is informed by various data sources. As said above, quantitative work tends to abstain from a consideration of result uncertainty of this kind.