Disentangling the effect of trade agreements on trade*

Samuel Standaert[1] and Glenn Rayp[1]

[1]Department of Economics, Ghent University

July 26, 2016

Abstract

While the endogeneity of trade and regional integration agreements was established early on, this issue has only been addressed explicitly in gravity models during the last decade and a half. Initial attempts using instrumental variables proved unreliable, causing authors to look for alternative solutions. This paper brings together the literature on both gravity equations explaining trade and probit regressions explaining the probability of an integration agreement. This is done by estimating them simultaneously in a qualitative vector autoregression model. The qualitative VAR allows us to estimate their interdependence without having to resort to instrumental variables. In addition, the endogenous nature of other control variables like the GDP or the capital labor ratio can be taken into account. Our preliminary findings confirm that an increase in trade raises the probability of an agreement and vice versa, although the response can differ over specific continents. We find a relatively small average treatment effect of RIAs: trade increases with 10% after one year and 40% after five years whereafter it slowly rises to 80% after 35 years.

Keywords: Endogenous trade agreements; Gravity equation; Qualitative choice models; Qualitative VAR.
JEL: C11; C25; F14; F15.

1 Introduction

Not long after Tinbergen (1962) introduced gravity models to study international trade flows, dummies were added to control for, and measure the effects of regional integration agreements (RIAs).[1] However, the results from these studies have not been very encouraging: depending on the methodology used, the sign and significance of the coefficients on the RIA dummies could change by a wide margin.[2]

The gravity model has evolved strongly since the sixties as its theoretical underpinnings were secured. Starting from a 'naive' log-linearized gravity model, the structural model has been adjusted to take multilateral resistance terms, zero-trade flows and heteroskedasticity into account. At the same time, it became clear that trade and trade agreements are highly endogenous: trading blocs are likely to form along the lines of natural trading partners, i.e. countries that already trade intensively (Krugman, 1997).

*We would like to thank Scott Baier, Dirk Van de gaer and Koen Schoors for their feedback and suggestions. Funding for this research was provided by the Research Foundation - Flanders and the National Bank of Belgium.
Email: Samuel.Standaert@UGent.be, Glenn.Rayp@UGent.be

[1]Throughout this paper we will use the term regional integration agreements as a container term for inter- and intra-regional free trade agreements, customs unions, common markets and economic unions.

[2]See Frankel (1997) for an overview of the earlier literature.

In contrast to the large literature on the effects of trade agreements on trade, the literature studying the endogeneity of both has remained limited. Initially, Baier and Bergstrand (2002) and Magee (2003) used an instrumental variables approach, proving the existence of the endogenous relationship. However, estimates of the effect of trade agreements remained unstable and if anything argued against using instrumental variables in cross-sectional studies (Magee, 2003). Baier and Bergstrand (2007) proposed using panel data with either country-year fixed effects or first differences to cope with endogeneity problems. Alternatively, Baier and Bergstrand (2009) used non-parametric matching econometrics to find the right counterfactual to countries that had signed an agreement. Finally, Egger, Larch, Staub, and R. (2011) returned to instrumental variables in a cross-sectional setting. Using a two-part Poisson pseudo-maximum likelihood estimator they controlled for general equilibrium effects and zero-trade flows in addition to the endogenous nature of trade agreements. Overall, the distortion in the effect of RIAs on trade caused by ignoring the endogeneity has been found to be highly significant, ranging from a 75% increase (Egger et al., 2011) to a quintupling (Baier and Bergstrand, 2007).

An alternative approach to deal with endogeneity could be to use a natural experiment, i.e. a completely exogenous event that led some countries to join while leaving others unaffected. By studying the changes in trade following this event, the effect of this RIA can be analyzed. The problem is that even if such an event can be found, it is not easy to argue that its results can be generalized as the average treatment effect of RIAs worldwide. A vector autoregression model (VAR) on the other hand would allows us to treat both trade and trade agreements as endogenous without having to identify instrumental variables. Instead, the focus lies on the dynamic behavior of both variables which is used to identify their long-term interaction. The only problem is that a VAR model requires continuous variables.

The solution is proffered in the macro-economic literature, where Dueker (2005a) explains how a binary indicator of recessions can be added to a VAR model of the (US) economy. To estimate such a *qualitative* VAR, the indicator variable is first defined in terms of a latent equivalent. In this case, the dummy trade agreements variable is said to depend on the *willingness to sign a trade agreement*. This continuous latent variable can be modeled as endogenous with trade using a normal VAR model. The long term relationship between the variables identified in the VAR can subsequently be used to generate counterfactuals, allowing us to determine the treatment effects of signing a RIA. While the model we present initially ignores zero-trade flows, we show that it can be expanded to deal with both problems simultaneously.

To our knowledge, this is the first time a qualitative VAR has been used to analyze the effect of trade agreements. However, it should be stressed that this paper is intended as an outline of how the qualitative VAR methodology can be used to study trade and trade agreements, rather than a fully worked out analysis. Instead, our aim is to explain the qualitative VAR, show its place in the trade literature and argue that the model produces sensible results. As Baier and Bergstrand (2009, p. 64) note, there is no well-accepted methodology to asses the impact of trade agreements on trade. Rather than a replacement of the current methodology, the qual VAR should be seen as a way to determine the robustness of earlier findings, specifically the average treatment effect of trade agreements on trade.

The next section continues with an overview of the literature on endogenous trade agreements, after which we discuss the qual VAR methodology. Section 5 surveys the results and computes the average treatment effects of a trade agreement. This is followed by a discussion of possible extensions to the model and a preliminary conclusion.

2 On the endogeneity of trade and trade agreements

Baier and Bergstrand (2002) and Magee (2003) were the first to the explicitly take the endogeneity of trade agreements into account. The former focused on economic determinants while the latter stressed the importance of political factors.

Using a review of the literature on trade and trade agreements Magee (2003) identified instruments for both. These were then used in two separate IV-regressions explaining either trade agreements or trade. To asses the determinants of trade he used as instruments for trade agreements: 1) the difference in log GDP, 2) the amount of intra-industry trade, 3) the bilateral trade surplus, 4) difference in capital labor ratios and 5) the level of democracy. The number of airports, manageable waterways and wether a country is landlocked were used to instrument trade. The instrumented probit regression explaining trade agreement formation confirmed the natural trading partners hypothesis, i.e. that trade agreements were more likely to form between countries that traded intensively. On the other hand, the instrumented gravity model found a highly volatile coefficient on trade agreements. Depending on the control variables, RIAs were even found to have a significant negative effect on trade.

Baier and Bergstrand (2002) on the other hand based their analysis on a general equilibrium model explaining the economic determinants of trade agreement.[3] They warned that (in a cross-sectional framework) allowing a simultaneous effect of trade on RIAs and RIAs on trade (cf. Magee, 2003) resulted in a logical inconsistency; one of the two has to be zero for the probability of having an agreement and the probability of not having an agreement to sum up to one –a necessary condition for a probability. While this ruled out the simultaneity as the cause of endogeneity, other factors (for example including a trade-imbalances variable cf. Magee, 2003) could still cause endogeneity. Using the instrumented RIA variable, the agreements' effect on trade quadrupled. However, further research showed that IV regressions of the treatment effect of RIAs were highly unstable (ranging from -92% to +1100%) and that the instruments's exogeneity was often rejected (Baier and Bergstrand, 2004b).

In response, Baier and Bergstrand (2007) turned to panel data, using fixed effects and first differencing to control for endogeneity caused by selection bias, measurement errors in the explanatory variables and missing variable bias. To be consistent with trade theory, the estimation of the gravity model required country-time fixed effects to control for time-varying multilateral resistance terms[4] in addition to the endogeneity issues mentioned. Furthermore, they argued that using first differences also controls for simultaneity since the natural trading partner hypothesis captures a long term relationship and does not extend to variations in the level of trade. Similar to their findings in the 2002 paper, signing a RIAs caused trade flows to double.

To test the robustness of earlier results, Baier and Bergstrand (2009) turned to non-parametric matching to estimate the average treatment effect of RIAs in cross-sectional data. By matching country-couples with a RIA with a credible counterfactual without one, the effect of an agreement could be computed regardless of self-selection issues or non-linearities. In contrast with the first differences approach, this enabled a computation of the long run treatment effects. In line with their earlier papers, RIAs were found to have doubled trade flows on average.

The latest attempt to model the endogeneity of integration agreements and trade flows explicitly was made by Egger et al. (2011), who returned to an instrumental variable approach using cross-sectional data. Their estimations combined the endogeneity literature with general equilibrium effects of trade agreements and a non-log-linear gravity equation that takes zero-trade flows into account. As instruments for trade agreements they used three dummy indicators indicating: 1) whether one of the countries used to be colony of the other; 2) whether they have a common colonial history; and 3) whether the countries-pair used to be one country. Their structural gravity model was estimated using a two-part Poisson pseudo maximum likelihood

[3]Their regressions also included a number of political variables taken from the literature.

[4]See also Baldwin and Taglioni (2006) and Head and Mayer (2013).

estimator with an instrumented RIA variable. The average treatment effect of trade agreements was subsequently computed by using the estimated parameters to generate a counterfactual trade flow. They found that ignoring endogenous selection biased the effect of RIAs downwards by as much 188%. Their average treatment effect of 235% was more than twice as large as was identified in Baier and Bergstrand (2002, 2007, 2009), but it concealed large differences between country couples.

3 The Qualitative VAR model

The foremost advantage of using a (qualitative) VAR is that it allows us to treat trade and trade agreements as completely endogenous. In contrast to Baier and Bergstrand (2002, 2004b), Magee (2003) or Egger et al. (2011) there is no need to look for instruments that explain trade while having no effect on trade agreements, or vice versa. Finding instruments for trade or RIAs is difficult as it is hard to rule out that they have no effect on the other variable and any that are found are unlikely to explain a large part of the variation in either variable. Accordingly, Baier and Bergstrand (2007) found that the IV approach produced too unstable estimates of the size of the effect of trade agreements on trade.

In addition, the qualitative VAR model allows us to take the endogeneity of other variables into account. For example, GDP and capital-labor ratios have been shown to affect both trade and integration agreements and are unlikely to remain unaffected by either. For this reason, the qualitative VAR is more appropriate than the multivariate probit since the latter *"is set up to emphasize cross-sectional correlations among a set of qualitative variables and the coefficients on exogenous covariates. VARs, in contrast, are better suited to a small system of endogenous variables and a relatively large number of autoregressive lags"* (Dueker, 2005a, p.97). The VAR allows us to model the endogeneity as autoregressive variables as opposed to autoregressive errors.

Finally, by modeling the interaction between trade and trade agreements dynamically, the logical inconsistency identified in Baier and Bergstrand (2002) can be avoided. Both trade and the willingness to form trade agreements depend on what happened in the past. By definition, trade agreements have a unit root: unless some action is taken by both governments, the existence of a trade agreement today will be the same as that of yesterday. Similarly, shocks to the aggregate trade flows show a high degree of persistence even if particular categories within those flows are more volatile. By modeling their interaction dynamically, trade can depend on trade agreements and trade agreements can depend on trade without creating the logical inconsistencies such dependency would cause in cross-sectional studies.

3.1 Building a simple qualitative VAR

Assuming for simplicity's sake that we have only two endogenous variables: trade (X) and regional integration agreements (RIA). Ignoring the endogeneity of trade, a *static* probit model explaining RIAs can be written down using a latent variable $RIA^{\star}$:

$$\begin{aligned} RIA^{\star}_{ij,t} &= \phi_1 \; X_{ij,t} + x_{ij,t} \; b_1 + c_{1_{ij}} + \epsilon_{1_{ij,t}} \\ RIA_{ij,t} &= \begin{cases} 0 & \text{if } RIA^{\star}_{ij,t} \leq 0 \\ 1 & \text{otherwise.} \end{cases} \end{aligned} \tag{1}$$

$X_{ij,t}$ denotes the (log of the) total trade between countries i and j at time t. $RIA_{ij,t}$ is a dummy variable indicating whether the two countries are members of the same trade agreement at time t and $RIA^{\star}$ is its latent continuous equivalent. $c_{1_{ij}}$ holds a vector of constants/fixed effects, while $x_{ij,t}$ contains the remaining exogenous explanatory variables. In a probit model, the error term ϵ_1 is assumed to come from a normal distribution in which variance is normalized to one on order to identify the model.

Baier and Bergstrand (2004a) interpret $RIA^\star$ as the *minimal* willingness of both countries to sign an integration agreement. Since both countries have to agree, it is the country with the smallest willingness that will ultimately decide whether or not an agreement is signed. However, this interpretation runs into some problems especially when used in the dynamic setting. Without additional assumptions, there is no guarantee that the minima of two linear functions is itself linear. Moreover, a change in which of the two countries has the smallest willingness would also alter the parameter values. An interpretation that would avoid both problems is if $RIA^\star$ is the *average* willingness to sign. The underlying assumption is that countries can compensate each other either monetarily or for example through concessions in other parts of the agreement. A county with a lot to gain from the agreement could in this way try to compensate an unwilling partner, making their average willingness the deciding factor. This would avoid the problems associated with minima, at the cost of introducing bartering to the RIA negotiations.

It should be pointed out that $RIA^\star$ is simply a mechanical feature that allows us to write the probit model in a linear way. The meaning we ascribe to it does not alter the parameters of the probit regression, although it does have repercussions for the way in which the theoretical model is translated to the empirical specification. However, as this discussion would lead us too far from the main point of this paper we will simply refer to $RIA^\star$ as the willingness to sign, leaving out whether this is a minimum or an average.

Secondly, a *static* log-linear gravity model that ignores the endogeneity of trade agreements is given by equation 2. The error term $\epsilon_{2_{ij,t}}$ also comes from a normal distribution and has variance σ_2. Using similar control variables x and fixed effects matrix $c_{2,ij}$ we get:

$$X_{ij,t} = \phi_2 \; RIA_{ij,t} + x_{ij,t} \; b_2 + c_{2_{ij}} + \epsilon_{2_{ij,t}} \tag{2}$$

To construct a qualitative VAR, the RIA dummy in the gravity equation is first replaced by the latent $RIA^\star$ from the probit model. Equations 2 and 1 are then stacked and the endogenous variables are modeled dynamically. Using p lags on each endogenous variable, the reduced form can be written as:

$$\begin{bmatrix} RIA^\star_{ij,t} \\ X_{ij,t} \end{bmatrix} = \sum_{k=1}^{p} \Phi^{(k)} \begin{bmatrix} RIA^\star_{ij,t-k} \\ X_{ij,t-k} \end{bmatrix} + b \; x'_{ij,t} + c_{ij} + \epsilon_{ij,t} \tag{3}$$

$$RIA_{ij,t} = \begin{cases} 0 & \text{if } RIA^\star_{ij,t} \leq 0 \\ 1 & \text{otherwise.} \end{cases} \tag{4}$$

$\Phi^{(k)}$ is an $(m \times m)$ matrix holding the parameters on the k^{th} lag of the m endogenous variables. In this simple example m is equal to two, but $X_{ij,t}$ could also be interpreted as a vector containing multiple continuous endogenous variables. The remaining parameters and the error term can be obtained by stacking their counterparts: $b = [b'_1, b'_2]'$, $c_{ij} = \left[c_{1_{ij}}, c_{2_{ij}}\right]'$ and $\epsilon_{ij,t} = \left[\epsilon_{1_{ij,t}}, \epsilon_{2_{ij,t}}\right]'$. The error term $\epsilon_{ij,t}$ is assumed to come from an independent and identically normal distribution with zero mean and variance matrix Σ. Similar to the probit regression with latent variables, identification of the model requires the assumption that the first diagonal element of Σ is one:

$$\Sigma = \begin{bmatrix} 1 & \sigma_{12} \\ \sigma_{21} & \sigma_2 \end{bmatrix}$$

3.2 Estimation using Bayesian Gibbs sampling

Using a Bayesian Gibbs sampler allows us to split up the estimation of this system into multiple parts. Instead of having to compute the entire (posterior) probability of all parameters at once, it is separated into various conditional probabilities that are much easier to solve. The Gibbs sampler iteratively draws from those probabilities while conditioning on the values from the previous draws: $a_1 \sim p(a|b_1)$, $b_2 \sim p(b|a_1)$, $a_2 \sim p(a|b_2)$, etc. After a certain number of draws, these draws will have converged to the unconditional posterior and the remaining draws can be used to reconstruct the distribution of the parameters (Koop and Korobilis).

To simplify the notation used in the remainder of this section, the parameters of the qualitative VAR are condensed to the variance Σ and the parameter coefficients $\Theta = \{c_{ij}, b, \Phi\}$ where $\Phi = \{\Phi^{(1)}, \ldots, \Phi^{(p)}\}$.

If the latent variable $RIA^{\star}_{ij,t}$ were known, equation 3 could be estimated using seemingly unrelated regression techniques. However, computing and drawing values for the latent variable conditional on the parameters in equation 3 (Θ and Σ) is less straightforward. The mean and standard deviation of $RIA^{\star}_{ij,t}$ depend on past and future values of the endogenous variables, as well as the current values of the exogenous variables. However, as Dueker (2005b) noted, a simple rewrite of this model reveals a state-space model which can be estimated and drawn from using a modified Kalman filter (cf. infra, section 3.2). In addition to the computational convenience this offers, the multi-move sampling technique also ensures a faster convergence.

By imposing an independent normal-Wishart prior on Θ and Σ, the conditional posterior distributions remain relatively simple. Throughout this paper, we used an uninformative prior on Σ, combined with a Minisota prior on Θ. The Minisota prior allows for prior shrinkage, exponentially decreasing the weight of the parameters on higher lags. This helps ensure that the Gibbs sampler converges even when the number of endogenous variables and lags increases (Koop and Korobilis).

The matrix c_{ij} can be adjusted to estimate a wide range of models, including sender and target fixed effects that control for (time-invariant) multilateral resistance terms. In a probit model, the incidental parameter problem cannot be circumvented by using demeaned variables. As a result, the fixed effects can only be estimated by including a large number of dummy variables (Egger et al., 2011). Following Guimarães and Portugal (2009), the estimation of the dummies is separated from the other variables in Θ, keeping the size of the matrix that needs to be inverted under control.

Figure 1 summarizes the different loops in the Gibbs sampler. From left to right, it provides an overview of how the Gibbs sampler separates the posterior distribution of θ and Σ into conditional probabilities. Step A shows how Dueker (2005a,b) first split up the posterior by introducing the latent variable $RIA^{\star}$. The next section describes how $RIA^{\star}$ can be computed and drawn from if we know what Θ and Σ are. Step B and C illustrate how those parameters can be drawn conditional on $RIA^{\star}$. Appendix A lists the probability distributions of each step, but for an exhaustive overview we refer the reader to Koop and Korobilis and Guimarães and Portugal (2009).

The conditional distribution of the latent variable $RIA^{\star}$

The final step of the Gibbs sampler computes and draws from the distribution of $RIA^{\star}$, conditional on the parameters of the qualitative VAR. In a static probit model this can be solved by drawing from a truncated normal distribution to ensure the values of $RIA^{\star}$ are positive when an agreement is signed and vice versa. In the qualitative VAR on the other hand, the dynamics make it so that the distribution of $RIA^{\star}$ at moment t will depend on the previous values and will in turn influence future values. However, instead of having to compute this dependence

Figure 1: Structure of the Gibbs sampler algorithm

$$\theta,\Sigma|RIA,X,x \underset{A}{\Rightarrow} \begin{cases} RIA^{\star}|RIA,\Theta,\Sigma,X,x \sim N \\ \Theta,\Sigma|RIA^{\star},X,x \underset{B}{\Rightarrow} \begin{cases} \Sigma|\Theta,RIA^{\star},X,x \sim iW \\ \Theta|\Sigma,RIA^{\star},X,x \underset{C}{\Rightarrow} \begin{cases} b,\Phi|\Sigma,RIA^{\star},X,x,c_{ij} \sim N \\ c_{ij}|\Sigma,RIA^{\star},X,x,\Phi,b \sim N \end{cases} \end{cases} \end{cases}$$

N	:	Normal distribution
iW	:	inverse Wishart distribution
$\underset{A}{\Rightarrow}$	:	Dueker (2005a,b)
$\underset{B}{\Rightarrow}$	:	Koop and Korobilis
$\underset{C}{\Rightarrow}$	:	Guimarães and Portugal (2009)

over p lags and estimate $RIA^{\star}$ for the entire time-period, the qualitative VAR can be rewritten into a state-space model which can solved observation by observation.

A state-space model is built around two equations that define the behavior of an unknown, to-be-estimated state vector. The state equation (equation 5) describes the change in the state vector S_t over time: the way in which it depends on its previous values (μ and F) and how big the changes in each period can be (ν_1). Secondly, the measurement equation (equation 6) specifies how this state-vector in turn is related to a number of observed variables (X_t). Specifically, it states how the observed variables are scaled (H) and what their reliability is (ν_2). The error terms ν_1 and ν_2 are assumed to be normally distributed.

$$S_t = \mu + FS_{t-1} + \nu_{1,t} \tag{5}$$
$$X_t = H\ S_t + \nu_{2,t} \tag{6}$$

The Kalman filter and smoother algorithms can be used to compute the distribution of the state vector at each point in time. The strength of these algorithms lies in the fact that they do this iteratively which significantly reduces the computational burden. In each step they use the state equation to predict the current value of S_t based on the past (Kalman filter) or future (Kalman smoother) estimates of S. This prediction is then updated using the information in X_t whose scaling and reliability is determined by the measurement equation (Kim and Nelson, 1999).

Applying this logic to the qualitative VAR model, the willingness to sign ($RIA^{\star}$) is the unknown state while the information in $RIA_{ij,t}$ and $X_{ij,t}$ serves as the observed measurements. To rewrite equation 3 as a state-space model, the vector of endogenous variables is first summarized as a $(m \times 1)$ vector $Y_{ij,t} = \left[RIA^{\star}_{ij,t}, X_{ij,t}\right]'$. The state variable is subsequently obtained by stacking p lags of this vector, $S_t = [Y'_{ij,t}, \ldots, Y'_{ij,t-p+1}]'$, resulting in the following model:

$$\begin{bmatrix} Y_{ij,t} \\ Y_{ij,t-1} \\ \vdots \\ Y_{ij,t-p+1} \end{bmatrix} = \begin{bmatrix} c_{ij,t} + b\ x'_{ij,t} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix} + \begin{bmatrix} \Phi^{(1)} & \Phi^{(2)} & \ldots & \Phi^{(p)} \\ \mathbf{I} & \mathbf{0} & \ldots & \mathbf{0} \\ \mathbf{0} & & \ddots & \mathbf{0} \\ \mathbf{0} & \ldots & \mathbf{I} & \mathbf{0} \end{bmatrix} \begin{bmatrix} Y_{ij,t-1} \\ Y_{ij,t-2} \\ \vdots \\ Y_{ij,t-p} \end{bmatrix} + \begin{bmatrix} \epsilon_{ij,t} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix} \tag{7}$$

$$X_{ij,t} = \begin{bmatrix} 0_{1\times m-1} & I_{m-1} & \mathbf{0} & \ldots & \mathbf{0} \end{bmatrix} \begin{bmatrix} Y_{ij,t} \\ Y_{ij,t-1} \\ \vdots \\ Y_{ij,t-p+1} \end{bmatrix} \tag{8}$$

The first row of the state equation (7) simply repeats the qualitative VAR model (equation 3). $c_{ij} + b\ x'_{ij,t}$ is a simple -albeit time-varying- scalar, since this step of the Gibbs sampler algorithm is conditional on the parameter values Θ and Σ. The measurement equation (8) establishes the relation between $Y_{ij,t}$ and the continuous endogenous variable(s) $X_{ij,t}$. Without an error term in the measurement equation, only the first element of the state variable can vary in each draw: $RIA^{\star}_{ij,t}$. The values of the other endogenous variables are kept fixed.

The main difference with a standard state-space model is that the error term is not multivariate normally distributed. Similar to the probit model, the error term has to be drawn from a truncated normal distribution to ensure that $RIA^{\star}$ is positive when a RIA is signed. This means that the expected value and standard deviation of $\epsilon_{ij,t}$ changes depending on whether or not a trade agreement has been signed. Appendix A gives an overview of how this affects the Kalman filter and smoother algorithms.

3.3 Identifying the structural model

Because this paper is intended more as a proof of concept of using a qualitative VAR in the analysis of trade flows, the identification of the structural model has purposefully been kept simple. A Cholesky decomposition is used to impose a strict ordering in the timing of each variable. Other possible identification methods are discussed in the extensions (section 6). It should be mentioned that the choice of identification strategy will only affect the structural impulse response functions. The average treatment effects on the other hand are computed using the reduced model's parameters.

While trade agreements are assumed to be able to immediately affect trade, the willingness to close trade agreements adjusts more slowly.[5] This reflects the fact that the negotiation of trade agreements takes time. When added as an endogenous variable, the remaining variables are ordered as: 1) RIA; 2) trade; 3) capital-labor ratio; 4) difference in GDP; 5) average GDP. The cholesky decomposition imposes that each variable has no immediate effect on those preceding it, but can be contemporaneously affected by them.

4 Data

The baseline model uses a simple dummy indicator that captures whether or not two countries are currently members of the same trade agreement (RIA). This variable was composed using the information in the WTO's Regional Integration Agreements Information System and the United Nations University's Comparative Regional Integration Studies electronic platform: the Regional Integration Knowledge System. Both databases combined provided information on 251 agreements covering 205 countries from 1950 to 2015. Agreements between a customs union and another country were ascribed to all members of the customs union at that time. The complete list can be found in appendix B.

Following Baier and Bergstrand (2004a), the trade agreements variable was defined per country-pair. This gave a total of $\frac{205\times204}{2} \approx 20,000$ country couples and 850,000 observations. However, when combined with the availability in trade data and discarding zero-trade flows about 275,000 observations are left. Trade flows were measured as the sum of the logs of exports and imports.[6] For now, zero trade flows were ignored, but a solution to this problem in the line of Egger et al. (2011) is discussed in the extensions (section 6). The other endogenous variables are the GDPs of both countries and the difference in their capital-labor ratio (DKL). Bilateral trade data was supplied by the IMF's Direction of Trade Statistics while the Penn

[5]This falls along the lines of the restriction used in Baier and Bergstrand (2002, section VII-A) that ensures the logical consistency of the cross-sectional model.

[6]This avoids the silver medal mistake of gravity equations which is to take the log of the sum (Baldwin and Taglioni, 2006).

world tables 8.0 provided information on GDP, population and capital (Feenstra, Inklaar, and Timmer, 2013).

Information on distance, population and capital was used to create variables expressing the remoteness of two countries relative to the other countries on their continent (*remote*) and the extent to which their capital-labor ratio differs from that of the rest of the world (*DROWKL*). Both variables were computed as described in Baier and Bergstrand (2004a). The availability of the capital-labor data was similar to that of GDP allowing us to use both (unlike for example Egger et al., 2011).

Proxies for ice-berg type trade costs were also included as control variables, most of which came from CEPII's gravity dataset (Head, Mayer, and Ries, 2010; Head and Mayer, 2013). These include the log of (population-weighted) *distance* and a series of dummies indicating whether two countries neighbor another (*contiguity*), whether one country was once a colony of the other (*colony*), whether they were once colonized by the same country (*common colony*), whether they share an ethnographic *language* and whether one of the countries is *landlocked*. Finally, following Egger et al. (2011) a number of political variables from the polity IV project were included (Marshall, Gurr, and Jaggers, 2014). *Autocracy*, political competition (*pol. comp.*) and *durability* measure the absolute distance of the country-couple in terms of those political characteristics. Appendix C provides summary statistics.

5 Results

Similar to the identification of the structural model, the model specification is kept simple. The starting point for the gravity equation is a log-linear version of the one used in Anderson and van Wincoop (2003), while the probit model's specification is based on Baier and Bergstrand (2004a). The gravity equation includes country-fixed effects to control for multilateral resistance terms, but unlike Baldwin and Taglioni (2006); Baier and Bergstrand (2007) or Head and Mayer (2013) they are kept constant over time.[7] A further simplification is that the same exogenous control variables are used in both equation. The issue of making the model specification more consistent with the trade theory is revisited in section 6.

Both equations are adjusted to the VAR framework by including the endogenous variables ($Y_{ij,t}$) dynamically. In other words, as opposed to static models that try to estimate the long-term equilibrium relation, the focus is shifted to the adjustment to the long-term equilibrium. This gives rise to two models: a *limited* model where only trade and RIAs are endogenous and the *full* model where the GDP and capital labor ratios are also modeled endogenously. In both cases, the reduced form of the qualitative VAR can be written as:

$$Y^{\star}_{ij,t} = \sum_{k=1}^{p} \Phi^{(k)}\; Y_{ij,t-k} + b\; x'_{ij,t} + c_i + c_j + \epsilon_{ij,t} \tag{9}$$

with $x_{ij,t}$ a vector of control variables, c_i and c_j country fixed effects and $\epsilon_{ij,t}$ the normally distributed error term with variance-covariance matrix Σ.

5.1 Limited model

In the limited model $Y_{ij,t}$ is equal to $[RIA^{\star}_{ij,t},\; X_{ij,t}]'$. The exogenous variables $x_{ij,t}$ control for the country size and relative factor endowments by including the log of the GDPs of both countries and the difference in their capital labor ratios (*DKL*) in addition to the other control

[7] Egger and Nigai (2015) note that the country-year fixed effects are correlated with the error term and as a result still produce biased results.

variables listed in the previous section. The GDPs were labeled such that country i is on average larger than country j throughout the period of the study.[8]

The parameter values of the reduced model are listed in table 1, however these cannot be used directly to study the effects of a change as this would ignore the dynamics of the system. To take these into account, the Cholesky decomposition is first used to transform the model into its structural equivalent as detailed in section 3.3. The structural parameters are subsequently used to compute the impulse response functions (irf) shown in figure 2. The irf show the change in the endogenous variables in response to a temporary shock (or impulse) in each of the endogenous variables. These shocks, indicated between brackets, happen at moment $t = 0$ and correspond to one standard deviation in the shocked variable. The x-axis shows the number of years since the shock and the y-axis shows the resulting change in the value of the variable in question. Finally, the 90% confidence intervals are indicated by the blue dotted lines. We will use coordinates to refer to an individual response function by counting the number of rows and columns starting from the top left corner (cf. matrices).

Table 1: Reduced parameter values of the limited model - World

	RIA*	st.e.	X	st.e.
L1.RIA*	0.0456^a	(0.0051)	0.0051^a	(0.0010)
L2.RIA*	-0.0036^a	(0.0013)	0.0008	(0.0007)
L1.X	0.0788^a	(0.0077)	0.6015^a	(0.0023)
L2.X	0.0548^a	(0.0067)	0.2430^a	(0.0022)
GDP$_i$	0.5394^a	(0.0206)	0.1825^a	(0.0039)
GDP$_j$	0.0478^a	(0.0072)	0.1641^a	(0.0035)
DKL	-0.1210^a	(0.0073)	-0.0082^a	(0.0025)
DROWKL	-0.7203^a	(0.0408)	0.0255^c	(0.0159)
Distance	-1.0381^a	(0.0220)	-0.1932^a	(0.0044)
Contiguous	-0.4161^a	(0.0310)	0.1122^a	(0.0114)
Landlocked	0.0508	(0.0563)	-0.0899^a	(0.0164)
Remote	0.0050^b	(0.0022)	0.0015^b	(0.0007)
Colony	0.061	(0.0489)	0.2466^a	(0.0162)
Common colony	-0.2591^a	(0.0292)	0.1289^a	(0.0109)
Language	0.0708^a	(0.0161)	0.0748^a	(0.0069)
WTO	0.1973^a	(0.0271)	-0.0018	(0.0074)
Autocracy	0.0416^a	(0.0034)	0.0012	(0.0012)
Pol. comp	-0.0404^a	(0.0033)	-0.0014	(0.0011)
Durability	-0.0038^a	(0.0003)	-0.0006^a	(0.0001)
nObs	167410		167410	
Fixed effects	sender & target		sender & target	

Reduced parameter estimates of the limited, worldwide qualitative VAR model with two lags. Standard errors between brackets. ^{a}, ^{b} and ^{c} indicate significance at the 1%, 5% and 10% level.

For example, the top right panel has coordinates [1,2]. The title $RIA^\star$ (X) indicates that it plots the change in the value of the latent variable $RIA^\star$ in response to a shock in the log of trade of one standard deviation. It reveals that an increase in trade will significantly raise the willingness to enter into a RIA, corroborating the natural trading partner hypothesis of Krugman (1997). Secondly, panel [2,1] shows that a shock to $RIA^\star$ will significantly raise bilateral trade. However, while the irf can reveal the sign and significance of the effect of trade

[8]This only altered the labels on the variables without affecting the selection of country-pairs.

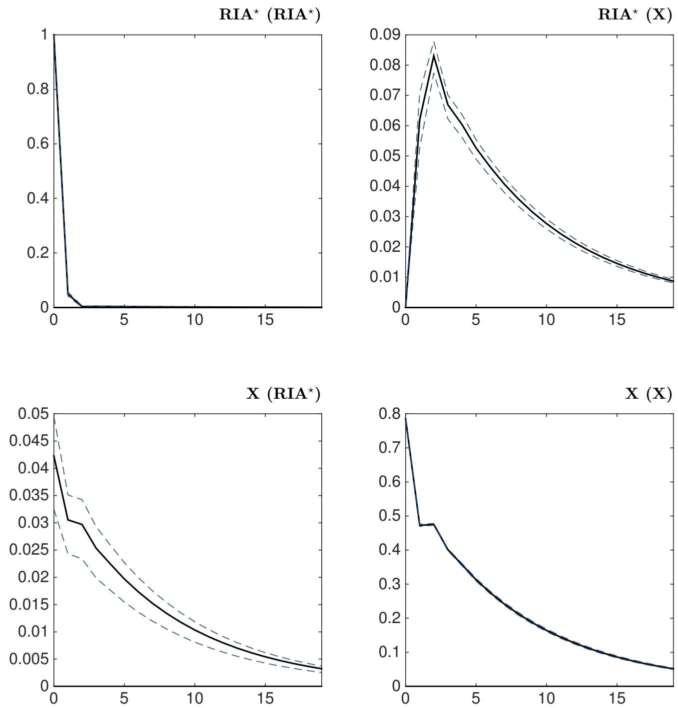

Figure 2: Structural impulse response functions of the limited model - World
Responses in trade and the willingness to form a trade agreement following a shock of one standard deviation in the impulse variable (between parentheses). The x-axis shows the number of years since the shock (at $t = 0$). 90% confidence intervals are indicated by the blue interrupted lines.

agreements on trade, they cannot be used to measure the size of the effect. The reason is that it is not clear whether a shock of one standard deviation in the *willingness* to sign an agreement would actually result in an agreement being signed (cf. section 5.3).[9]

With a few exceptions the behavior of most control variables falls within expectations (table 1). The long-term parameter on GDP and distance in the gravity equation are (slightly) higher than one, but lie within the bounds of what is found in other studies (Head and Mayer, 2013): $\bar{\beta}_{GDP_i} = \frac{0.183}{1-(0.602+0.243)} \approx 1.17$; $\bar{\beta}_{GDP_j} \approx 1.01$ and $\bar{\beta}_{\text{Distance}} \approx -1.24$. The negative coefficient on DKL in the $RIA^{\star}$ equation does not match with the findings of Baier and Bergstrand (2004a), but for example Magee (2003) and Márquez-Ramos, Martínez-Zarzoso, and Suárez-Burguet (2011) found similar signs in their probit regression.[10] The negative coefficients on DROWKL and contiguity are unexpected, but are counteracted through their effect on trade. Moreover, they disappear when DKL and GDP are considered endogenous (cf. infra). In contrast with the instruments used in Egger et al. (2011), colonial history is an inconsistent predictor of trade agreements once the level of trade is controlled for: *colony* is insignificant and while common colonial history is significant it changes sign in the full model. This lends further weight against the practice of estimating the effect of trade agreements through an instrumental

[9] The sign and significance can nevertheless be identified because the values of $RIA^{\star}$ are determined by the actual value of the RIA dummy (equation 4).

[10] Magee (2003) connects the negative coefficient on DKL to the political economy argument of Levy (1997) that agreements are more likely to form between homogenous countries. A small difference in capital-labor ratios indicates a similar economic structure, which raises the likelihood that an agreement can be reached.

variable approach (Baier and Bergstrand, 2004b). The remaining political variables also perform inconsistently. Only the similarity in terms of political competition will consistently positively affect the willingness to sign.

5.2 Full model

In contrast with the limited model, the full model uses the average and difference in the log of the GDPs. This is done so that all endogenous variables vary on three dimensions (sender-target-year), as opposed to two dimensions when the level of GDP of both countries is entered separately (country-year). Combining data in different dimensions would otherwise create problems when stacking data on different countries/country-pairs.[11] Using the averages and differences is how GDP is typically modeled in the probit regression (Baier and Bergstrand, 2004a). The implication for the gravity model is that the same coefficient is imposed on both GDPs, an assumption that is consistent with the theory and can be found throughout the literature (e.g. Baldwin and Taglioni, 2006; Baier and Bergstrand, 2007).

When the difference in capital labor ratios is also considered endogenous, $Y_{ij,t}$ is equal to $[RIA^{\star}_{ij,t},\ X_{ij,t},\ DKL_{ij,t},\ \text{GDP}\mathit{diff}_{ij,t},\ \text{GDP}\mathit{av}_{ij,t}]'$ in the full model. The control variables in $x_{ij,t}$ remain the same (except for those that are now treated as endogenous) and country fixed effects are included in all equations.

The model was first run for the entire world (figure 3) after which the estimation repeated for only European countries (figure 4) and African countries (figure 5). The three figures paint a very similar picture overall, but the sign and significance of some irf can change depending on the region studied. Overall the interaction between trade and trade agreements is not altered when GDP and DKL are considered endogenous. The effect of a shock to the willingness to sign on trade remains positive when DKL and GDP are considered endogenous (panel [2,1]). The effect of a shock to trade on $RIA^{\star}$ is also positive and while it is barely significant for the world, it is strongly significant in both subsamples (panel [1,2]). Furthermore, an increase in the willingness to sign will decreases the difference in GDP and increase the average GDP in all samples (panels [4,1] and [5,1]). A shock to trade on the other hand will increase average GDP (panel [5,2]), but its effect on DKL and the GDP_{diff} changes depending on the estimation sample (panels [3,2] and [4,2]). As was the case in the limited model, an increase in DKL will lower the willingness to sign (panel [1,3]). Worldwide it will also lower trade but the opposite is true in the European and African subsamples (panel [2,3]). The effect of an increase in the difference in GDP on $RIA^{\star}$ is ambiguous, but it will decrease trade (panels [1,4] and [2,4]). Finally an increase in the average GDP will increase both trade and the likelihood of signing an agreement, but this is not always significant (panels [1,5] and [2,5]).

5.3 Assessing the effect of trade agreements on trade

The impulse response functions shown earlier help give an insight into the sign and long run dynamics of the effect of trade on the willingness to join a regional integration agreement. However, there is a difference between the effect of "a rise in the willingness to sign" on trade and the effect of "signing" a trade agreement. Similar to the interpretation of the estimation results of a probit model, the parameter values are not equal to the marginal effect on the dependent variable. While the impulse response functions can show the importance of taking the dynamics and endogeneity into account, they cannot be used to estimate the average treatment effect of signing a trade agreement.

[11] The literature on global VARs deals with variables of different dimensions (e.g. Pesaran, Schuermann, and Weiner, 2004), but in this framework this would imply estimating a model with more than 40,000 equations as each country-couple's trade and willingness to sign RIAs would have to be estimated simultaneously.

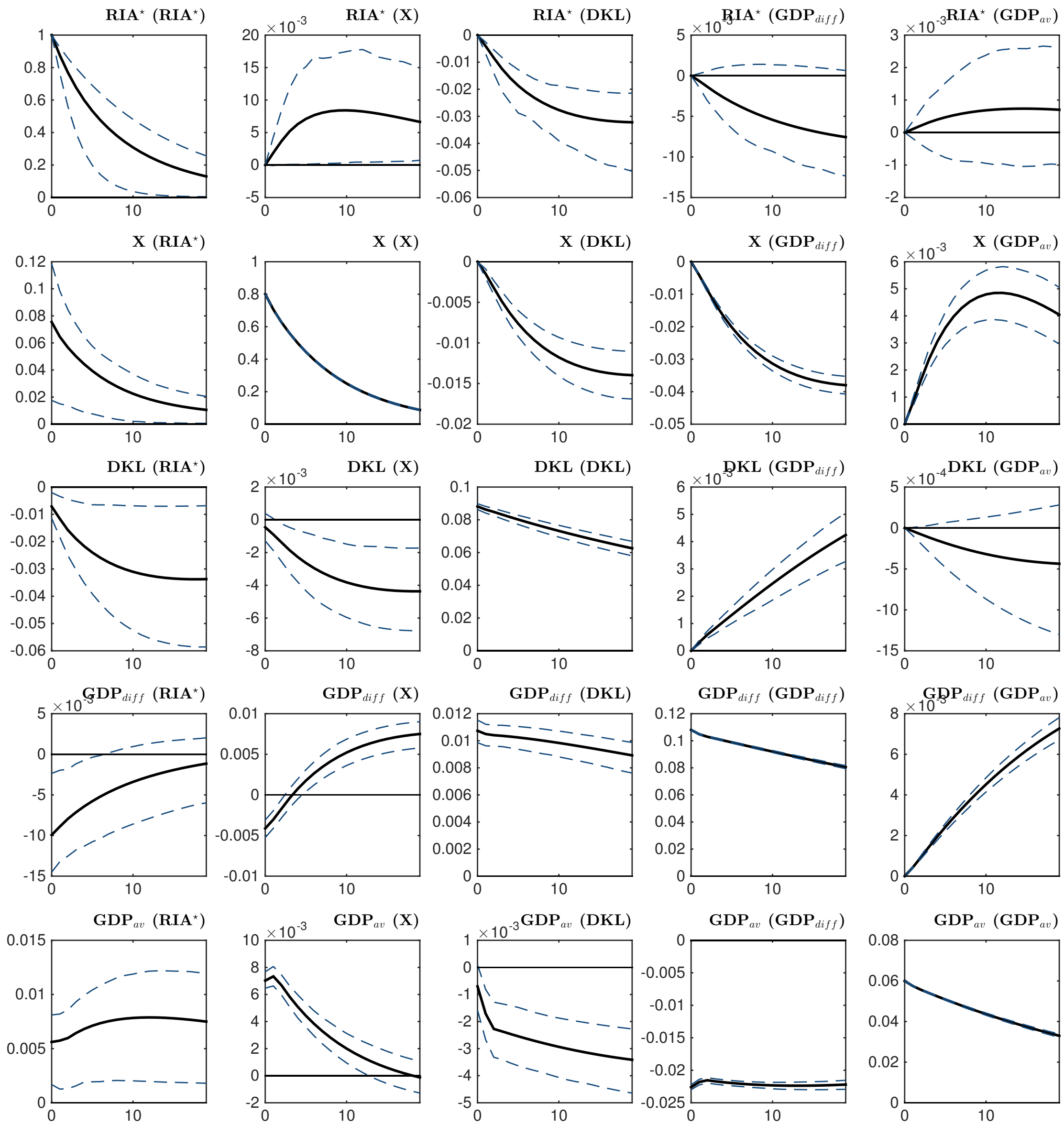

Figure 3: Structural impulse response functions of the full model - World

Responses in trade, the willingness to form a RIA, average and difference in GDP and the capital-labor ratio to a shock of one standard deviation in the impulse variable (between parentheses). The x-axis shows the number of years since the shock (at $t = 0$). 90% confidence intervals are indicated by the blue interrupted lines. The variables are listed in the order of the Cholesky decomposition.

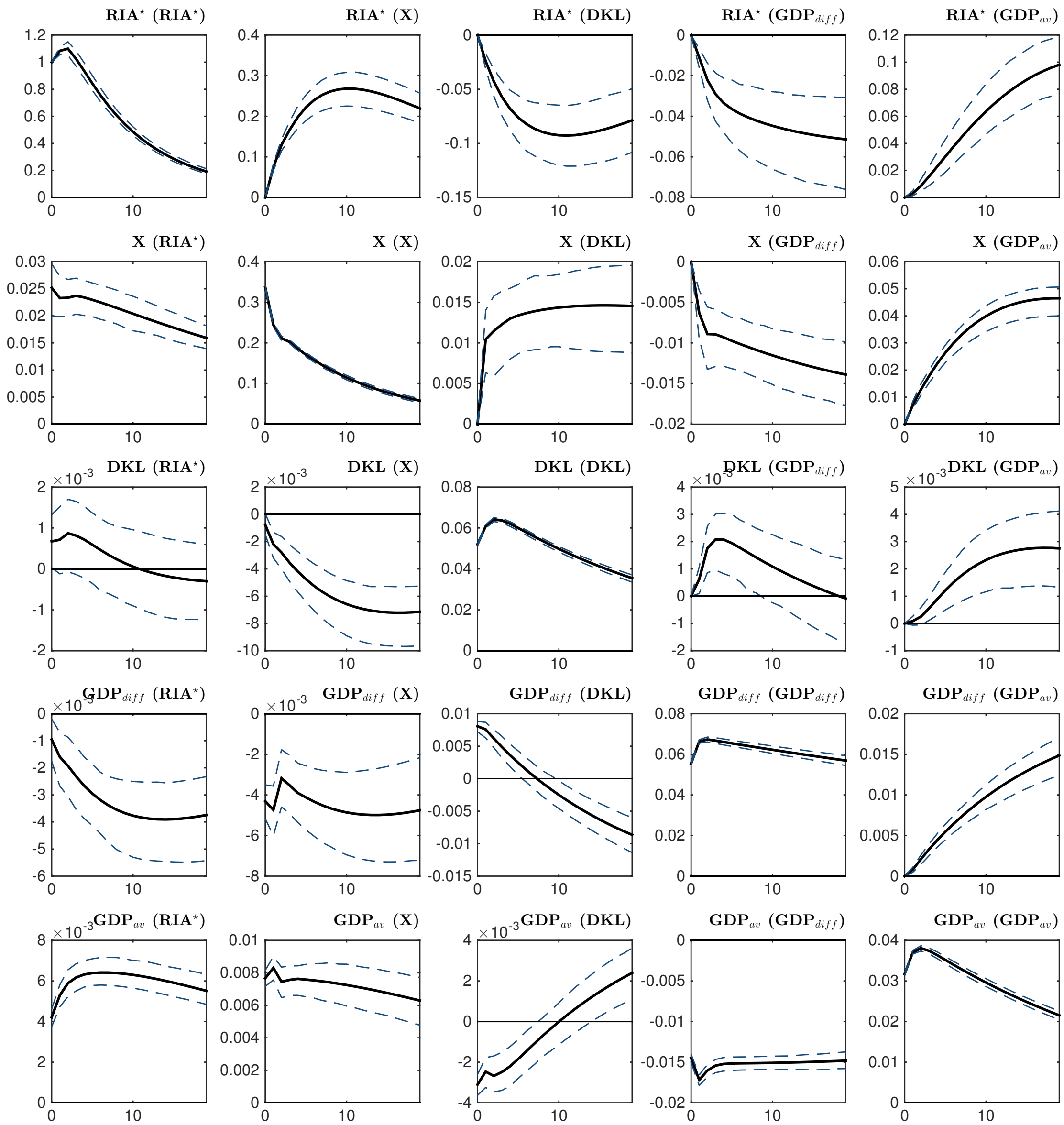

Figure 4: Structural impulse response functions of the full model - Europe

Responses in the willingness to form a RIA, trade, average and difference in GDP and the capital-labor ratio to a shock of one standard deviation in the impulse variable (between parentheses). The x-axis shows the number of years since the shock (at $t = 0$). 90% confidence intervals are indicated by the blue interrupted lines. The variables are listed in the order of the Cholesky decomposition.

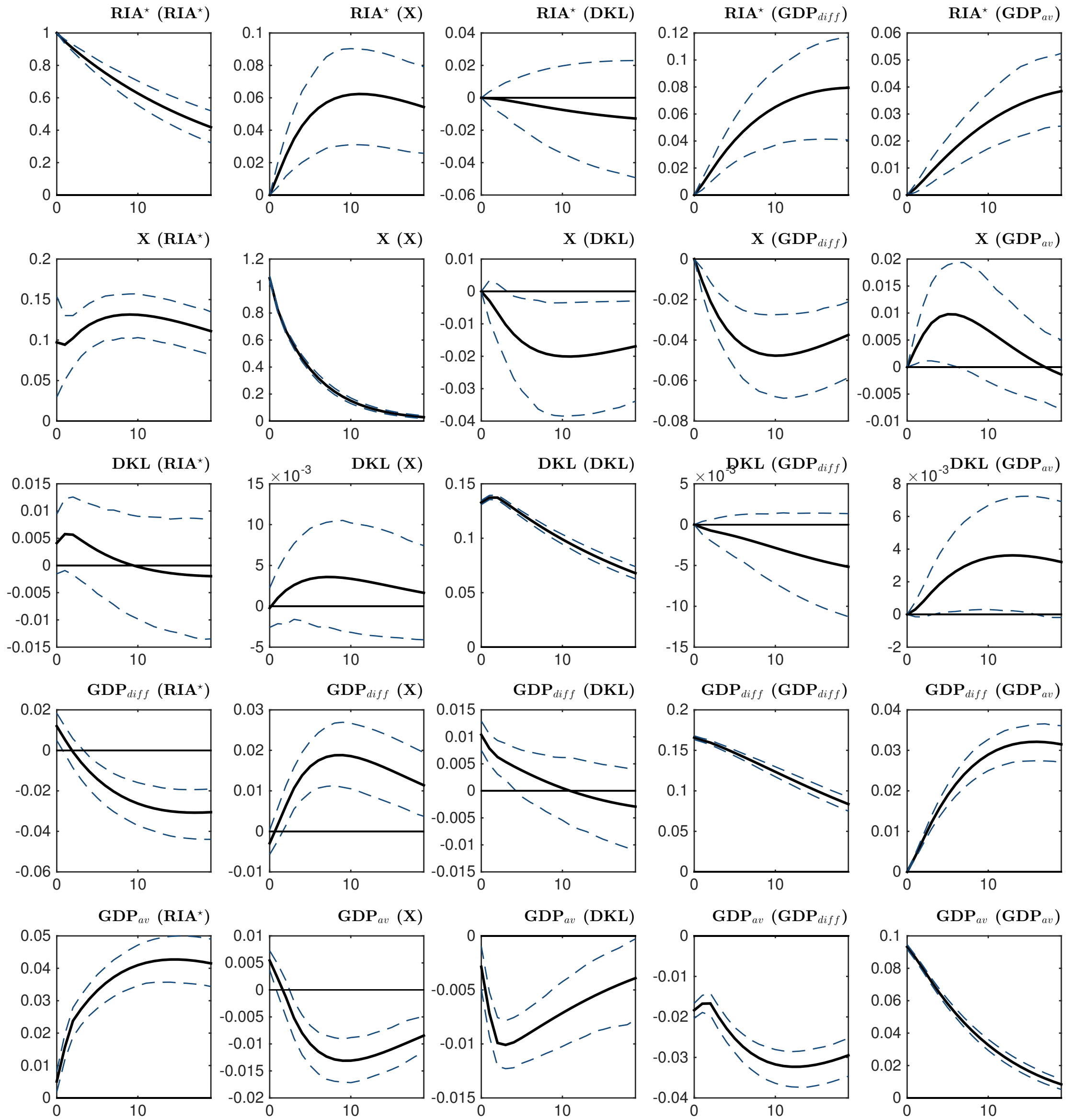

Figure 5: Structural impulse response functions of the full model - Africa

Responses in trade, the willingness to form a RIA, average and difference in GDP and the capital-labor ratio to a shock in the impulse variable of one standard deviation (between parentheses). The x-axis shows the number of years since the shock (at $t = 0$). 90% confidence intervals are indicated by the blue interrupted lines. The variables are listed in the order of the Cholesky decomposition.

The average treatment effect of RIA on trade can be expressed as $ATE = E(X|., RIA = 1) - E(X|., RIA = 0)$. The difficulty assessing the treatment effect is identifying the right counterfactual. Either a country-pair signed an agreement and what trade would be without an agreement is unknown, or vice versa. The dummies that traditionally have been used in gravity equations have been shown to lead to severe parameter instability, even when controlling for endogeneity. Their sign, size and significance changes depending on the study, methodology and even the included control variables (e.g. Magee, 2003). Instead, Baier and Bergstrand (2009) used a non-parametric matching technique to find existing county-couples with similar characteristics but without a trade agreement. Egger et al. (2011) used the estimated parameters on trade and trade agreements to generate the appropriate counterfactual for each country-couple.

The approach we suggest is similar to that of Egger et al. (2011). Using the business-cycle filter from Dueker and Nelson (2006) it is possible to generate values of trade conditional on any value of $RIA^{\star}$. By ensuring that the willingness to sign is never greater than zero, we can impose that no trade agreement was signed. The counterfactuals are generated by reversing the roles of the variables in the state-space model described in section 3.2. $RIA^{\star}$ is fixed at $\bar{r}$ while new values of the other endogenous variables are computed and drawn $(\tilde{X})$. Substituting $\tilde{Y}_{ij,t} = \left[RIA^{\star}_{ij,t},\ \tilde{X}_{ij,t}\right]'$ results in a similar state equation, but changes the measurement equation.

$$\begin{bmatrix} \tilde{Y}_{ij,t} \\ \tilde{Y}_{ij,t-1} \\ \vdots \\ \tilde{Y}_{ij,t-p+1} \end{bmatrix} = \begin{bmatrix} c_{ij,t} + b\, x'_{ij,t} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix} + \begin{bmatrix} \Phi^{(1)} & \Phi^{(2)} & \dots & \Phi^{(p)} \\ \mathbf{I} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \ddots & & \mathbf{0} \\ \mathbf{0} & \dots & \mathbf{I} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \tilde{Y}_{ij,t-1} \\ \tilde{Y}_{ij,t-2} \\ \vdots \\ \tilde{Y}_{ij,t-p} \end{bmatrix} + \begin{bmatrix} \epsilon_{ij,t} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix} \tag{10}$$

$$\bar{r} = \begin{bmatrix} 1 & 0_{1\times m-1} & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix} \begin{bmatrix} \tilde{Y}_{ij,t} \\ \tilde{Y}_{ij,t-1} \\ \vdots \\ \tilde{Y}_{ij,t-p+1} \end{bmatrix} \tag{11}$$

The model specified in equations 10 and 11 treats the latent integration agreement variable as the only observed data. However, this approach can be further augmented to also take historical data into account. In that case, the counterfactual will try to follow historical data to the extent that it corresponds with an unchanged willingness to sign a RIA. Incorporating the historical aspect becomes especially interesting as more variables (for example GDPs and capital-labor ratios) are modeled as endogenous. To generate values of trade that fall in between these two cases, Dueker (2005a) proposes the following measurement equation:

$$\begin{bmatrix} \bar{r} \\ \alpha\, X_{ij,t} \end{bmatrix} = \begin{bmatrix} 1 & 0_{1\times m-1} & \mathbf{0} & \dots & \mathbf{0} \\ 0_{m-1\times 1} & \alpha\, I_{m-1} & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix} \begin{bmatrix} \tilde{Y}_{ij,t} \\ \tilde{Y}_{ij,t-1} \\ \vdots \\ \tilde{Y}_{ij,t-p+1} \end{bmatrix} + \begin{bmatrix} 0 \\ \alpha\, \eta_{ij,t} \end{bmatrix} \tag{12}$$

If the smoothing parameter α is zero, equation 12 is the same as 11. However, as α grows the counterfactual will increasingly reflect the historical data. The error term $\eta_{ij,t} = X_{ij,t} - \tilde{X}_{ij,t}$ is normally distributed with mean zero and variance matrix Ω. The latter can be drawn from an inverse Wishart distribution in the same way as Σ (Dueker and Nelson, 2006). To further reduce the informational value of the historical series, their values were set to missing whenever a trade agreement was signed.

To illustrate, figure 6 plots both actual values and the computed counterfactual for the bilateral trade between Mexico and the United States. The black lines show the actual values of the endogenous variables, while the counterfactual and its 90% confidence interval are indicated by the blue interrupted and dotted lines. In addition to the dummy indicating whether or not a trade agreement was signed (RIA), the top panel also shows the willingness to sign trade agreements ($RIA^\star$) and its 90% confidence interval. This shows quite clearly that as an agreement is signed, $RIA^\star$ changes from negative to positive. Also plotted in the top panel is the value of $RIA^\star$ that was used to compute the counterfactual. $\bar{r}$ follows $RIA^\star$ until a trade agreement is signed after which is set to zero. This means that the counterfactuals are generated under the highest possible willingness to sign that still corresponds to no agreement being signed. In this way, they correspond to a lower bound on the effect of the RIA.

The remaining panels of figure 6 show what trade, the difference in the capital labor ratios and the difference in, and average of GDP would have been if Mexico's and the United States' willingness to sign an agreement never rose above zero. Almost immediately after signing the agreement, the counterfactual level of trade (in logs) starts to diverge from the actual level and the estimated increase from signing a trade agreement only becomes bigger over time. However, this difference remains within the 90% confidence bounds. The counterfactual difference in the capital labor ratios and the GDPs is lower than the actual values, indicating that NAFTA led both countries to diverge. At the same time, the effect on the average GDP is negligible.

The average treatment effect is computed from the individual counterfactual flows. The percentage difference between real values and counterfactual was averaged starting from the moment a trade agreement was signed. If y_{ij}^s year in which the country-couple ij signed a trade agreement, the average treatment effect of an agreement after τ years is:

$$ATE_\tau = \text{mean}_{ij}\left(X_{ij,t-y_{ij}^s+\tau} - \tilde{X}_{ij,t-y_{ij}^s+\tau}\right) \tag{13}$$

where the mean is taken over all country couples that have signed a trade agreement at least τ years ago, with the exception of those that entered the dataset with an active trade agreement.

Figure 7 plots the worldwide average treatment effect of a trade agreement over time for all endogenous variables. It shows that the average percentage increase in trade is 10% in the first year, 40% after 5 years and 50% after 10 years. It subsequently rises slowly to 80% after 35 years. However, this estimate is based on fewer country-couples, causing the width of the confidence interval to increase strongly. The bottom panel shows that the number of country couples decreases steadily from around a thousand in the first five years to less than a hundred for the last five years. Overall, integration agreements have lead to a convergence of the capital labor ratios, but a divergence in terms of GDPs. The effect on the average GDP is small to zero in the first 20 years. It subsequently starts to increase to about 10% after 35 years. In combination with the increase in the difference in GDP, this seems to indicate that the increase in GDP is one-sided and possibly even at the expense of the growth of the partner country. However, the effects after 20 years might simply be a characteristic of the smaller group of country-couples that have had an agreement for this long.

6 Extensions

In contrast with the dynamic nature of the qualitative VAR, the theories underlying the gravity model and the formation of trade agreements are essentially static. The model estimated in equation 9 has naively translated the econometric specification to a dynamic setting, while ignoring the underlying theoretical models. A first important extension would be to ensure that the the dynamic equations are theoretically sound, especially if they are used to generate counterfactuals. A first extension to the model would be to explicitly incorporate the time-varying multilateral resistance terms as latent variables, allowing us to control for the indirect, general-equilibrium effect of trade agreements (cf. Egger et al., 2011).

Secondly, in the current model the equations on the endogenous variables are treated the same and include the same control variables. Moreover, the endogenous variables have all been

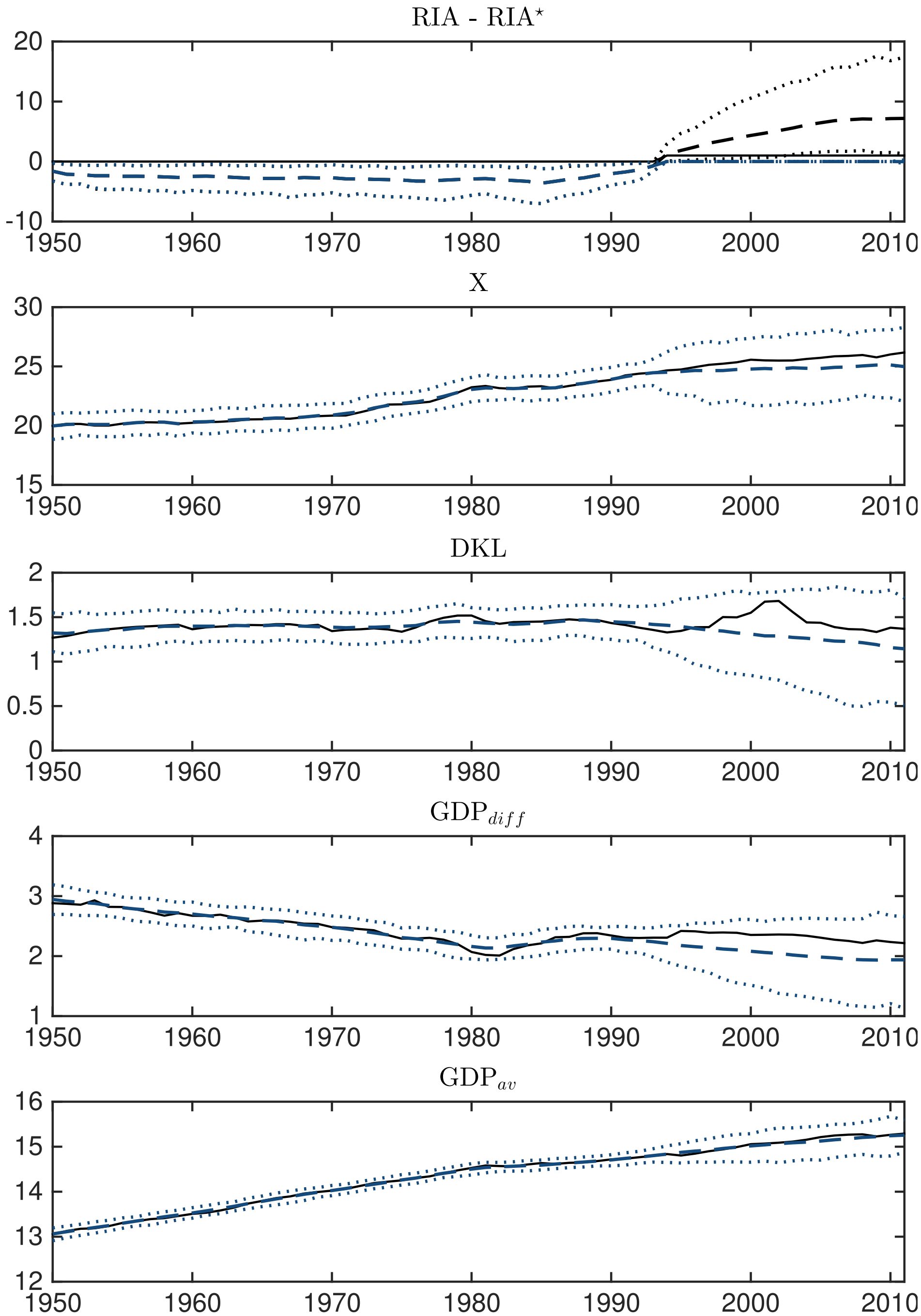

Figure 6: Counterfactual flows for Mexico-United States (full model)
Estimated treatment effect of trade agreements on the Mexico-United States willingness to form trade agreements, log trade, difference in captial-labor ratio, difference in log GDP and average of log GDP. Actual values are indicted by the full black line. The counterfactual and its 90% confidence interval are indicated by the blue interrupted and blue dotted lines, respectively.

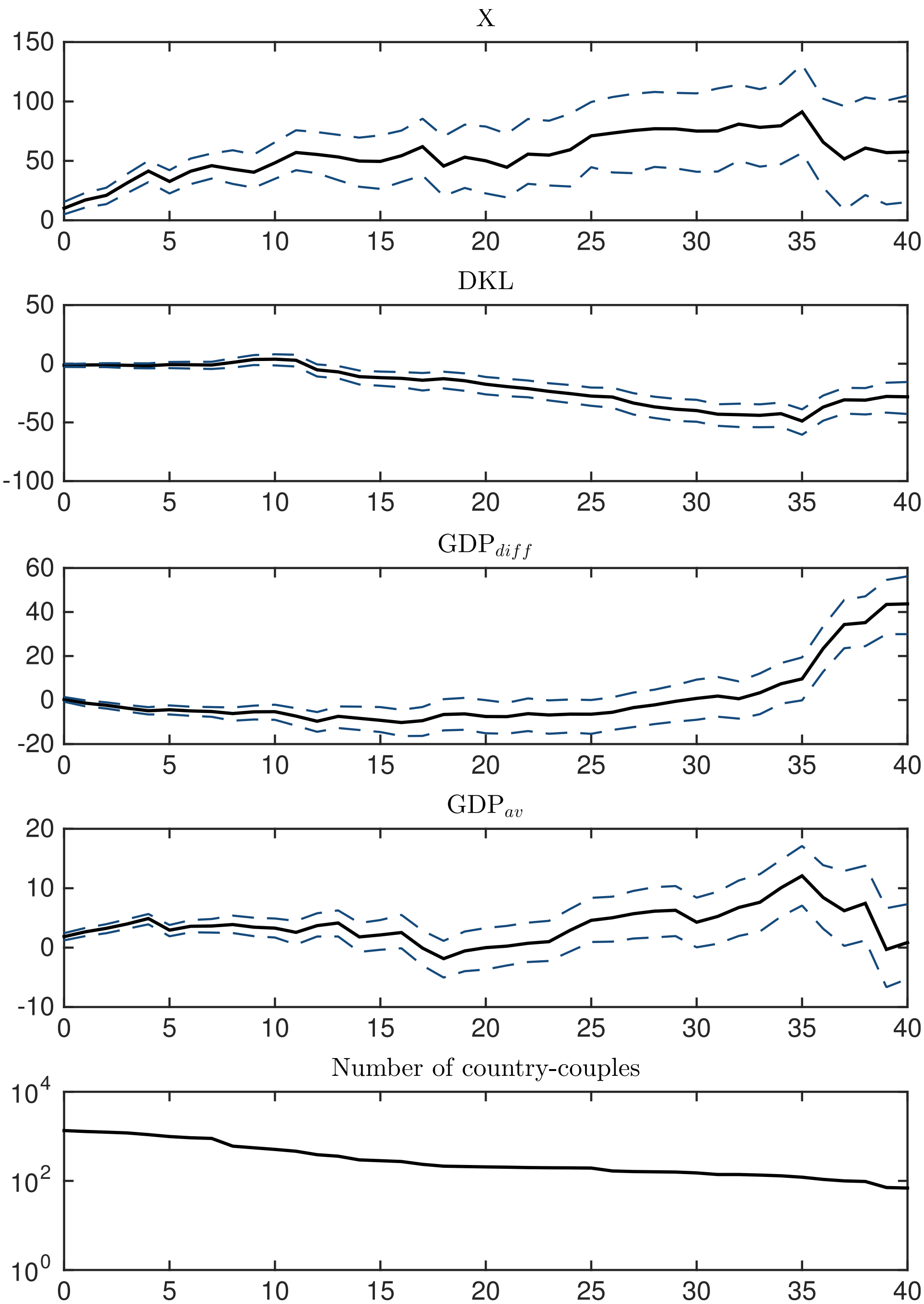

Figure 7: Average treatment effects in percentage terms (full model)

Average treatment effect of trade agreements on trade, the difference in capital-labor ratios, difference in GDP and average GDP. 90% onfidence interval indicated by the interrupted blue lines.

allowed to directly influence one another. However, through a simple change in the priors the direct influence of for example the average GDP on the difference in capital labor ratio could be removed. These and other restrictions, including the number of lags, could subsequently be tested using Bayesian model selection techniques (Koop, 2003).

A third simplification concerns the way integration agreements have been incorporated. The $RIA_{ij,t}$ dummy considered all integration agreements equal, overlooking the vast differences between them. The qualitative VAR model can be extended relatively easily to incorporate agreements of different depth by extending the probit model to an ordered probit model (Dueker, 2005b). The difficulty would lie in the categorization of the integration agreements.[12] Wu (2006) for example constructed a database dividing agreements into preferential trade agreements, customs unions, common markets, and economic unions. Alternatively, Kohl, Brakman, and Garretsen deconstructed the depth of 296 trade agreements, checking whether they made any legally enforceable restrictions in 17 trade-related policy domains. This dataset would allow the construction of a index of the depth of an agreement in a way that did not depend so strongly on a one-track, EU-dominated view of regional integration.

Additionally, while the identification of the structural model does not affect the average treatment effects, its influence on the impulse response functions should be checked. A first robustness test would be to impose a different ordering of the variables in the Cholesky decomposition. Other possible ways of identifying the structural model include sign restrictions. The latter would also allow us to look at the timing of the effects of trade agreements in addition to strengthening the link between the qual VAR with the theory on trade and trade agreements.

Zero trade flows

Finally, the estimations presented thus far have ignored the issue of zero-trade flows. Trade was simply log-transformed, removing any zero trade flows from the regressions. Egger et al. (2011) have found that the resulting selection effects can bias the estimate of the effect of trade agreements downwards by as much as 35%. However, similar to the treatment of the binary trade agreement variable, it should be possible to control for this selection bias using a latent variable.[13]

Equation 14 is the multiplicative version of the gravity model used in the qualitative VAR model (equation 3).

$$X_{ij} = \exp\left(\phi_2 \; RIA_{ij,t-1} + x_{ij,t} \; b_2 + c_{2_{ij}}\right) \; \zeta_{ij,t} \tag{14}$$

where ζ is drawn from a log-normal distribution $\mathcal{N}(0, \sigma_2)$.

By creating a new latent variable, $X^\star$, equation 14 can be log-transformed without losing the zero-trade flows. This latent trade variable could be seen as the desired trade given the present supply, demand and trade costs. If it is positive, trade will be equal to its exponent while if it is negative, trade is simply zero (Li, 1998).

$$X^\star_{ij} = \phi_2 \; Y_{ij,t-1} + x_{ij,t} \; b_2 + c_{2_{ij}} + \epsilon_{2_{ij,t}} \tag{15}$$

$$X_{ij,t} = \begin{cases} 0 & \text{if } X^\star_{ij,t} \leq 0 \\ \exp(X^\star_{ij,t}) & \text{otherwise.} \end{cases} \tag{16}$$

Combining this with the determinants of trade agreements and adding p lags, the qualitative

[12]Since the model is used to assess the impact of trade agreements, the initial categorization can only be based on ex ante differences in scope and depth of the agreement. Any indicator of its effectiveness should be left out.

[13]See for example Koop (2003) for the Bayesian estimation of a Tobit model using latent variables.

gravity model becomes:

$$\begin{aligned}
\begin{bmatrix} RIA^{\star}_{ij,t} \\ X^{\star}_{ij,t} \end{bmatrix} &= \sum_{k=1}^{p} \Phi^{(k)} \begin{bmatrix} RIA^{\star}_{ij,t-k} \\ X^{\star}_{ij,t-k} \end{bmatrix} + b\, x'_{ij,t} + c_{ij} + \epsilon_{ij,t} & (17) \\
RIA_{ij,t} &= \begin{cases} 0 & \text{if } RIA^{\star}_{ij,t} \leq 0 \\ 1 & \text{otherwise} \end{cases} & (18) \\
X_{ij,t} &= \begin{cases} 0 & \text{if } X^{\star}_{ij,t} \leq 0 \\ \exp\left(X^{\star}_{ij,t}\right) & \text{otherwise.} \end{cases} & (19)
\end{aligned}$$

Estimating the qualitative VAR model with the untruncated trade variable follows the approach outlined in section 3.2. To that end the state-space model is adjusted to draw values of both $X^{\star}$ and $RIA^{\star}$:

$$\begin{bmatrix} Y_{ij,t} \\ Y_{ij,t-1} \\ \vdots \\ Y_{ij,t-p+1} \end{bmatrix} = \begin{bmatrix} b\, x'_{ij,t} + c_{ij} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix} + \begin{bmatrix} \Phi^{(1)} & \Phi^{(2)} & \dots & \Phi^{(p)} \\ \mathbf{I} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \ddots & & \mathbf{0} \\ \mathbf{0} & \dots & \mathbf{I} & \mathbf{0} \end{bmatrix} \begin{bmatrix} Y_{ij,t-1} \\ Y_{ij,t-2} \\ \vdots \\ Y_{ij,t-p} \end{bmatrix} + \begin{bmatrix} \epsilon_{ij,t} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix} \tag{20}$$

$$\log\left(X_{ij,t}\right) = \begin{bmatrix} 0_{1\times m-1} & I_{m-1} & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix} \begin{bmatrix} Y_{ij,t} \\ Y_{ij,t-1} \\ \vdots \\ Y_{ij,t-p+1} \end{bmatrix} \quad \text{if } X_{ij,t} > 0 \tag{21}$$

$$0 = \begin{bmatrix} 0_{1\times m-1} & 0_{m-1} & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix} \begin{bmatrix} Y_{ij,t} \\ Y_{ij,t-1} \\ \vdots \\ Y_{ij,t-p+1} \end{bmatrix} \quad \text{if } X_{ij,t} = 0 \tag{22}$$

7 Preliminary Conclusion

This paper uses a qualitative VAR to bring together the literature explaining the causes of regional integration agreements with gravity equations in which its effects are measured. By taking the dynamic behavior of trade and RIAs into account, there is no need to look for the elusive instruments that affect trade but not agreements or vice versa. Furthermore, their endogenous relation can be identified without running afoul of any logical inconsistencies that pose a problem in cross-sectional studies.

Our preliminary findings confirm the usefulness of studying the behavior of trade and RIAs dynamically. An increase in trade motivates countries to sign integration agreements and an increase in the willingness to sign in turn raises trade. As could be expected, these effects take a long time to fully play out. Overall, the effect of trade agreements on trade and the average GDP are relatively small compared to what is typically found in the literature. The former increases quickly in the first 5 years, after which the growth slows down. Trade grows with 10% in the first year, 40% after 5 years and with about 50% after 10 years, while the average GDP initially remains unaffected. After about 35 years, trade has risen 80% and average GDP with 10%. However, the model needs to be extended further if we want to compute reliable average treatment effects. The link between the qualitative VAR model and the theory on trade and trade agreements in particular needs to be strengthened before any final conclusions can be drawn.

References

J. E. Anderson and E. van Wincoop. Gravity with gravitas: a solution to the border puzzle. *American Economic Review*, 93(1):170–192, 2003.

S. L. Baier and J. H. Bergstrand. On the endogeneity of international trade flows and free trade agreements. August 2002.

S. L. Baier and J. H. Bergstrand. Economic determinants of free trade agreements. *Journal of International Economics*, 64(1):29 – 63, 2004a.

S. L. Baier and J. H. Bergstrand. Do free trade agreements actually increase members' international trade? 2004b.

S. L. Baier and J. H. Bergstrand. Do free trade agreements actually increase members' international trade? *Journal of International Economics*, 71:72–95, February 2007.

S. L. Baier and J. H. Bergstrand. Estimating the effects of free trade agreements on international trade flows using matching econometrics. *Journal of International Economics*, 77:63–76, 2009.

R. Baldwin and D. Taglioni. Gravity for dummies and dummies for gravity equations. Technical Report 12516, National Bureau of Economic Research, 2006.

M. Dueker. Dynamic forecasts of qualitative variables: A qual VAR model of u.s. recessions. *Journal of Business & Economic Statistics*, 23(1):96–104, 2005a.

M. Dueker. Kalman filtering with truncated normal state variables for bayesian estimation of macroeconomic models. working paper 2005-057, Federal reserve Bank of St. Louis, 2005b.

M. Dueker and C. R. Nelson. Business cycle filtering of macroeconomic data via a latent business cycle index. *Macroeconomic dynamics*, 10:573–594, 2006.

J. Durbin and S. Koopman. *Time Series Analysis by State Space Methods*. Oxford University Press, 2 edition, 2012.

P. Egger and S. Nigai. Structural gravity with dummies only. Technical Report 10427, Centre for economic policy research, 2015.

P. Egger, M. Larch, K. Staub, and W. R. The trade effects of endogenous preferential trade agreements. *American Economic Journal: Economic Policy*, (113-143), 2011.

R. C. Feenstra, R. Inklaar, and M. P. Timmer. The next generation of the penn world table, 2013.

J. Frankel. *Regional trading blocks in the world economic system*. Peterson institute press, Washington (DC), 1997.

P. Guimarães and P. Portugal. A simple feasable alternative procedure to estimate models with high-dimensional fixed effects. *IZA Discussion paper*, 3935, 2009.

K. Head and T. Mayer. Gravity equations: Workhorse, toolkit, and cookbook. *Centre for Economic Policy Research*, 9322, 2013.

K. Head, T. Mayer, and J. Ries. The erosion of colonial trade linkages after independence. *Journal of International Economics*, 81(1):1–14, 2010.

C.-J. Kim and C. R. Nelson. *State-Space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications.* MIT Press, 1999.

T. Kohl, S. Brakman, and G. Garretsen. Do trade agreements stimulate international trade differently? evidence from 296 trade agreements.

G. Koop. *Bayesian Econometrics.* John Wiley & Sons, Chichester, 2003.

G. Koop and D. Korobilis. Bayesian multivariate time series methods for empirical macroeconomics. Technical Report 20125, Munich Personal Repec archive paper.

P. Krugman. The move toward free trade zones. *American Economic Review*, 87(2):387–400, 1997.

P. I. Levy. A political-economy analysis of free-trade agreements. *The American Economic Review*, 87(4):506–519, September 1997.

K. Li. Bayesian inference in a simultaneous equation model with limited dependent variables. *Journal of Econometrics*, 85:387–400, 1998.

C. Magee. Endogenous preferential trade agreements: an empirical analysis. *Contributions to Economic Analysis & policy*, 2(1):1166–1217, 2003.

L. Márquez-Ramos, I. Martínez-Zarzoso, and C. Suárez-Burguet. Determinants of deep integration: Examining socio-political factors. *Open Economic Review*, 22(3):479, September 2011.

M. Marshall, T. Gurr, and K. Jaggers. Polity IV project: Political regime characteristics and transitions, 1800-2010. Technical report, Center for systemic peace, 2014.

M. Pesaran, T. Schuermann, and S. Weiner. Modeling regional interdependencies using a global error-correcting macroeconomic model. *Journal of Business & Economic Statistics*, 22(2): 129–162, 2004.

J. Tinbergen. *Shaping the World Economy.* The Twentieth Century Fund, New York, 1962.

J. P. Wu. Measuring and explaining levels of regional economic integration. In P. De Lombaerde, editor, *Assessment and Measurement of Regional Integration*, chapter 9, pages 162–179. Routledge, 2006.

A Estimating a Qual VAR

A. Drawing the paramater values

Let $z_{ij,t}^{(k)}$ be the vector of all exogenous and lagged endogenous explanatory variables in the k^{th} equation and m the number of endogenous variables, we can write the qualitative VAR model (3) as:

$$Y_{ij,t} = c_{ij} + Z_{ij,t}\beta + \epsilon_{ij,t} \tag{23}$$

with

$$Z_{ij,t} = \begin{bmatrix} z_{ij,t}^{(1)} & 0 & \dots & 0 \\ 0 & z_{ij,t}^{(2)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & z_{ij,t}^{(m)} \end{bmatrix},$$

$Y_{ij,t} = [Y_{ij,t}^{(1)}, \dots, Y_{ij,t}^{(m)}]'$, $\beta = [\beta^{(1)}, \dots, \beta^{(m)}]'$ and $\epsilon_{ij,t} = [\epsilon_{ij,t}^{(1)}, \dots, \epsilon_{ij,t}^{(m)}]' \sim N(0, \Sigma)$.

The prior distribution of the parameters employed can be written as:

$$\beta \sim N(\underline{b}, \underline{V}_b) \tag{24}$$

$$\Sigma \sim iWish(\underline{S}, \underline{\nu}) \tag{25}$$

Using the the maximum likelihood estimates as a starting point, the Gibbs sampler progresses through the following conditional posterior probabilities (Koop and Korobilis):

1. $\beta | c_{ij}, \Sigma, RIA^{\star}, Z \sim N\left(\bar{\beta}, \bar{V}_{\beta}\right)$
   with
   $$\bar{V}_{\beta} = \left(\underline{V}_{\beta}^{-1} + \sum_{ij,t} Z'_{ij,t} \Sigma^{-1} Z_{ij,t}\right)^{-1}$$
   and
   $$\bar{\beta} = \bar{V}_{\beta}\left(\underline{V}_{\beta}^{-1}\underline{\beta} + \sum_{ij,t} Z'_{ij,t} \Sigma^{-1}(Y_{ij,t} - c_{ij})\right).$$

2. $c_{ij} | \beta, \Sigma, RIA^{\star}, Z \sim N(\bar{c}_{ij}, \bar{V}_{c_{ij}})$
   with
   $$\bar{c}_{ij} = \frac{\sum_{t=1}^{T_{ij}} (Y_{ij,t} - Z_{ij,t}\beta)}{T_{ij}}$$
   and $\bar{V}_{c_{ij}} = diag(\Sigma)/T_{ij}$. When controlling for sender-target fixed effects, T_{ij} is the number of observations covering the country-couple ij. With separate country fixed effects, it can be split up as$c_{ij} = c_i + c_j$. To estimate this step 2 is run twice: the first time grouping per sender and the second time per target (Guimarães and Portugal, 2009).

3. $\Sigma | \beta, RIA^{\star}, Z \sim iWish(S, T)$
   with
   $$S = \sum_{ij,t} (Y_{ij,t} - Z_{ij,t}\beta - c_{ij})(Y_{ij,t} - Z_{ij,t}\beta - c_{ij})'.$$
   and T the total number of observations. Σ is subsequently normalized such that the first diagonal element is one while preserving the correlation coefficients (Dueker, 2005a).

After a new value for the variance-covariance matrix is drawn, the new parameter values for Θ and Σ are used in the Kalman filter and Kalman smoother to draw new values for $RIA^{\star}$. The process is then repeated from step 1 until convergence has been achieved.

B. The adjusted Kalman filter and smoother

Unlike the estimation of the parameters Θ, the latent variable can be generated for each country-couple separately. Dropping the country indices and simplifying equations 7 and 8 reveals the familiar state-space model structure.

$$\begin{aligned} S_t &= \mu_t + F S_{t-1} + \nu_t & (26) \\ X_t &= H S_t & (27) \end{aligned}$$

with $var(\epsilon) = Q$.

Instead of having to estimate the entire model at once, the Kalman filter and smoother allows us to iteratively estimate and draw from the probability of the latent variable. Starting from $t = 0$, the Kalman filter iterates forward through time, computing the mean and variance of $RIA^\star$ at time t, conditional on all information up until that moment. After completing the Kalman filter, a standard simulation smoother algorithm can be used to draw values of $RIA^\star$ starting at the final observation and iterating backward. The end result is a new draw of the latent variable which contain all information in the dataset. These can subsequently be used to re-estimate the parameters of the qualitative VAR model. More information on the Kalman filter and simulation smoother can be found in Kim and Nelson (1999) and Durbin and Koopman (2012).

The difference with a normal Kalman filter is that the value of RIA has to be taken into account. The expected value and variance of the latent variable changes depending on whether the countries have signed an agreement or not. First, the distribution of S_t is predicted using the outcome of the previous iteration (Dueker, 2005b):

$$\begin{aligned} S_{t|t-1} &= E(S_t|S_{t-1}) = \mu_t + F\ S_{t-1|t-1} + E(\nu_t|RIA_t) & (28) \\ P_{t|t-1} &= var(S_t|S_{t-1}) = F\ P_{t-1|t-1}\ F' + var(\nu_t|RIA_t) & (29) \end{aligned}$$

Let F_1 and μ_{t_1} be the first row of matrix F and the first element of the vector μ_t. If we define $\tau = \mu_{t_1} + F_1\ S_{t|t}$ and using ϕ and Φ to denote the normal pdf and cdf, the conditional distribution of ν_t can be written as:

$$E(\nu_t|RIA_t) = a = \begin{cases} -\frac{\phi(\tau)}{\Phi(-\tau)} & \text{if } RIA_t = 0 \\ \frac{\phi(\tau)}{1-\Phi(-\tau)} & \text{if } RIA_t = 1 \end{cases} \quad (30)$$

$$var(\nu_t|RIA_t) = \begin{cases} 1 - a^2 + \frac{\tau\ \phi(\tau)}{\Phi(-\tau)} & \text{if } RIA_t = 0 \\ 1 - a^2 - \frac{\tau\ \phi(\tau)}{1-\Phi(-\tau)} & \text{if } RIA_t = 1 \end{cases} \quad (31)$$

After prediction, $RIA^\star$ is subsequently updated using the information contained in the measurement equation. The difference between the two is called the Data Forecast Error, while the weight the new information receives, κ, is the Kalman gain.

$$\begin{aligned} DFE &= X_t - H\ S_{t|t-1} & (32) \\ \kappa_t &= P_{t+1|t}\ H'(H\ P_{t|t-1}\ H')^{-1} & (33) \\ S_{t|t} &= S_{t|t-1} + \kappa_t\ DFE & (34) \\ P_{t|t} &= P_{t|t-1} - \kappa_t\ H\ P_{t|t-1} & (35) \end{aligned}$$

After the Kalman filter has completed, a normal Kalman smoother can be used to compute the distribution of $RIA^\star$ using all available information, which can be drawn from using a truncated normal distribution (Dueker, 2005b).

B List of the regional integration agreements

Table 2: List of the regional integration agreements

Andean Community of Nations	Georgia - Azerbaijan
Arab Maghreb Union (AMU)	Georgia - Kazakhstan
Armenia - Kazakhstan	Georgia - Russian Federation
Armenia - Moldova	Georgia - Turkmenistan
Armenia - Russian Federation	Georgia - Ukraine
Armenia - Turkmenistan	Guatemala - Chinese Taipei
Armenia - Ukraine	Hong Kong, China - Chile
ASEAN - Australia - New Zealand	Hong Kong, China - New Zealand
ASEAN - China	Iceland - China
ASEAN - India	Iceland - Faroe Islands
ASEAN - Japan	India - Bhutan
ASEAN - Korea, Republic of	India - Japan
ASEAN Free Trade Area (AFTA)	India - Malaysia
Australia - Chile	India - Singapore
Australia - New Zealand (ANZCERTA)	India - Sri Lanka
Australia - Papua New Guinea (PATCRA)	Indian Ocean Commission (IOC)
Brunei Darussalam - Japan	Intergovernmental Authority on Development (IGAD)
Canada - Chile	Israel - Mexico
Canada - Colombia	Japan - Australia
Canada - Costa Rica	Japan - Indonesia
Canada - Israel	Japan - Malaysia
Canada - Jordan	Japan - Mexico
Canada - Panama	Japan - Peru
Canada - Peru	Japan - Philippines
Canada - Rep. of Korea	Japan - Singapore
Caribbean community CARICOM / CARIFORUM	Japan - Switzerland
Caribbean free trade association (CARIFTA)	Japan - Thailand
Caribbean single market and economy (CSME)	Japan - Viet Nam
Central European Free Trade Agreement (CEFTA)	Jordan - Singapore
Chile - China	Korea, Republic of - Australia
Chile - Colombia	Korea, Republic of - Chile
Chile - Costa Rica (Chile - Central America)	Korea, Republic of - India
Chile - El Salvador (Chile - Central America)	Korea, Republic of - Singapore
Chile - Guatemala (Chile - Central America)	Korea, Republic of - Turkey
Chile - Honduras (Chile - Central America)	Korea, Republic of - US
Chile - Japan	Kyrgyz Republic - Armenia
Chile - Malaysia	Kyrgyz Republic - Kazakhstan
Chile - Mexico	Kyrgyz Republic - Moldova
Chile - Nicaragua (Chile - Central America)	Kyrgyz Republic - Russian Federation
China - Costa Rica	Kyrgyz Republic - Ukraine
China - Hong Kong, China	Kyrgyz Republic - Uzbekistan
China - Macao, China	Latin America Free Trade Association LAFTA / LAIA
China - New Zealand	Malaysia - Australia
China - Singapore	Mano River Union (MRU)
Colombia - Mexico	Melanisian spearhead group (MSG) trade agreement
Colombia - Northern Triangle (El Salvador, Guatemala, Honduras)	Mexico - Central America
Common Economic Zone (CEZ)	Mexico - Uruguay
Common Market for Eastern and Southern Africa (COMESA)	New Zealand - Chinese Taipei
Common market of the South (MERCUSOR)	New Zealand - Malaysia
Commonwealth of Independent States (CIS)	New Zealand - Singapore
Community of Sahel-Saharan States (CEN-SAD)	Nicaragua - Chinese Taipei
Costa Rica - Peru	North American Free Trade Agreement (NAFTA)
Costa Rica - Singapore	Pacific Island Countries Trade Agreement (PICTA)
Dominican Republic - Central America	Pakistan - China
Dominican Republic - Central America - United States Free Trade Agreement (CAFTA-DR)	Pakistan - Malaysia
East African Community (EAC)	Pakistan - Sri Lanka
Economic and Monetary Community of Central Africa (CEMAC)	Pan-Arab Free Trade Area (PAFTA)

Economic Community of Central African States (ECCAS)
Economic Community of the Great Lakes Countries (CEPGL)
Economic Community of West African States (ECOWAS)
EFTA
EFTA - Albania
EFTA - Bosnia and Herzegovina
EFTA - Canada
EFTA - Central America (Costa Rica and Panama)
EFTA - Chile
EFTA - Colombia
EFTA - Egypt
EFTA - Former Yugoslav Republic of Macedonia
EFTA - Hong Kong, China
EFTA - Israel
EFTA - Jordan
EFTA - Korea, Republic of
EFTA - Lebanon
EFTA - Mexico
EFTA - Montenegro
EFTA - Morocco
EFTA - Palestinian Authority
EFTA - Peru
EFTA - SACU
EFTA - Serbia
EFTA - Singapore
EFTA - Tunisia
EFTA - Turkey

EFTA - Ukraine
Egypt - Turkey
El Salvador- Honduras - Chinese Taipei
EU - Albania
EU - Algeria

EU - Bosnia and Herzegovina
EU - Cameroon
EU - CARIFORUM States EPA
EU - Central America
EU - Chile
EU - Colombia and Peru
EU - Cte d'Ivoire
EU - Eastern and Southern Africa States Interim EPA
EU - Egypt
EU - Faroe Islands
EU - Former Yugoslav Republic of Macedonia
EU - Georgia
EU - Iceland
EU - Israel
EU - Jordan
EU - Korea, Republic of
EU - Lebanon
EU - Mexico
EU - Montenegro
EU - Morocco
EU - Norway
EU - Overseas Countries and Territories (OCT)
EU - Palestinian Authority
EU - Papua New Guinea / Fiji
EU - Rep. of Moldova
EU - Serbia
EU - South Africa
EU - Switzerland - Liechtenstein
EU - Syria
EU - Tunisia
EU - Ukraine
Eurasian Economic Union (EAEU)
European Union (EU)
Faroe Islands - Norway

Panama - Chile

Panama - Chinese Taipei

Panama - Costa Rica (Panama - Central America)

Panama - El Salvador (Panama - Central America)
Panama - Guatemala (Panama - Central America)
Panama - Honduras (Panama - Central America)
Panama - Nicaragua (Panama - Central America)
Panama - Peru

Panama - Singapore
Peru - Chile
Peru - China
Peru - Korea, Republic of
Peru - Mexico
Peru - Singapore
Russian Federation - Azerbaijan
Russian Federation - Belarus
Russian Federation - Kazakhstan
Russian Federation - Republic of Moldova
Russian Federation - Serbia
Russian Federation - Tajikistan
Russian Federation - Turkmenistan
Russian Federation - Uzbekistan
Singapore - Australia
Singapore - Chinese Taipei
South Asian Free Trade Agreement (SAFTA)
Southern Africa Customs Union (SACU)
Southern African Development Community (SADC)
Switzerland - China
Thailand - Australia
Thailand - New Zealand
Trans-Pacific Strategic Economic Partnership
Treaty on a Free Trade Area between members of the Commonwealth of Independent States (CIS)
Turkey - Albania
Turkey - Bosnia and Herzegovina
Turkey - Chile
Turkey - Former Yugoslav Republic of Macedonia
Turkey - Georgia
Turkey - Israel
Turkey - Jordan
Turkey - Mauritius

Turkey - Montenegro
Turkey - Morocco
Turkey - Palestinian Authority
Turkey - Serbia
Turkey - Syria
Turkey - Tunisia
Ukraine - Azerbaijan
Ukraine - Belarus
Ukraine - Former Yugoslav Republic of Macedonia
Ukraine - Kazakhstan
Ukraine - Moldova
Ukraine - Montenegro
Ukraine - Russian Federation
Ukraine - Tajikistan
Ukraine - Uzbekistan
Ukraine -Turkmenistan
US - Australia
US - Bahrain
US - Chile
US - Colombia
US - Israel
US - Jordan
US - Morocco
US - Oman
US - Panama
US - Peru

Faroe Islands - Switzerland	US - Singapore
Georgia - Armenia	West African Economic and Monetary Union (UE-MOA)

C Summary statistics

Table 3: Summary statistics

Variable	Source	Obs	Mean	Std. Dev.	Min	Max
RIA	WTO	854,959	0.046	0.209	0	1
Trade	DoTS	455,521	15.029	3.602	-27.457	27.2
GDP_{av}	pwt 8.0	485,112	10.344	1.473	4.925	16.277
GDP_{diff}	pwt 8.0	485,112	2.488	1.837	$1.40e-6$	11.231
DKL	pwt 8.0	480,457	1.663	1.186	$3.59e-6$	6.184
DROWKL	pwt 8.0	480,452	1.287	0.644	0.001	4.231
Distance	CEPII	854,959	8.733	0.772	4.107	9.892
Remote	CEPII	854,959	2.179	3.835	0	9.517
Landlocked	CEPII	854,959	0.276	0.447	0	1
Contiguity	CEPII	854,959	0.019	0.137	0	1
Common language	CEPII	816,181	0.170	0.376	0	1
Colony	CEPII	816,181	0.015	0.122	0	1
Common colony	CEPII	816,181	0.115	0.319	0	1
WTO	WTO	854,959	0.341	0.474	0	1
Pol. comp	Polity IV	516188	9.900	21.810	0	98
Durability	Polity IV	514757	27.089	31.865	0	204
Autocracy	Polity IV	516188	9.391	21.120	0	98

D Reduced parameter values of the full model - World

Table 4: Reduced parameter values of the full model - World

	RIA*	st.e.	X	st.e.	DKL	st.e.	GDP$_{diff}$	st.e.	GDP$_{av}$	st.e.
L1.RIA*	0.8751^a	(0.0781)	-0.0024	(0.0023)	-0.0046^a	(0.0019)	0.0006	(0.0004)	0.0002	(0.0005)
L2.RIA*	-0.0045	(0.0140)	0.0008	(0.0008)	-0.0003	(0.0004)	0.0001	(0.0002)	0.0001	(0.0002)
L3.RIA*	-0.0019	(0.0082)	0.0001	(0.0006)	0.0004	(0.0004)	-0.0000	(0.0002)	0.0003	(0.0003)
L1.X	0.0023	(0.0026)	0.8811^a	(0.0008)	-0.0005^a	(0.0002)	0.0012^a	(0.0001)	0.0007^a	(0.0002)
L2.X	0.0005	(0.0006)	0.0058^a	(0.0005)	-0.0001	(0.0001)	0.0005^a	(0.0001)	-0.0012^a	(0.0002)
L3.X	0.0003	(0.0003)	0.0031^a	(0.0003)	-0.0001	(0.0001)	0.0002^a	(0.0001)	-0.0004^a	(0.0001)
L1.DKL	-0.0454^a	(0.0197)	-0.0125^a	(0.0036)	0.9783^a	(0.0023)	0.0008	(0.0009)	-0.0116^a	(0.0015)
L2.DKL	-0.0105^a	(0.0044)	-0.0038^b	(0.0022)	0.0043^a	(0.0005)	0.0003	(0.0006)	0.0048^a	(0.0011)
L3.DKL	-0.0046^a	(0.0017)	-0.0016	(0.0015)	-0.0023^a	(0.0003)	0.0001	(0.0004)	0.0055^a	(0.0009)
L1.GDP$_{diff}$	-0.0056	(0.0060)	-0.0357^a	(0.0024)	0.0027^a	(0.0004)	0.9715^a	(0.0006)	-0.0013	(0.0009)
L2.GDP$_{diff}$	-0.0014	(0.0017)	-0.0086^a	(0.0016)	-0.0002	(0.0003)	0.0123^a	(0.0004)	-0.0027^a	(0.0008)
L3.GDP$_{diff}$	-0.0006	(0.0009)	-0.0037^a	(0.0011)	-0.0003^b	(0.0002)	0.0044^a	(0.0003)	-0.0036^a	(0.0005)
L1.GDP$_{av}$	0.0018	(0.0041)	0.0131^a	(0.0015)	-0.0006	(0.0005)	0.0072^a	(0.0004)	0.9586^a	(0.0008)
L2.GDP$_{av}$	0.0005	(0.0011)	0.0032^a	(0.0008)	-0.0001	(0.0002)	0.0017^a	(0.0002)	0.0088^a	(0.0005)
L3.GDP$_{av}$	0.0002	(0.0005)	0.0015^a	(0.0004)	-0.0000	(0.0001)	0.0007^a	(0.0001)	0.0027^a	(0.0003)
Distance	-0.5075^a	(0.1534)	-0.0926^a	(0.0049)	-0.0099^a	(0.0028)	0.0101^a	(0.0008)	0.0139^a	(0.0007)
DROWKL	1.7331^a	(0.2874)	0.1956^a	(0.0187)	0.0455^a	(0.0070)	-0.0564^a	(0.0027)	0.0239^a	(0.0019)
Landlocked	-0.3718^b	(0.2343)	-0.0053	(0.0189)	-0.0013	(0.0030)	-0.0167^a	(0.0023)	0.0121^a	(0.0012)
Remote	0.0338^a	(0.0364)	0.0089^a	(0.0012)	-0.0010^a	(0.0003)	-0.0003^c	(0.0002)	0.0014^a	(0.0001)
Contiguous	-0.0666	(0.2311)	0.1291^a	(0.0130)	-0.0073^a	(0.0024)	-0.0020	(0.0017)	0.0105^a	(0.0011)
Colony	0.0020	(0.0800)	0.1448^a	(0.0181)	0.0044^b	(0.0023)	0.0070^a	(0.0023)	-0.0027^c	(0.0015)
Common Colony	0.4354^b	(0.1199)	0.1360^a	(0.0121)	-0.0001	(0.0022)	-0.0247^a	(0.0018)	0.0043^a	(0.0010)
Language	0.1287^a	(0.1223)	0.0551^a	(0.0086)	0.0017	(0.0011)	-0.0040^a	(0.0012)	-0.0017^a	(0.0006)
WTO	1.0482^a	(0.4330)	0.1876^a	(0.0103)	0.0045^c	(0.0024)	-0.0292^a	(0.0015)	0.0245^a	(0.0008)
Autocracy	0.0227^a	(0.0150)	-0.0024^c	(0.0013)	0.0009^a	(0.0002)	0.0011^a	(0.0002)	-0.0012^a	(0.0001)
Pol. comp	-0.0230^a	(0.0138)	0.0016	(0.0012)	-0.0007^a	(0.0002)	-0.0006^a	(0.0002)	0.0008^a	(0.0001)
Durability	0.0077^a	(0.0030)	0.0008^a	(0.0001)	0.0001^a	(0.0000)	-0.0001^a	(0.0000)	0.0001^a	(0.0000)
	1669741		1669741		1669741		1669741		1669741	
	sender & target		sender & target		sender & target		sender & target		sender & target	

Reduced parameter estimates of the full, worldwide qualitative VAR model with three lags.
Standard errors between brackets. ^{a}, ^{b} and ^{c} indicate significance at the 1%, 5% and 10% level.